International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 5336-5344

https://doi.org/10.70517/