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A scheduling scheme in the cloud computing environment using deep Q-learning

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A B S T R A C T

Task scheduling, which plays a vital role in cloud computing, is a critical factor that determines the performance of cloud computing. From the booming economy of information processing to the increasing need of quality of service (QoS) in the business of networking, the dynamic task-scheduling problem has attracted worldwide attention. Due to its complexity, task scheduling has been defined and classified as an NP-hard problem. Additionally, most dynamic online task scheduling often manages tasks in a complex environment, which makes it even more challenging to balance and satisfy the benefits of each aspect of cloud computing. In this paper, we propose a novel artificial intelligence algorithm, called deep Q-learning task scheduling (DQTS), that combines the advantages of the Q-learning algorithm and a deep neural network. This new approach is aimed at solving the problem of handling directed acyclic graph (DAG) tasks in a cloud computing environment. The essential idea of our approach uses the popular deep Q-learning (DQL) method in task scheduling, where fundamental model learning is primarily inspired by DQL. Based on developments in WorkflowSim, experiments are conducted that comparatively consider the variance of makespan and load balance in task scheduling. Both simulation and real-life experiments are conducted to verify the efficiency of optimization and learning abilities in DQTS. The result shows that when compared with several standard algorithms precoded in WorkflowSim, DQTS has advantages regarding learning ability, containment, and scalability. In this paper, we have successfully developed a new method for task scheduling in cloud computing.

1. Introduction

Currently, scientific computing and e-commerce applications are coherent models with interrelated tasks that can be described as models of workflow, and these dependent tasks can be decomposed into tens of thousands of small tasks, depending on the application complexity. The workflow model is extensively applied to represent these applications via DAG, in which its nodes represent tasks, and its directed edges represent dependencies as in precedence task relations [1]. These large-scale workflow applications are deployed in the cloud computing environment rather than the traditional distribution

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system for a shorter task execution time. None of the current approaches or methods can singly fulfill task scheduling due to its unique characteristics. Specifically, guided random search-based scheduling is a new computing paradigm with robust capability for solving task-scheduling problems. However, such stochastic algorithms have drawbacks, such as creating considerable time complexity and contending with the dynamic cloud environment and its miscellaneous complications that have made it even more unadaptable.

With the development of artificial intelligence, researchers now use stochastic algorithms such as the genetic algorithm (GA) [2] to optimize the weight and threshold of back-propagation (BP) neural networks. This approach is used to solve the problem of performing a task under multiplex conditions with unknown properties, where an agent is particularly needed. Nevertheless, it is difficult to train a BP neural network without an obtainable training set from a complex environment with indeterminable factors. Obviously, an agent is a correct action performed by an intelligent object trying to complete a task. The action of an object in any given environment can be described as the process of the model's decision making, called Markov decision processes (MDPs) [3].

The indeterminate nature of the cloud computing environment poses challenges to finding a proper algorithm for the solution because of the typical phenomenon of randomness that accompanies task execution time. Although objective function is explicit to an equation or a value, the computing resource is dynamic, and feedback regarding the action of an object in the scheduler is uncertain. In other words, a stochastic algorithm can hardly solve this random state process due to the unclear objective function. Reinforcement learning methods, such as *Q*-learning [4], are more reliable because a discounted future reward is obtained when transiting from one state to another. Based on the foundation of MDP theory, *Q*-learning is a useful and meaningful method for solving problems of agent actions under different complicated conditions. However, in *Q*-learning, as the number of object states increases, the table matrix of the state action set in *Q*-learning becomes too large to store and perform the search. With widely used BP neural networks, this problem is solved with a more concise and accurate table matrix, and this approach is applied by more researchers.

Recently, the environment in dynamic decision-making is becoming more and more complex for a large number of alternatives, high time constraints and uncertainty decision. However, the simple task that consisted of decision process is simple that with less properties and constraints. Simple tasks can also have dynamic complexity in the continuous time strategy. RL algorithms advance modeling in a continuous dynamic and complexity environment, using RL algorithms for dynamic decision making has become a new research direction [5]. RL is highly effective in dynamic dispatch optimization problems [6]. Recent works present deep reinforcement learning as a framework to model the complex interactions and cooperation in dynamic decision-making environments. Yang et al. [7,8] have done multi researches on DRL in decision-making with the subject of Deep Multi-agent Reinforcement Learning (RDMRL). Wang et al. [9] applied deep reinforcement learning to dynamic resource scheduling for network slicing, and dynamically adjust the resources allocated to each slice through interaction with network environment. Grag et al. [10] proposed a traffic light control strategy based on the deep reinforcement learning method to solve the congestion problem near the road intersections. Google's DeepMind applied a deep *Q*-network (DQN) [11] to train agents in a convolutional neural network (CNN) that acquired only image pixels of games and successfully surpassed human-level skill. This method has also provided new approaches to autonomous driving, artificial intelligence, big data analysis, and so on. Motivated by this method, we implement the deep *Q*-learning method to complete jobs in task scheduling accurately and to verify the adaptability in a more complex environment, such as in the elastic cloud environment and online task scheduling.

In this paper, we propose a novel artificial intelligent workflow-scheduling algorithm, called deep *Q*-learning task scheduling (DQTS). This new approach combines a back-propagation network and *Q*-learning algorithm for their respective advantages in obtaining less makespan of workflow in the cloud computing environment and achieving the best load balance in each computing node. The main contribution of this paper is as follows:

- We propose a training algorithm along with a training set defined in a dynamic online task-scheduling problem and illustrate the structure of the DQTS algorithm in the cloud computing environment, defining the cloud model, task model, and scheduling architecture.
- We design the program framework, forward the model using cross-platform implementation, optimize hyperparameters within programs and implement the DQTS algorithm for dependent workflow task scheduling.
- We implement the entropy weight method to the principle design of a bi-objective optimization problem (including makespan and load balance) and apply the novel DQTS algorithm to produce a high-quality solution in dynamic cloud computing.
- We assess the algorithm performance using WorkflowSim and compare it with different workflow benchmarks (including CyberShake_2000, Inspiral_2000, Montage_2000 and Sipht_2000). The results show that our algorithm improves the performance both in makespan and load balance.

The rest of this paper is organized as follows. Section 2 presents the related work on scheduling algorithms in the cloud computing environment. Section 3 describes the cloud computing environment, task model, and scheduling structure. Section 4 explains the main content of DQTS, with the theory and design principle. Section 5 compares the performance of the proposed algorithm with existing classic algorithms and analyzes the experimental results. Section 6 concludes the paper and introduces directions for future work.

2. Related work

Task scheduling is a well-known NP-hard problem since an efficient polynomial-time algorithm does not exist; consequently, a considerable number of artificial intelligence algorithms have been proposed to obtain a suboptimal solution. Furthermore, these algorithms commonly focus on minimizing the execution time, called makespan. There are three typical scheduling algorithms that have been proposed: the list-scheduling algorithm, clustering-scheduling algorithm, and duplication-scheduling algorithm. Among them, the list-scheduling algorithm is the most widely used heuristic algorithm, and the classic list-based heuristics-scheduling algorithm implements features that include heterogeneous earliest finish time (HEFT) [12], stochastic dynamic-level scheduling (SDLS) [13], predicted earliest finish time (PEFT) [14], and improved predicted earliest finish time (IPEFT) [15]. Commonly, these algorithms accomplish scheduling in two steps: first, constructing a sequence of tasks by assigned task priorities, and second, sequentially allocating each task from the sequence to computing nodes that allow for the earliest start time. Clustering heuristics algorithms map all tasks with an indefinite quantity to different clusters [16]. In contrast to list-scheduling heuristics, clustering heuristics algorithms require a second phase to schedule task clusters to the processors. Under these conditions, only a sufficient number of processors can result in an advantage, which is impractical in practice. Typical clustering heuristics algorithms include techniques of dominant sequence clustering (DSC) [17], task duplication-based scheduling (TDS) [18], and heterogeneous selection value (HSV) [19]. The duplication-scheduling algorithm can efficiently reduce the makespan of scheduling DAG tasks when the communication cost is significant, that is, the duplication method can effectively reduce or avoid interprocessor communication. Many algorithms have been proposed to incorporate this technique into scheduling [20,21]. Bozdag et al. [22] addressed the problem of scheduling that requires a prohibitively large number of processors, proposing a combination of the SDS and SC algorithms to obtain a two-stage scheduling algorithm that produces schedules with high quality and low processor requirements. However, for computation-intensive tasks, the performance of these algorithms is not significant. In recent years, most researchers are studying grids, clusters and other typical heterogeneously distributed computing environments, and task scheduling is performed for only a fixed number of resources. In contrast to the cloud computing environment, cloud service providers often offer a better and scalable resource, and the tasks accepted are also arranged differently according to their variance and type.

In the cloud computing environment, some related work on workflow scheduling strategies research is presented. For instance, Teylo et al. [23] proposed a new workflow representation, in which nodes of the workflow graph represent either tasks or data files, the edges of the workflow graph represent their relationship, and this workflow defines the task-scheduling and data assignment problem as a new model. It is worth noting that they also formulated this problem as an integer-programming problem. Wang et al. [24] presented a solution, the objective of which is to minimize the data transfer of workflows allocated in multiple data centers. In this way, the purpose of reducing communication between nodes can be achieved. To this end, his work defined the initial data locality by using the *k*-means clustering algorithm. Arabnejad and Barbosa [25] proposed the multi-QoS profit-aware scheduling algorithm and achieved good adaptability by studying the scalability of the algorithm with different types of workflows and infrastructures. The experimental results proved that their strategies improved cloud provider revenue significantly and obtained comparably successful rates of completed jobs. Zhao and Sakellariou [26] proposed the merging of multiple workflow applications into a single DAG workflow, and by using this method, the job can be finished through any traditional DAG scheduling algorithms to minimize the total makespan and achieve overall fairness. This approach is formulated and resolved based on issues of competition in resources with multiple other DAGs. Kanemitsu et al. [27] proposed a prior node-selection algorithm (LBCNS) to select a subset of given nodes to minimize the schedule length while fairly scheduling each job. The experimental results show that their algorithms have the best fairness for scheduling multiple workflow jobs, while the priority-based approach achieves the minimum schedule length with the highest efficiency for single- or multiple-workflow jobs. Chen et al. [28] proposed a scheduling algorithm incorporating both event-driven and periodic rolling strategies for dynamic workflow scheduling. The experimental results show that their proposed algorithm performs better than classic algorithms. Zhang et al. [29] proposed a novel reliability maximization with energy constraint (RMEC) algorithm that incorporates three important phases, including task priority establishment, frequency selection, and processor assignment, and the RMEC algorithm can effectively balance the tradeoff between high reliability and energy consumption. Based on both randomly generated task graphs and the graphs of some real-world applications, the result shows that RMEC surpasses the existing algorithms. Wei et al. [30] proposed an intelligent QoS-aware job-scheduling framework for application providers, which learns to make appropriate online job-to-VM decisions for continuous job requests directly from its experiences without any prior knowledge. The experiment uses the real-world NASA workload traces, and the results show that the algorithm reduced the average job response time to 40.4 compared with the best baseline for NASA traces. Zhang et al. [31] proposed an energy efficient scheduling scheme based on deep Q-learning model for periodic tasks in real-time systems (DQL-EES). The especial feature is the paper combining a stacked auto-encoder in the deep *q*-learning model to replace the *Q*-function for learning the Q-value of each DVFS technology for any system state.

Jiang et al. [32] proposed a corresponding algorithm that cooperates with a dynamic-voltage and frequency-scaling (DVFS) technique to address the above concern and evaluated the algorithm in terms of randomly generated DAGs, real-application DAGs and their hybrids under DVFS-enabled HCS. However, these scenarios, in general, are designed for a single application that is not suitable for a dynamic cloud environment, where a large number of workflows will be submitted from time to time. In addition, these complex environments have made task scheduling a difficult problem.

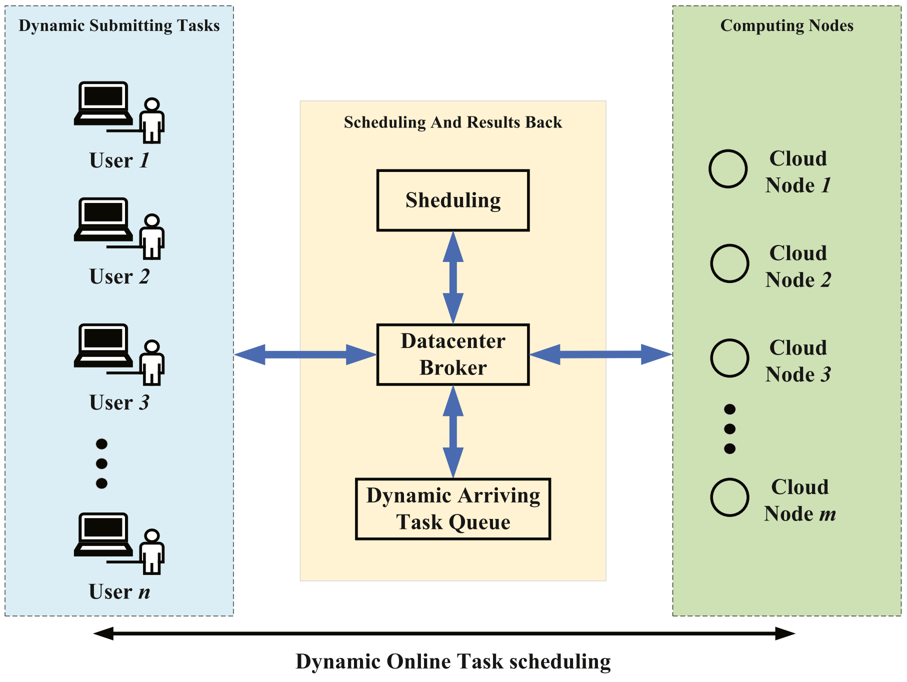


Fig. 1. Model of task scheduling in cloud computing.

To the best of the authors' knowledge, the approach proposed in this article is the first to use a deep Q-learning algorithm to solve the workflow problem. In this way, we can consider both problems together by proposing a model as well as an algorithm to minimize the makespan and find the best load balance of workflows in cloud environments. Our approach takes into account different process capacities of the computing node, task execution time and data transfer time in these cloud computing environments. The following section formulates the problems that are considered in this article.

3. System architecture and problem description

In this section, we first define the task model and model of cloud computing corresponding to the task-scheduling scheme. Second, we propose the deep Q-learning scheduling architecture for the cloud environment and explain approaches to obtain the training set for this model, the architecture of DQTS in WorkflowSim, and the neural network structure used in this paper. Accordingly, we formulate the task-scheduling problem.

3.1. Cloud computing model

In cloud computing, tasks submitted by a user are allocated to cloud nodes based on the scheduling strategy. Therefore, a proper selection of the scheduling strategy is vital for an optimal task completion time. Fig. 1 illustrates the model of online dynamic task scheduling for a typical cloud computing scenario, in which users can submit their tasks at any time. In this case, a task dynamically arrives at the task queue after user submission. The data center broker, depending on different requirements such as makespan, load balance, economic principle, etc., selects the best scheduling strategy to allocate the task to the computing nodes. In this paper, tasks are dynamically submitted to the scheduler by users, and the number of tasks and types is unknown before they arrive at the task queue. We aim for the optimal distribution strategy to the cloud nodes. Meanwhile, it is assumed that the tasks submitted to the scheduler are nonpreemptive. The computing nodes are heterogeneous and scalable, but the bandwidth is the same.

3.2. Task model

The task model can be divided into the dependent task and independent task. Moreover, an independent task model has the relationship of tasks such that they are independent and do not require any communication. Therefore, to achieve a faster scheduling target, tasks can be preempted. Additionally, this kind of task scheduling is easy to implement. Generally, dependent task scheduling models are composed of a set of dependent tasks and an interconnected processor. The dependency of data and order of execution can be represented by a DAG. Therefore, the DAG scheduling model can be defined as a quaternion:

$$G = (T, E, C, W) \tag{1}$$

Table 1
Commonly used terms in DAG scheduling.

Notation	Definition
t_i	task node
w_i	entropy weight
n	total number of virtual machines
m_i	current task-processing time of each virtual machine
l_i	accumulated processing time of each virtual machine
$Pred(t_i)$	the predecessor set of node t_i
$Succ(t_i)$	the successor set of node t_i
$IL(t_i)$	the level of node t_i
P^k	no. k processor
$ST(t_i: p^k)$	the start time of task t_i on processor p^k
$FT(t_i: p^k)$	the completion time of task t_i on processor p^k
$EFT(t_i)$	the earliest completion time of the task

where $T = \{t_i|i = 1, 2, \ldots, n\}$, denotes the collection of n task nodes. $|T| = n$ corresponds to the vertices in the DAG. Each node in the DAG represents a task of a parallel program. It is usually a code or instruction in the program and is the smallest unit of task scheduling; it cannot be preempted. The directional edges in the DAG $\{E_{ij} = e(i, j)\} \in E$ denote the relationship between task t_i and t_j. When task t_i is implemented, the results of t_i must be passed to t_j. Therefore, we also call task t_i the predecessor of task t_j (parent node), and task t_j is the successor of task t_i (child node). The weight of the directed edge is defined as $c(i, j) \in C$, which represents the communication cost between task t_i and task t_j. However, a communication cost is only required when two tasks are assigned to different computing nodes. Therefore, the communication cost can be ignored when tasks are assigned to the same node. The weight on a task t_i is denoted as $w_i \in W$, which represents the computation cost of the task. Commonly used terms in DAG scheduling are shown in the Table 1.

Some of the definitions in DAG scheduling are as follows:

Definition 1. The set of all parent nodes of node t_i is called the parent node set of t_i and is denoted by $pred(t_i)$. The set of all child nodes of node t_i is called the child node set of t_i and is denoted by $succ(t_i)$.

Additionally, if a node does not have any parent nodes, it is called an entry node, denoted by t_{entry}. If a node does not have any child nodes, it is called an exit node, denoted by t_{exit}. If there are multiple entry nodes in a DAG, it is necessary to add a virtual entry node to the DAG. This node has zero cost on each processor, and all real entry nodes are connected to the virtual entry node by a directed edge with zero communication weight. Similarly, if there are multiple exit nodes in a DAG, it is necessary to add a virtual exit node to the DAG. This node has zero cost on each processor, and all real exit nodes are connected to the virtual exit node by a directed edge with zero weight. This approach ensures that the DAG contains only one entry node and one exit node and guarantees the equivalency of the DAG.

Definition 2. When processor p^k has just started a task or completed a task and becomes idle, the time is called the processor idle time, denoted by $AT(p^k)$.

Definition 3. The start time of task t_i on processor p^k is denoted as $ST(t_i: p^k)$:

$$\begin{aligned} ST(t_i : p^k) = \max\Big(&max_{t\,j\in pred(t_i)}(FT(t_j : p^l) \\ &+ C(E_{ji})/W(p^l, p^k)), AT(p^k)\Big) \end{aligned} \tag{2}$$

where $FT(t_j: p^l)$ is the completion time of task t_j on processor p^l, $t_j \in pred(t_i)$. $W(p^l, p^k)$ represents the communication rate between processor p^l and processor p^k. If $l = k$, then task t_i and its parent task t_j are assigned to the same processor, and the communication cost between them is zero.

Definition 4. The completion time of task t_i on processor p^k is denoted as $FT(t_j: p^k)$:

$$FT(t_i : p^k) = ST(t_i : p^k) + W(t_i : p^k) \tag{3}$$

Definition 5. The earliest execution time of task t_i on processor p^k represents the earliest start time, denoted as $EST(t_i)$:

$$EST(t_i, p^j) = \max\{avail_j, \max(AFT(t_k) + c(t_k, p^j))\},\ t_k \in pred(t_i) \tag{4}$$

where $avail_j$ represents the earliest time to prepare for task execution of processor p^j. $AFT(t_k)$ denotes the actual completion time. EST is calculated from t_{entry}. Thus, the earliest start time of task t_{entry} is $EST_{entry,p^j} = 0$.

3.3. Problem description

In general, the task-scheduling problem is considered the assignment and execution of tasks under QoS requirements. In the QoS requirements, we considered two aspects of task scheduling, including reaching the minimum makespan of task scheduling in cloud computing and a simple load-balance policy of total time per processor processed. To merge the two objectives into a reward value to accommodate *Q*-learning, we used weights for the expression. In this paper, we use the entropy weight method (EWM) to compute task feedback. Entropy is a measure of the disorder of a system. If the information entropy of the variable is smaller, the more information the variate provides, the larger the role it plays in the comprehensive evaluation, and the higher the weight should be. Therefore, the tool of information entropy can be used to calculate the weight of each variable to provide a basis for the comprehensive evaluation of multiple variables [33]. The task execution size and the processing time are two different types of data, and their quantitative properties vary widely [34]; therefore, to settle this problem, they must first be normalized to the feedback. The current task-processing time of each virtual machine is $m_i(i = 1, 2, \ldots, n)$, and the number of virtual machines is n. In addition, we use $l_i(i = 1, 2, \ldots, n)$ to express the current accumulated processed time of each virtual machine. Then, we define the normalized matrix $N_{i,j} = \{n_{i,j};\ i = 1, 2, \ldots, n;\ j = 1, 2\}$. The step of the entropy method is as follows:

1. The normalization matrix is normalized for each criterion $N_{i,j}(j = 1, 2)$. The normalized values $n_{i,j}$ are calculated using Eqs. (5)-(6):

$$n_{i,1} = 1 - \frac{l_i - \min l}{\max l - \min l} \tag{5}$$

$$n_{i,2} = 1 - \frac{m_i - \min m}{\max m - \min m} \tag{6}$$

2. The proportion of each column of each criterion $n_{i,j}(i = 1, 2, \ldots, n)$ is calculated using Eq. (7):

$$H_{i,j} = \frac{n_{i,j}}{\sum_{i=1}^{n} n_{i,j}} \tag{7}$$

3. The entropy E_j of each criterion N_j can be found in Eq. (8):

$$E_j = -(\ln(n))^{-1} \sum_{i=1}^{n} H_{i,j} \ln\left(H_{i,j}\right) \tag{8}$$

4. The entropy weight w_j of each objective value can be found in Eq. (9):

$$w_j = \frac{1 - E_j}{2 - E_1 - E_2} \tag{9}$$

5. Finally, we can obtain the input vector and the state of NN can be found in Eq. (10):

$$input[i] = w_1 \times n_{i,1} + w_2 \times n_{i,2} \tag{10}$$

In the end, we can obtain the total processing time for each virtual machine and makespan when all of the tasks are completed. To evaluate the load-balance degree, we calculate the standard total processing time of each virtual machine.

4. Description and design of scheduling

In this section, we first describe the Markov decision processes and one of the reinforcement learning technologies, *Q*-learning. Second, we introduce the deep *Q*-learning and the design principle for using the deep *Q*-learning algorithm to solve the task-scheduling problem in the cloud computing environment.

4.1. Markov decision processes and Q-learning

Markov decision processes (MDPs) are widely used to provide a mathematical framework for modeling decision making to solve stochastic sequential decision problems, in situations where an outcome is partly random and partly under the control of the decision maker. The MDPs' goal is to find an optimal policy that will maximize the expected return from a sequence of actions that leads to a sequence of states. The expected return can be defined as a policy function that calculates the sum of the discounted rewards. The goal of finitely satisfying the Markov property in reinforcement learning is to form a state transition matrix that consists of each possibility of transitioning to the next state from a given state. In *Q*-learning, the state transition process is an important step to train the model of the neural network for optimal classification in action selection, and this process can be denoted as an agent to the environment finding the best policy. During this process, a reward signal is produced as a measurement of the agent's current behavior, and the reward value is backfed to the agent, adjusting the policy to find the optimal selection. The agent aims to find the maximum return on the sum of discounted rewards with respect to different iteration time steps. In each time step, the reward to the current state is calculated from expected discounted sum rewards of future steps, where all future rewards are weighted by a discounted factor. Specifically, a reward in the time step close to the current one is weighted more, as it is worth more, and conversely, a farther time step reward is weighted less. In this way, the possibility of a state to an action can be defined under a discounted reward calculation, and consequently, discrete state-action pairs formulate the state transition matrix. To measure the evaluation of the agent's behavior, a value function is needed, which is another important MDP to determine the long-term reward, starting from the given state and calculated by the discounted return value of successor states and immediate rewards. The value function can be regarded as one of the main factors to influence the state-transition probabilities. Lastly, the optimal state-value function calculates the maximum value function overall policies to find the best performance policy. In conclusion, MDPs have been a useful approach for studying a wide range of optimization problems solved via dynamic programming and reinforcement learning. A Markov decision process is a 5-tuple (S, A, $P_.(\cdot, \cdot)$, $R_.(\cdot, \cdot)$, and γ), where

- S is a finite set of states;
- A is a finite set of actions (alternatively, A_s is the finite set of actions available from states s;
- $P_a(s, s')=\Pr(s_{t+1} = s'|s_t = s, a_t = a)$ is the probability that action a in state s at time t will lead to state s' at time $t+1$;
- $R_a(s, s')$ is the immediate reward (or expected immediate reward) received after transitioning from state s to state s', due to action a; and
- $\gamma \in [0, 1]$ is the discount factor, which represents the difference in importance between future rewards and present rewards.

Q-learning is a model-less reinforcement learning technique, and its implementation is similar to the MDP strategy. Specifically, Q-learning can be used to find the best behavior choice for any given (finite) MDP. The working principle of Q-learning is to learn an action value function and give the final expected result. The algorithm performs in a specified operation with a given state and follows the optimal strategy. A policy is a rule that the agent follows when selecting an action by taking into account the state it is in. When such an operation value function is learned, the optimal strategy can be constructed by selecting the maximum number of operations in each state. One of the advantages of Q-learning is that it can compare with the expected result to know available operations without any environmental model. Additionally, Q-learning can address problems such as random conversion and rewards without any modification and proves that by any of the algorithms in finite MDPs, Q-learning can ultimately find an optimal strategy. In this way, all consecutive steps with a total return of expected values starting from the current state can achieve the maximum return [35]. The model consists of an agent, a state S, and a set of actions for each state A. The model stores all the information in a Q-table, which represents the Q-value between different states. Using the policy declared in MDPs and performing an action $a \in A$, the agent can move from one state to another. Performing an action in a given state provides a reward for the agent. The goal of this agent is to maximize the total reward on Q-value. Moreover, as a result, the algorithm learns which action is optimal for each state. In addition, for every state, the best behavior is the behavior with the highest long-term reward. In Q-learning, we can obtain the reward using the same process as in MDPs, which is the weighted sum of the expected return value from the current state and all the steps in the future, where step Δt calculates the weight of the future step $\gamma^{\Delta t}$. In this case, the value of γ is a number between 0 and 1, which is called the discount factor, and the importance of early and late rewards is a tradeoff. γ can also be interpreted as the probability of success at each step Δt. Q-learning is considered one of the machine learning algorithms that can obtain the best strategy π^* when the task class and size are unknown. A state-action function, i.e., Q-function, is defined as Eq. (11):

$$Q^{\pi}(x, a) = R(x, a) + \epsilon \sum_{x' \in X} P_{xx'}(a) V^{\pi}(x') \tag{11}$$

such that when a is executed in state x, it represents a cumulative discounting reward. Starting at this point, a continues to execute the optimal policy. The maximum Q-value will be

$$Q^{\pi^*}(x, a) = R(x, a) + \epsilon \sum_{x' \in X} P_{xx'}(a) V^{\pi^*}(x') \tag{12}$$

and the discounted cumulative state function can be written as Eq. (13):

$$V^{\pi^*}(x) = \max_{a \in A}[Q^{\pi^*}(x, a)] \tag{13}$$

Therefore, from finding the best strategy to finding the right Q-function, the target is usually interchangeable. Generally, the Q-function is obtained by recursion using available information (x, a, x', and a'). Specifically, state x, immediate reward r and action a at the current time t are used to calculate state x' and action a' at time $t+1$. Therefore, the Q-function can be updated to

$$Q_{t+1}(x, a) = Q_t(x, a)' + a\left(r + \epsilon\left[\max_{a'} Q_t(x', a')\right] - Q_t(x, a)\right) \tag{14}$$

where a is the learning rate, and the discount factor ϵ is one of the most important parameters in the learning process. The learning rate determines to what extent newly acquired information can override old information. A factor of 0 makes the agent learn nothing, while a factor of 1 makes the agent consider only the most recent information. By utilizing a proper learning rate, it is certain that $Q_t(x, a)$ will converge to $Q^*(x, a)$ [36]. Therefore, the algorithm has a function that calculates the quality of a state-action combination as follows:

$$Q : S \times A \to \mathbb{R} \tag{15}$$

The standard steps in the Q-learning algorithm [4] are shown in Algorithm 1.

Algorithm 1: Q-learning algorithm.

```
Input: Random state process
Output: Q-table
Initialize $Q(s,a)$ arbitrarily;
repeat
    Initialize state $s$;
    Choose action $a$ from $s$ using the policy derived from $Q(e.g., \varepsilon - greedy, \varepsilon \in (0,1))$;
    Take action $a$, and observe $r, s'$;
    Update $Q(s,a)$ with Equation (14);
    $s \leftarrow s'$;
until end(s = terminal);
```

4.2. Schedulers with deep Q-learning

In fact, the Q-function is usually estimated by a function approximator. Several kinds of approximators can be used to approximate [37–39]. The approximators sometimes is nonlinear, such as a neural network (NN) $Q(x,\ a;\ \theta) \approx Q^*(x,\ a)$. This neural network is named the Q-network. The parameter θ is the weight of the neural network, which reduces the mean square error by adjusting θ in each iteration.However, there are some unstable situations in the actual application of the Q-network, which are explained in [11]. In deep Q-learning, the deep neural network is used to approximate the Q-function, which has recently been proposed and proven to be more beneficial than Q-learning. In this case, we modify the regular Q-learning for deep Q-learning with the following two techniques:

1. Experience replay. At each instant time t, the agent stores its interaction experience tuple $e(t) = (x(t), a(t), r(t), x(t+1))$ into a replay memory $D(t) = \{e(1), \ldots, e(t)\}$. Then, the parameters of the deep neural network are trained by random sampling in the pool of experience rather than directly using continuous samples to participate in the training, as in the study of Q-learning. In this way, the learning speed is accelerated.
2. Periodical update. Deep Q-learning adjusts the target value to update after every N time steps, instead of updating each time step. The target value is expressed as $y = r + \epsilon \max_{a'} Q(x', a', \theta_i^-)$. In Q-learning, the weight θ_i^- is updated as $\theta_i^- = \theta_{i-1}$, whereas in deep Q-learning, $\theta_i^- = \theta_{i-N}$, i.e., the weights update every N time steps. Using such modifications can make the learning process more stable.

The Q-value of the current state can be calculated by Eq. (16),

$$Q(x, a, \theta) = NN_{output} \times a_{hotindex} \tag{16}$$

where NN_output means the value of neural network output, and $a\_hotindex$ is the action of the current state in the form of replaying the memory as in the hot index (all values in a vector are 0 except for the real action value of 1). The deep Q-learning training function minimizes the value of the loss function in each iteration, and the loss function can be written as

$$Loss(\theta) = E\left[(y - Q(x, a, \theta))^2\right] \tag{17}$$

The DRL technique in cloud computing is a recently proposed technology that has been applied in task scheduling [11,40]. The system construction process is broadly similar to the process of Q-learning. To use the deep Q-learning algorithm in task scheduling, the specific training set is required in neural network training. Every state with dynamic resource changing is saved as a reward into the training set. Specifically, the task queue retrieves the least recent task generates state s, which represents the current network state condition. The action a defines a selection of choice that is taken from the random scheduling of tasks, which generates state s', and in an optimal policy, accumulates in a progressive and iterative manner. The rewards principle is a key factor to convergence with the neural network. It will effectively reach the preset objective function if a good reward principle for every state's change is designed. After taking action a in state s, an immediate reward r is generated to the neural network. Moreover, the action a, which is taken from random scheduling and noted as interaction experience, is sent to replay for training. The model to obtain the training set is illustrated in Fig. 2.

4.3. Scheduling architecture of DQTS

In this paper, we design a deep Q-learning algorithm architecture for the cloud computing environment, as shown in Fig. 3. The workflow, as indicated, is considerably referenced by a typical scientific computing scenario, where task submission is commonly associated with dynamic schedules. Most significantly, this workflow assigns tasks that are dynamically allocated to ensure maximum efficiency. A resource dynamic adjustment controller is used in this design to constantly refresh the available cloud computing resource, which ensures the effectiveness of the scheduling. All types of workflow tasks consist of a task pool that is waiting to be processed. Workflow will be addressed as follows. First, tasks of the dependent

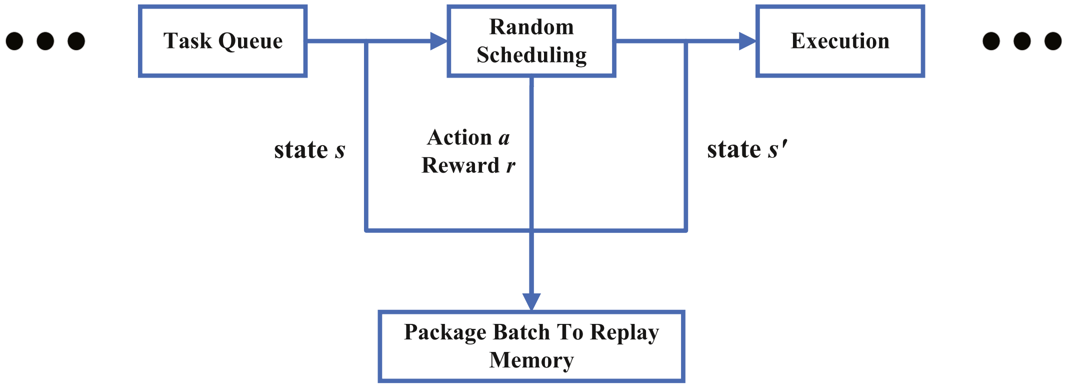


Fig. 2. Random scheduling to obtain the training set.

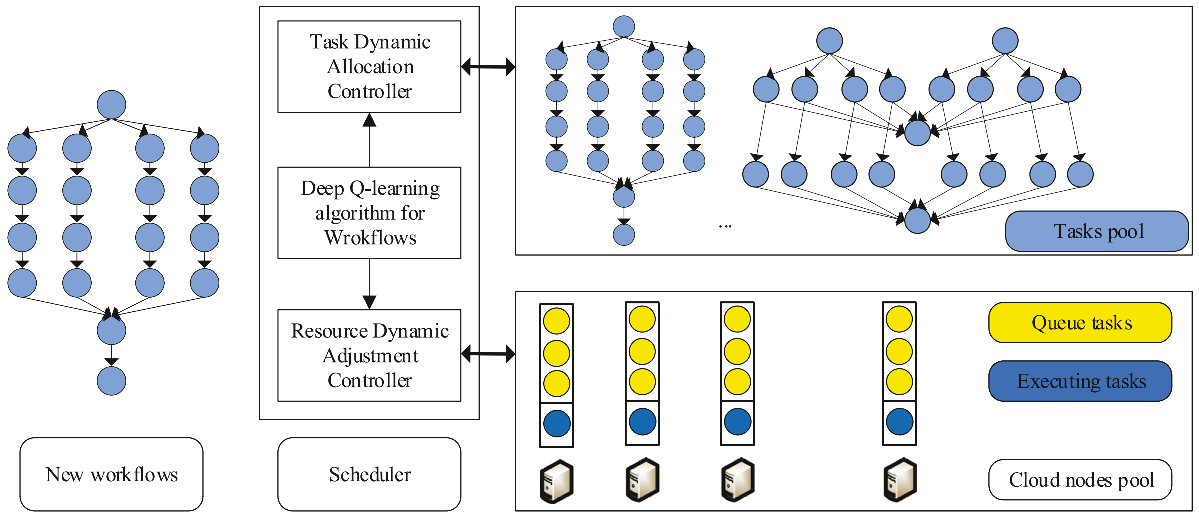

Task Dynamic Allocation Controller
Deep Q-learning algorithm for Wrokflows
Resource Dynamic Adjustment Controller
Tasks pool
Queue tasks
Executing tasks
Cloud nodes pool
New workflows
Scheduler

Fig. 3. Architecture of Deep Q-learning Algorithm in Cloud Computing.

type dynamically arrive in the allocation controller (also called the datacenter). Second, the deep Q-learning algorithm is applied to handle tasks. Lastly, tasks are allocated to the resource in the cloud nodes' pool according to the scheduling plan by the deep Q-learning algorithm.

The architecture of DQTS in the simulation platform WorkflowSim is shown in Fig. 4. There are three layers in this system: the task-submission layer, deep Q-learning algorithm layer, and workflow management system layer. In the cloud computing systems, users will dynamically submit their tasks to the cloud platform. In the deep Q-learning algorithm layer, there are two modules that are included: reward function and DQTS. In the reward function, when the task is allocated to the computing node, it will generate a reward to the DQTS model. The DQTS model will select the best reward, meaning the scheduling to the best computing node. In the workflow management system, there are seven modules, such as workflow engine, scheduling fragments, task queue, action set, action a′, scheduler, and workflow data center. The function of this system is to manage dynamically generated tasks. The scheduling algorithm will map tasks to the computing nodes according to the type of task submitted by the users and certain objectives. The workflow management system layer consists of large-scale computing nodes with many types (including CPU, GPU, MAC, etc.), and all computing nodes can be scaled up or down elastically.

In this paper, we design a BP neural network for this architecture, as illustrated in Fig. 5. Since task scheduling in cloud computing is dynamic and random in most environments, the state and action pair obtained from Q-learning is difficult to classify using a traditional neural network. Specifically, Q-learning generates multiple discrete state sets in a continuously changing cloud computing parameter condition, and the action set corresponding to a specific environment state is difficult to classify.

Since the arrival of the task is real-time and the length of the task is uncertain, the dimensions of the state and action space are large. The RL method is suitable for solving the discretization problem. When solving continuity problems, the dimension explosion problem is easy to occur due to the excessive state and action space. Therefore, the DRL method combined with RL and deep neural network is used to solve the dimensional explosion problem that is easy to occur in the

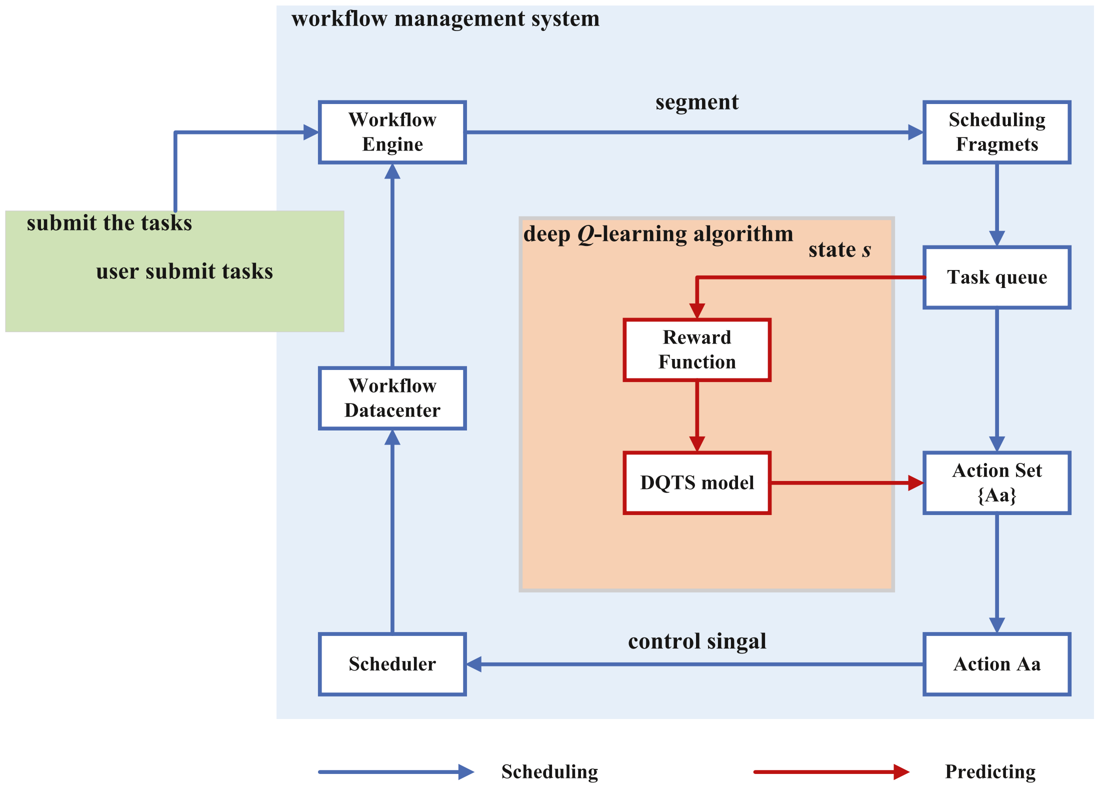


Fig. 4. Architecture of DQTS in WorkflowSim.

RL method. The state is used as the input of the deep neural network, and the Q-value representing the action selection is obtained by fitting. So, it is necessary to use deep neural networks to approximate.

Therefore, we combine *Q*-learning with the BP neural network to reduce the complexity introduced by traditional *Q*-learning. The model uses a BP neural network composed of an input layer, multiple hidden layers and an output layer with fully connected neurons. The BP neural network is a multilayer feedforward neural network that features mainly an error back-propagation adjustment to the network parameters. It has a reversal learning process in supervised learning to minimize an error between the expected output and actual output. The back-propagation process calculates the error between the expected and actual output as a loss function if they do not match and adjusts neurons backward, starting from the last of the hidden layers. Consequently, the learning process corrects every neuron in a fully connected network in reverse, employing an iterative gradient technique until an error is minimized. We design the neural network as fully connected to contend with the randomness of the scheduling scheme and achieve a high level of reasoning, meaning that each of the neurons in a layer is related to all the neurons in its neighbor layers, and a classification process will likely run through most of the training model. We defined an activation function in each neuron by using the ReLU activation function to increase the likelihood of classifying an action.

First, the neuron and layer configurations are initialized for the feedforward neural network. The number of nodes and layers in the hidden layer is certain at this point. Then, the input layer receives a set of state vectors with multiple environment variables and passes the variables to each node of the first layer in the hidden layers. Second, each neuron's weight in the hidden layers is configured randomly so that by updating the value in the learning process, the state vector will be forwarded and converge to the corresponding action as an output. The state vector is operated through each layer by calculating each weight of the neuron through the activation function; the variables are computed into the neuron of the next layer. Lastly, the output layer imports the *Q*-values of each action from *Q*-learning and calculates the error between the state vector output and *Q*-values. The training process then distributes corrections based on a calculation of the neuron's weight gradient from the error and back-propagates into the hidden layers, updating each node. The process operates repeatedly and iteratively until convergence to a maximum of *Q*-values. We use the deep *Q*-learning algorithm to optimize the performance of task scheduling in the cloud computing environment, and the formulation process is described in Algorithm 2.

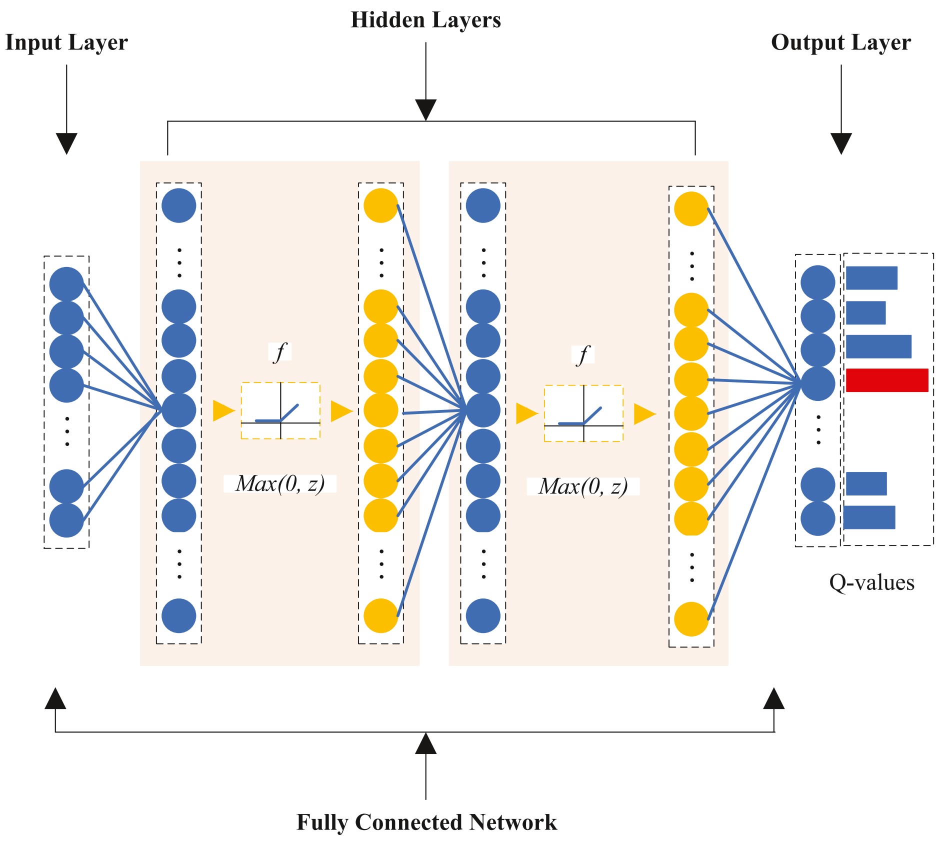


Fig. 5. Neural Network.

Algorithm 2: DQTS algorithm.

```
Input: Training sets consist of replay memory
Output: Trained model
Initialize replay memory;
Initialize NN with parameter settings;
repeat
    Sample uniformly a batch of continuous state experiences to minibatch;
    Use current state in minibatch to calculate output $Q$-value by Equation (16);
    Use Equation (14) to calculate the fitting $Q$-value;Calculate the error of fitting, and update NN using Equation (17);
    Empty minibatch;
until Maximum generation;
Save NN model.
```

4.4. Design principle

4.4.1. Training principle

In the process of training, the training set is needed to train the neural network, and the effect of different training methods on the training set is also different. In general, the current training methods can be divided into offline policies and online policies. The so-called offline strategy refers to the large-scale training of the neural network by using the training set that has been generated, and then, the neural network model that has been trained is obtained. The trained model is used for the corresponding recognition and prediction, for example, the trained model of image recognition is provided in Google's ImageNet project. The advantage of the model is that after a long training time, its prediction accuracy and the integrity of the prediction are very high, and a good training model can be used in different platforms, given this strong adaptability. The disadvantage is that the model training takes a long time and is not easy to change. When the model is not effective, it needs to be retrained. The so-called online mode refers to the real-time generation of training sets according to the environment, and the training is carried out at the same time as the decision making. The advantage of this method is that it can adjust the strategy in real time according to the changes in the environment. It does not need to wait until the model has been trained before using it. It can make decisions and learn in real time. The disadvantage is that the application effect of the model is worse than that of the offline mode, and the application scope is narrower, which is applicable to the scenario where the environment often needs to change, such as the AI game scene. The policy for our neural network training is an offline policy that applies random scheduling to generate the training set. Instead of the online policy, we design the learning method from the offline policy's feature to maintain the algorithm's precision and stability. In DQTS, the object explores the environment and is simultaneously trained in the neural network. In this way, it is appropriate for an object to have relatively simple actions. Once the action reaches a certain precision, the system of learning must have a sufficient number of states to start training by the NN while making the convergence rate of the model slow. Furthermore, the reason that we do not select online training such as DQTS is that the simulation platform is coded with Java, which lacks an integrated library to support deep learning such as TensorFlow. Additionally, the most important factor under our consideration is that the deep learning framework, such as in TensorFlow and Python in Java, cannot be adapted to the learning approach in DQTS and is thus unsuitable.

4.4.2. Reward principle

The reward in the Q-learning method is usually set oppositely, to plus or minus, such as −1 and 1. Before designing the reward principle, it should be known that a virtual machine only has two states: busy or idle. We can also be certain that if a virtual machine is idle, then the state is positive instead of busy. Evidently, a well-trained neural network should have the ability to evaluate positive situations. If we consider only one virtual machine, the positive reward situation should be an idle state. However, if we increase the number of virtual machines to 8, the situation can become complicated. In addition, if we add two objective functions to the allocation, such as when tasks arrive with different execution lengths, it can be understood that the feedback of each virtual machine is related to the task length and its speed, where the feedback of each virtual machine almost impossible to calculate. In a large state space, DQTS fits a neural network that decreases the learning cost. In this paper, we define the state of all virtual machines to consist of the reward separately. According to the updating strategy in DQL [41], Eq. (14) can be simplified to the following form:

$$R(NN_{t+1}) = R(r) + R(NN_t);\ \big(R(r) \in [-1, 1]\big) \tag{18}$$

where $R(NN)$ represents the range of the neural network and r indicates the reward. The finite interval of NN is necessary for DQL to converge if we design the range of r to $[-1, 1]$, and we can obtain the range of NN accordingly. Regarding the condition of multiprocessors in WorkflowSim, if we set the maximum positive feedback to 1 and minimum negative feedback to -1, then we can obtain the range of Q-value, called the output of NN, as follows:

$$R(NN) \in [-1 + \min R(NN), 1 + \max R(NN)] \tag{19}$$

Consider that many activation functions are in the range of [0,1]; thus, we can design the range of NN to $[-1, 1]$. By the left side of Eq. (18) and the statement, we can conclude that NN should be set to $[-2, 2]$, but NN only represents the range of $[-1, 1]$; therefore, the equation changes to the following:

$$\begin{aligned} R(NN_{t+1}) &= 1/2 \times \big(R(r) + R(NN_t)\big); \\ &\big(R(r) \in [-1, 1], R(NN) \in [-1, 1]\big) \end{aligned} \tag{20}$$

4.4.3. Neural network design

The design of replay memory in the procedure of the DQL algorithm is a key step to convergence. In DQL, the training set stands for the replay memory that is also called experience. In our approach to learning, we set the replay memory to the main training set that consists of random scheduling. The DQTS program framework of TensorFlow in Python is a reference to a good project on [42].

4.4.4. Train model

WorkflowSim is coded with Java, and our NN was trained in Python with TensorFlow, thus creating a problem for a model that is used across platforms. In addition, TensorFlow in Java only supports the Android version to read the.pb model. Therefore, we revised the Android interface of TensorFlow to the Java platform to support our model. The.pb model is a binary file that can store structure information and graph definitions of NN, and it can be used in many fields such as Google image identification.

5. Experiments and analysis

In this section, we will test DQTS's fitting ability as well as the accuracy and extensibility by a series of simulation experiments. The experiments are conducted in environments ranging from simple to complex. First, we test and prove the DQTS algorithm's fitting ability. Second, different factor settings are applied to verify the convergence of the algorithm, including the learning rate and activation function. Lastly, we use single-class and hybrid-class training sets for the model training in TensorFlow and verify the performance of the model with different test sets. All the comparison algorithms and test sets are internally included and installed. It should be noted that the large test set cannot be used in WorkflowSim,

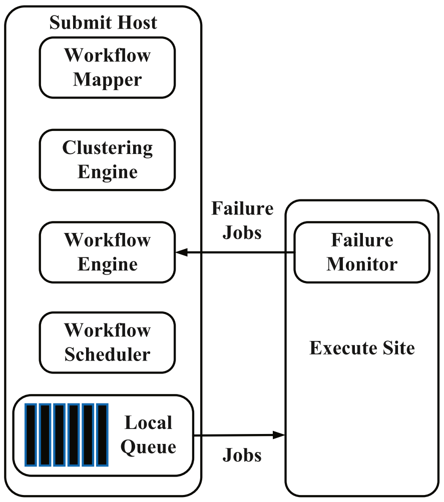


Fig. 6. Structure of WorkflowSim.

such as CyberShake with 2000, 4000 and 8000 data points being generated by WorkflowGenerator [43–45], which is based on models of real applications that have been parameterized with file size and task runtime data from execution logs and publications that describe the workflow.

5.1. Workflowsim

CloudSim, the simulation platform of cloud infrastructure and management service, was developed by Rajkumar Buyya and can be programmed in Java [46]. Assigning operations to a cloud simulation platform instead of actual experimentation can save resources and repeated debugging. In this paper, the objective function of the simulation experiment is to reach the minimum makespan of task scheduling in cloud computing. Furthermore, WorkflowSim [47] extends the CloudSim simulation toolkit and supports a multilayered model of failure and delay occurring in the various levels of the workflow management system.

Fig. 6 shows the different components of WorkflowSim involved in preparing and executing a workflow. All the processing procedures form a workflow management system (WMS), which is similar to that of the Pegasus WMS [48]. As shown in Fig. 6, the components consist of the Workflow Mapper, Clustering Engine, Workflow Engine, and Workflow Scheduler.

5.2. FCFS fitting

The first experiment is designed to test and verify the simple fitting ability. In this experiment, the setting of the simulation platform WorkflowSim has no overhead and no clustering. All the simulations are tested in the same software environment with the same objective function and parameter settings. The bandwidth environment is set to be homogeneous to simplify the experiment settings, i.e., the bandwidth is the same for all processors. In addition, each virtual machine has different million instructions per second (MIPS), ranging from 100 to 3200. With sets of WorkflowSim, the transfer cost between a parent and child is calculated as the size of the input file/bandwidth, and the computation cost of a task on a virtual machine is computed as the runtime of the task MIPS of the virtual machine.

In addition, in the first experiment, we use the training set CyberShake_1000 with the count of 1000 tasks to run random scheduling 5 times and train the training set 50,000 times. The experiment's parameter settings are described in Table 2.

In TensorFlow, we use Python to train the neural network iteratively 50,000 times to obtain a.pb model. Then, we use this model in WorkflowSim that is coded with Java. Since the support for TensorFlow in Java is not complete and lacks detail, the only way demonstrated to read the.pb model in Android is from the image recognition of GitHub. Therefore, we revised some codes for Android and used Python and Java hybrid programming to adapt WorkflowSim, which makes the interface work well.

The principle of the first come, first serve (FCFS) algorithm allocates tasks to the first virtual machine idle state along with the order ID number of the virtual machine. Because of this feature, we decrease the reward of each virtual machine in turn, according to their ID order number when the state is idle. Otherwise, if the state is busy, the reward will go to $reward_{busy} = reward_{idle}$ - 1. This method is used to update the state value of the virtual node. For example, in the initial state, the node reward is 1.0, 0.9, 0.8, and 0.7. When the state becomes busy, the reward will change to 0.0, -0.1, -0.2, and -0.3. The principle of fitting the FCFS approach to the DQTS is to generate a model that can identify the first idle virtual machine along with its ID number. We used a relatively small number of training sets and training steps to finish the training process and obtained the same result as with the FCFS approach. The loss value with the fitting curve can be found

Table 2
Parameter settings.

Parameter	Value
Number of vms	8
Number of actions	8
ϵ	0.5
Batch size	100
Max generation	50000
Layers of NN(contain inand out layer)	4
Number of neurons in each layer(except in and out layer)	20*8
Learning rate	1*E*-3
Activation function	*ReLU*
Optimizer	*AdamOptimizer*
Loss function	*Meansquareerror*

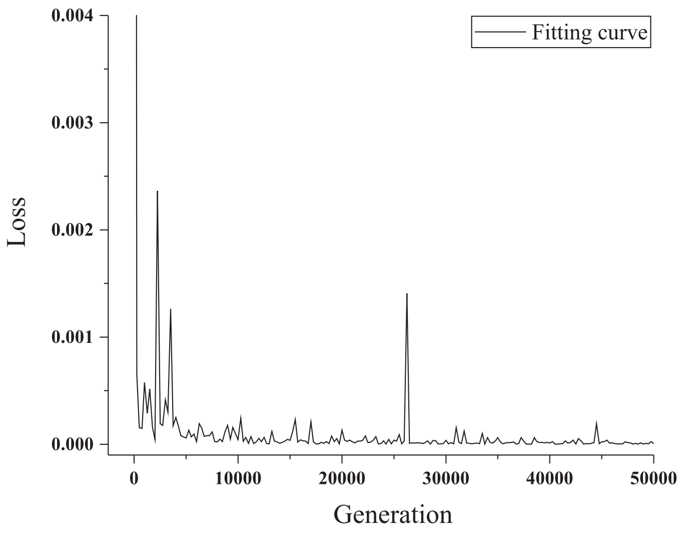


Fig. 7. Fitting curve of FCFS.

in Fig. 7. Additionally, the loss figure shows that the training is almost convergent at approximately 5000 iterations; hence, we can conclude that the DQTS algorithm has a strong learning ability.

5.3. Hyperparameter optimization

In the second experiment, we tested what may be two of the most significant hyperparameters that influence the convergence rate: the first is the learning rate, which dominates the step length of updating the weight to each layer, and the second is the choice of the activation function. We tested two of the most popular activation functions: rectified linear unit (ReLU) and hyperbolic tangent (TANH).

5.3.1. Convergence performance with different learning rates

Different learning rates have a determinative influence on convergence. The main purpose of studying the learning rate is to control the step size of gradient descent, while monitoring training cost is the best way to detect whether the step size is too large. In this experiment, all the parameter settings are the same as the first experiment except for the maximum generation and training set. We use a larger training set that was produced by CyberShake_2000, with the count of 2000 tasks, to run random scheduling 50 times, and the iteration number proportionally increases to 100,000. The reason for using a training set this large is to help the following experiments that need a much larger count of states.

We set different learning rates to test their effects on the convergence. These parameters are 1*E*-1, 1*E*-2, 1*E*-3, 1*E*-4 and 1*E*-5. The results in Fig. 8 show that when we select the convergence rate with 1*E*-1, 1*E*-2, and 1*E*-5, perturbation occurs frequently. The convergence rates of 1*E*-3 and 1*E*-4 are better in terms of instability and convergence speed.

5.4. Experiments with benchmark of CyberShake

After selecting the best learning rate and activation function from the experiments, we obtain relatively good parameter settings for our NN. The configuration for the learning rate is 1*E*-3, and we select ReLU as the activation function. The other

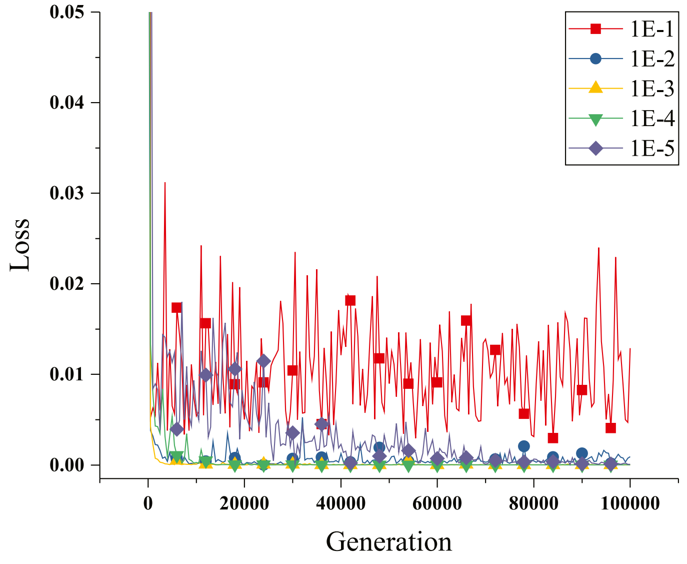


Fig. 8. Convergence performance with different learning rates.

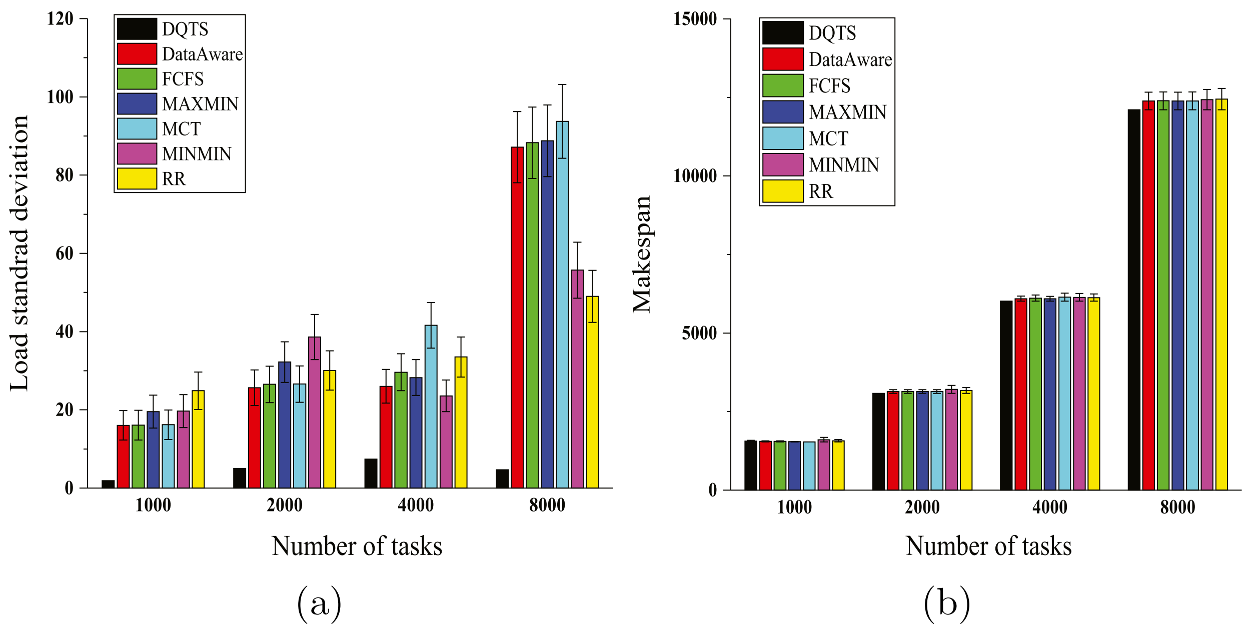


Fig. 9. **(a)** Load standard deviation with 8 virtual machines. **(b)** Makespan with 8 virtual machines.

settings are the same as the last activation function experiment. In this section, we use random scheduling to explore the state space of the virtual machine, and we try to develop an even better solution with the state space. Before the training starts for processing, it should be noted that we need a sufficient number of training sets about these states; thus, we run the random scheduling algorithm 50 times to obtain 100,050 Markov decision process rows. After 100,000 times of training, we obtain a.pb model and use it in WorkflowSim to schedule every upcoming task.

There are 5 models in total, and each model is generated after 100,000 times of training. Then, we average the five results containing the load standard deviation and makespan. Finally, the averaged results are used to compare the models with other algorithms in WorkflowSim. More details about the comparison algorithms can be found in WorkflowSim.

As Fig. 9 shows, (a) displays the single index of the load standard deviation with 8 virtual machines. The result illustrates that DQTS has a smaller fluctuation with the load. Additionally, the load standard deviation of the other algorithms increases with some tasks, except MINMIN, which shows instability.

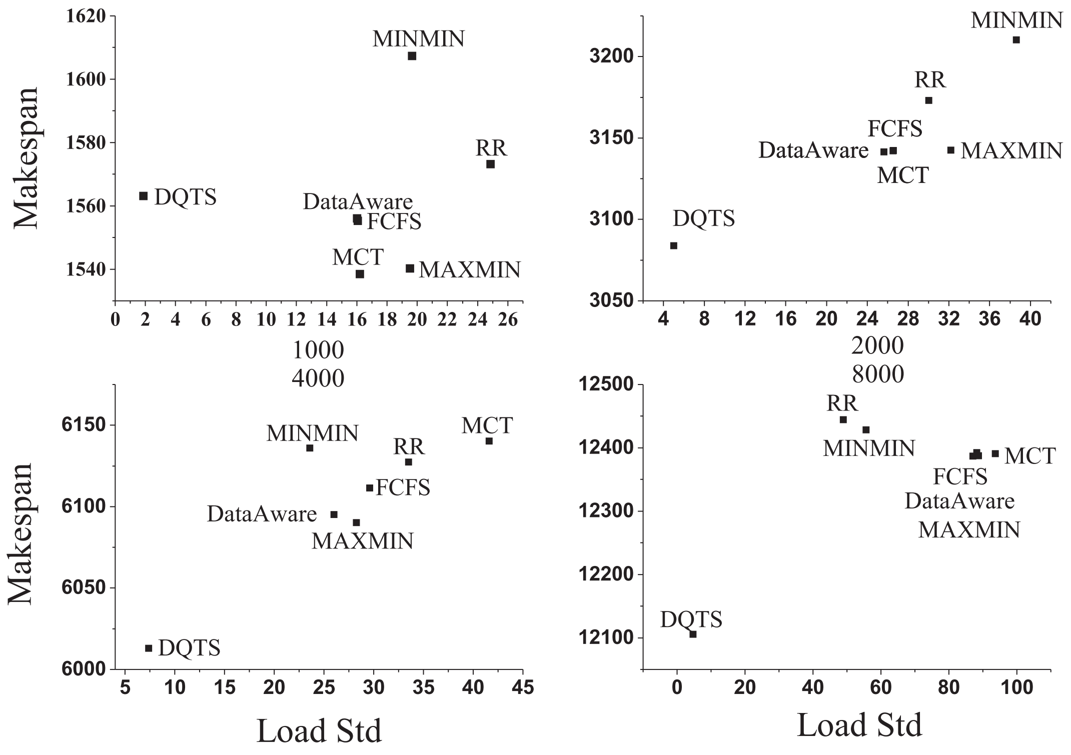


Fig. 10. Pareto scatter with 8 virtual machines.

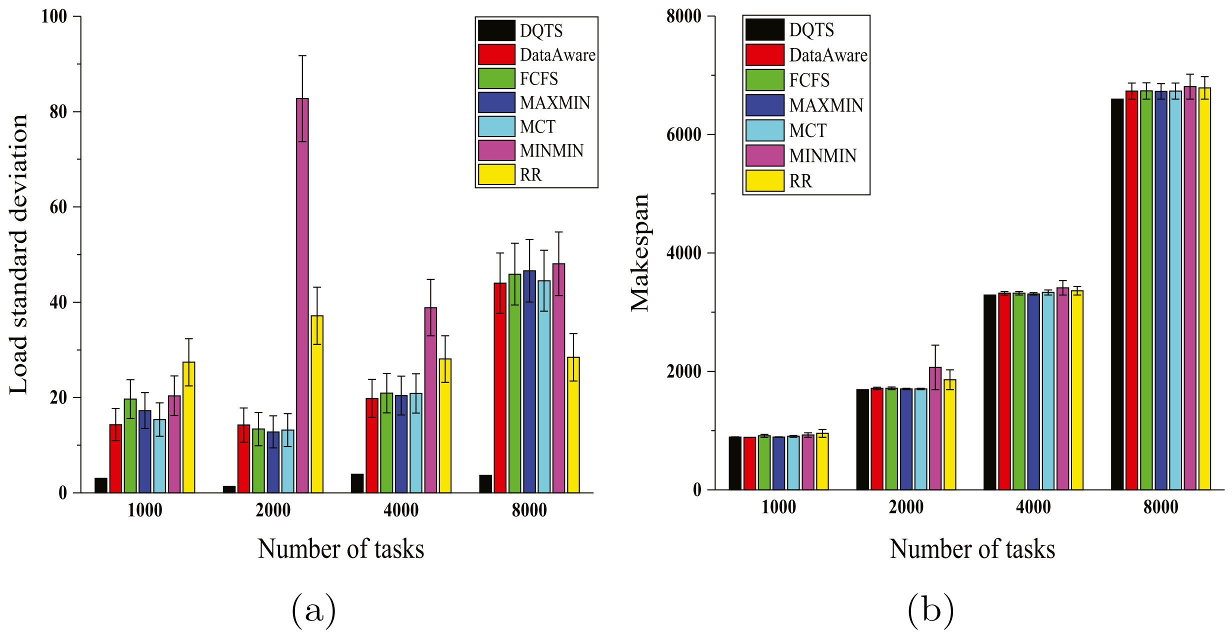


Fig. 11. (a) Load standard deviation with 16 virtual machines. (b) Makespan with 16 virtual machines.

Fig. 9 (*b*) shows that DQTS underperforms in the 1000 task but outperforms in other situations, and other algorithms achieve almost the same result. The reason why DQTS obtains a relatively poor result is that the objective function is bio-objective, including the load and makespan, and it will have to make some sacrifices from one object to another.

Pareto-optimal solutions [49] are an effective measurement approach to evaluate the solutions when considering the bi-objective problem. The competitive relation between multi-objectives could be reflected in the graph using the Pareto method. In this paper, there are two objectives considered, and we could use a scatter graph to describe the relative relation.

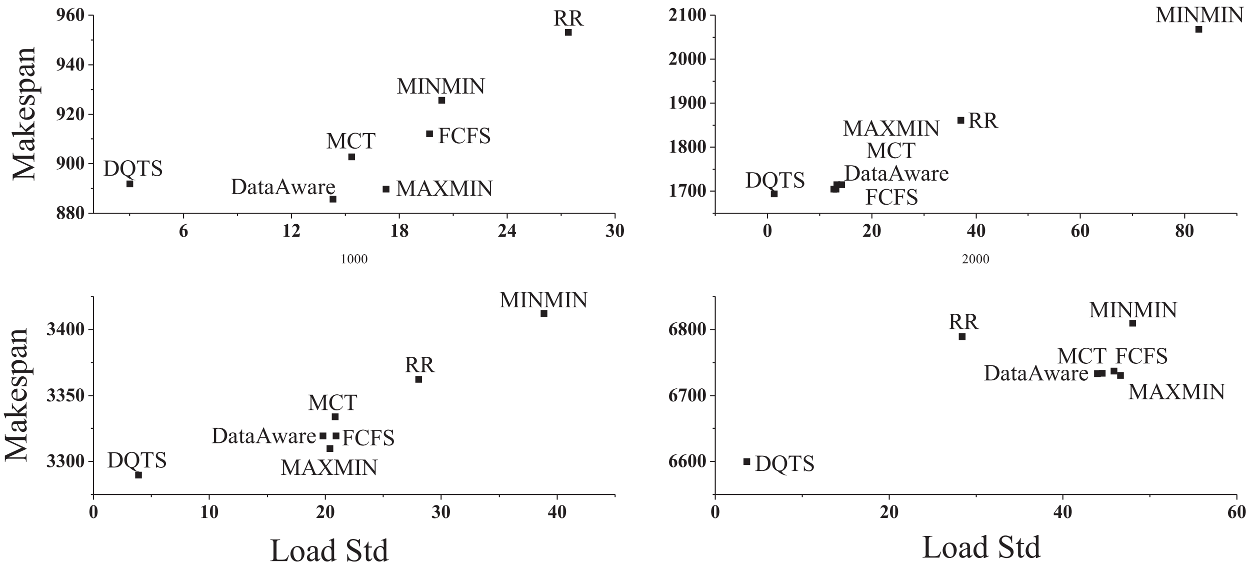


Fig. 12. Pareto scatter with 16 virtual machines.

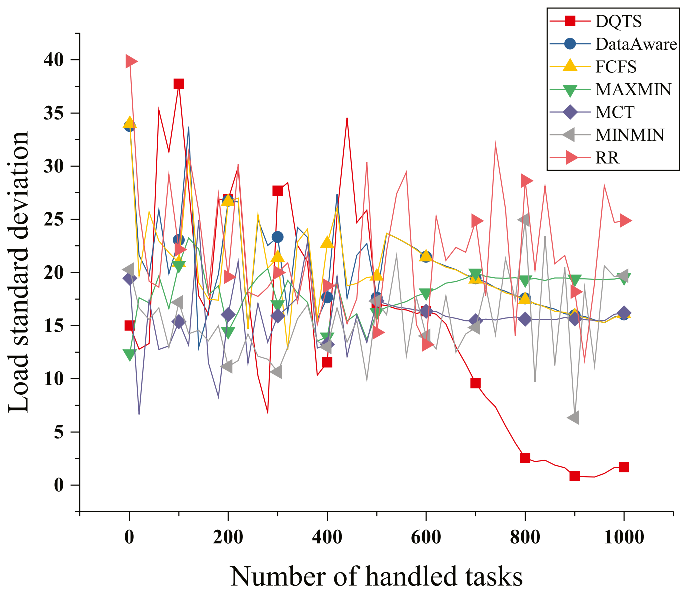
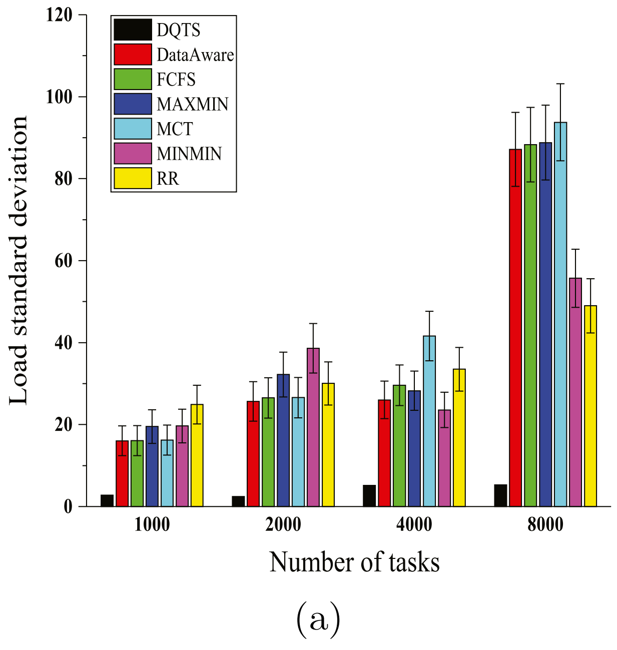


Fig. 13. Load standard deviation with different amounts of handled numbers.

In addition, by considering the two objectives together, and as the Pareto scatter that consists of points defined by two indexes in Fig. 10 shows, DQTS obtains three relatively strong-dominated solutions in four different experiment sizes when compared with other algorithms. Moreover, in the test set of 1000, DQTS obtains a relatively nondominated solution, which may be because the objective of the load balance has a relatively large influence on makespan when handling fewer counts of the number of tasks. The above experiments show that DQTS still achieves better results than those of other algorithms and prove that using random scheduling to explore the state space is a useful method.

Next, to verify whether DQTS is useful in a more complicated state space, we increase the number of virtual machines to 16. Obviously, the state space enlarges more than twofold that in 8 virtual machines, and the distance of the states is smaller. Therefore, we run the random scheduling 100 times and keep the training set as CyberShake_2000. In addition, in consideration of the state density, we adjust the learning rate to $1E$-4 to adapt a smaller change in exploration. It should be noted that the process of this experiment is the same as the experiment with 8 virtual machines. From Fig. 11, we can observe that DQTS shows similar performance compared with 8 virtual machines. The main reason of similar performance is that the test set has the same structure, and DQTS has sufficient ability to learn. Additionally, by considering with the two objectives at the same time, as the Pareto scatter in Fig. 12 shows, DQTS obtains the same performance compared



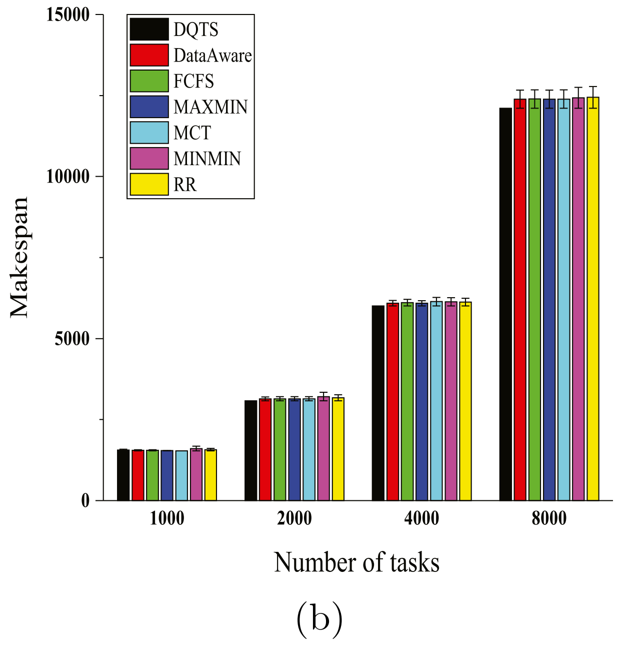
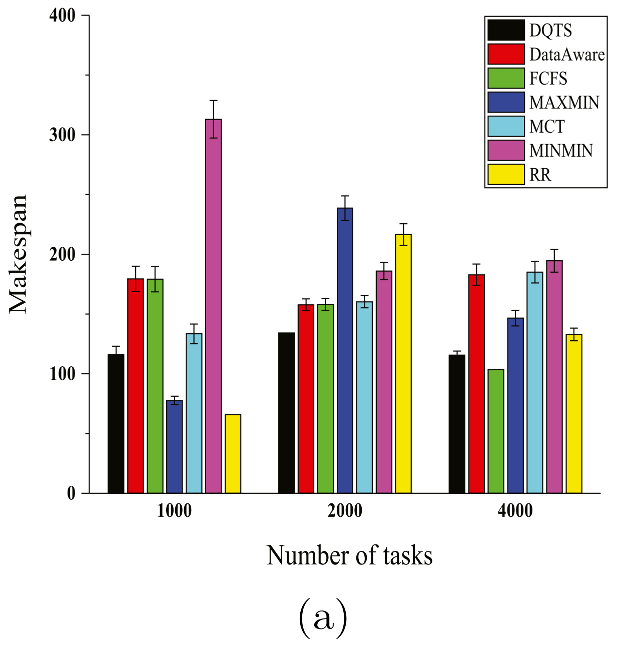


Fig. 14. **(a)** Load standard deviation with test set of CyberShake. **(b)** Makespan with test set of CyberShake.



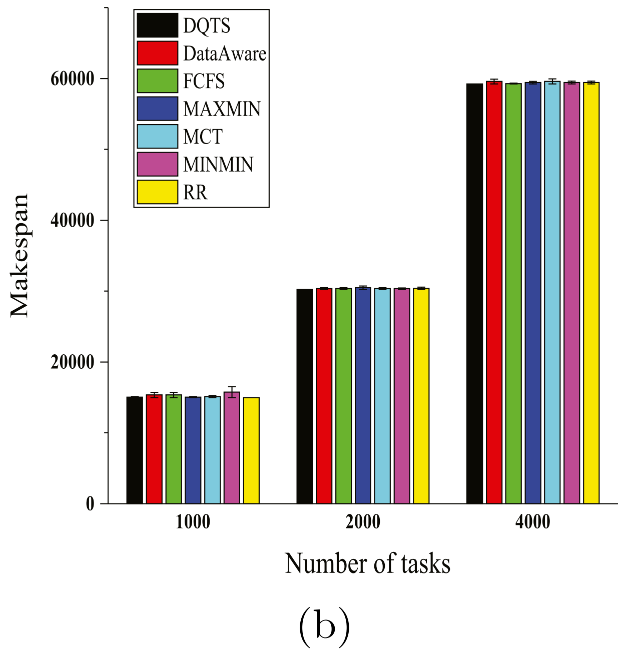


Fig. 15. **(a)** Load standard deviation with test set of Inspiral. **(b)** Makespan with test set of Inspiral.

with the situation of 8 virtual machines. However, it should be noted that the change in hyperparameters can cause a large swing, and the process to select the hyperparameters needs more caution, such as when setting the learning rate to 1*E*-4 or another rate, and the performance will be greatly affected.

Next, to verify whether DQTS is useful in a more complicated state space, we increase the number of virtual machines to 16. The state space enlarges more than twofold that in 8 virtual machines, and the distance of the states is smaller. Therefore, we run the random scheduling 100 times and keep the training set as CyberShake_2000. Additionally, in consideration of the state density, we adjust the learning rate to 1*E*-4 to adapt a smaller change in exploration. It should be noted that the process of this experiment is the same as the experiment with 8 virtual machines. From Fig. 11, we can observe that DQTS shows similar performance compared with 8 virtual machines. The main reason for this similar performance is that

Table 3
Performance on benchmark of Inspiral_2000.

	Load Std	Makespan
DQTS	190.0878655	30312.85
DataAware	157.7639315	30379.46
FCFS	157.9354705	30378.55
MAXMIN	238.6068311	30487.17
MCT	160.2887975	30366.20
MINMIN	185.9714359	30363.13
RR	216.4874891	30418.05

Table 4
Performance on benchmark of Montage_2000.

	Load Std	Makespan
DQTS	32.17318958	1743.22
DataAware	70.93124509	1683.90
FCFS	70.93124509	1683.90
MAXMIN	71.04491097	1671.84
MCT	70.54326354	1681.13
MINMIN	70.15721547	1679.70
RR	71.08510002	1680.00

Table 5
Performance on benchmark of Sipht_2000.

	Load Std	Makespan
DQTS	309.6397016	23928.19
DataAware	470.6224257	24838.23
FCFS	470.6224257	24838.23
MAXMIN	336.1103080	24546.45
MCT	564.8682626	25206.45
MINMIN	400.5922386	24867.65
RR	705.8387776	25176.95

the test set has the same structure, and DQTS has sufficient ability to learn. Additionally, by considering the two objectives at the same time, as the Pareto scatter in Fig. 12 shows, DQTS obtains the same performance compared with the situation of 8 virtual machines. However, it should be noted that the change in hyperparameters can cause a large swing, and the process to select the hyperparameters needs more caution, such as when setting learning rate to 1E-4 or another rate, and the performance will be greatly affected.

To observe the real-time variance in the load balance, we design an experiment that calculates the load standard deviation after each of a certain number of handled tasks. The variation curve with the increasing number of processed tasks can be found in Fig. 13. The figure shows that compared with other classic algorithms, the DQTS decreases in load std after 600 tasks because the upcoming tasks are relatively stable along with its length.

Additionally, we also know that DQTS reduces the instability and acquires a balanced final state. Therefore, we believe that the DQTS algorithm is more suitable for dynamic online task scheduling in the cloud computing environment when considering the load balance.

5.5. Performance on other benchmarks with the single-set model

In this section, we show the performance of a trained model that is generated in the above experiments with other benchmarks on CyberShake. By training the NN 100,000 times, the model has already learned enough Markov decision processes. To evaluate the performance of this model, it is necessary to test it with other benchmarks. We select Inspiral_2000, Montage_2000 and Sipht_2000 as the test sets. Table 5 shows that DQTS obtains relatively strong-dominated solutions with Sipht_2000, and Table 3–4 shows relatively nondominated solutions with Inspiral_2000 and Montage_2000. We conclude from Table 3 to 5 that the DQTS algorithm, when compared with other classic algorithms for various test sets, is better and much more robust. Different benchmarks show its unique structure via the results recorded in the tables. In addition, DQTS achieves relatively good solutions because of its adaptive capacity, containment and expandability when implemented in a complex environment.

5.6. Performance on benchmarks with the hybrid-set model

We can see from the above experiments that each DAG benchmark still has differences. In addition, DQTS should have the ability of containment and expandability. Thus, a hybrid training experiment should be conducted for this matter. We

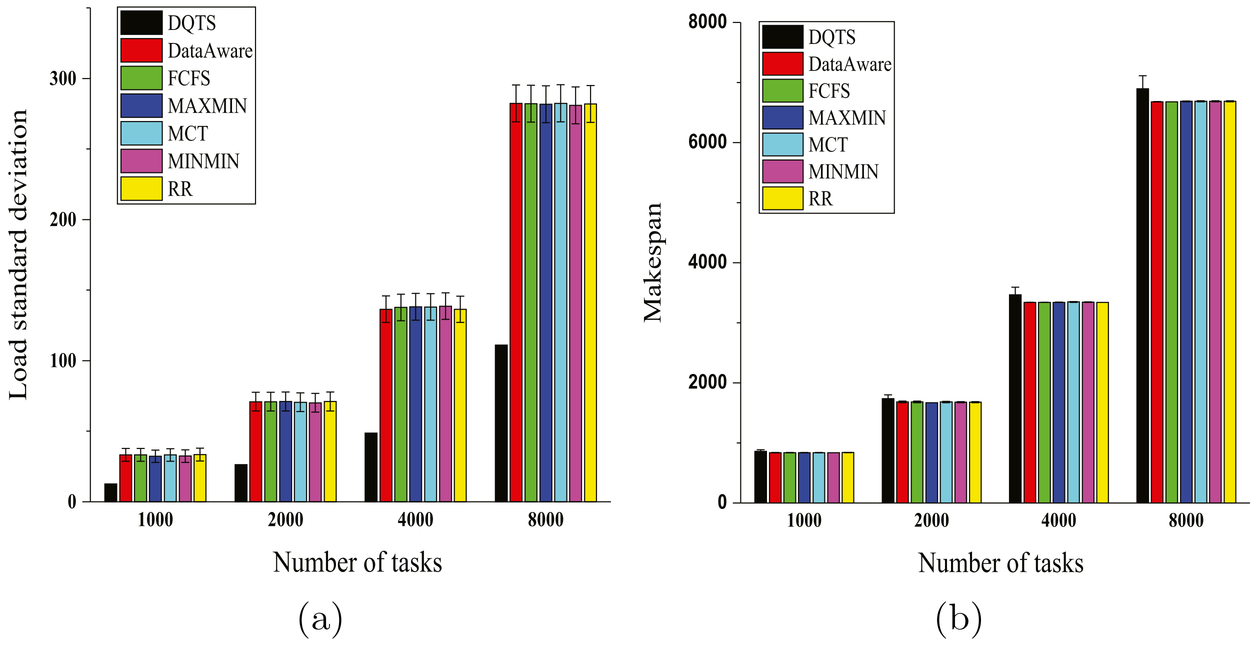


Fig. 16. **(a)** Load standard deviation with test set of Montage. **(b)** Makespan with test set of Montage.

run the random scheduling with CyberShake_2000, Inspiral_2000 and Montag_2000 5 times separately. Then, we train the set 100,000 times. As Figs. 14–16 shows, DQTS outperforms in the load std and makespan with different test sets. The results show that DQTS maintains good containment and learning ability when the states become complex. Moreover, it should be noted that using multiple types of training sets and a smaller train set has no impact on the results when compared to the above CyberShake benchmark experiments. We can demonstrate that DQTS can adapt to even more complex environments such as the multi-objective problem without the need for a more complex model to achieve its goal.

6. Conclusion and future work

In this paper, we have proposed a novel artificial intelligence algorithm, DQTS, to solve the problem of scheduling DAG tasks in a cloud computing environment. According to experimental results, DQTS outperforms other algorithms and has the advantages of excellent performance and a strong capability for learning, which proves that DQTS can be applied to task scheduling in cloud computing environments, especially in complex environments. Additionally, we tested these algorithms on WorkflowSim and processed them with scientific workflow benchmarks. The algorithm compares classic algorithms to state-of-the-art algorithms under both makespan and load balance. The results show that DQTS obtains the lowest makespan and best load-balance measurement.

In future works, we intend to propose a new model of energy consumption, which is an effective way to reduce costs when the deadline is loose.

Declaration of Competing Interest

None.

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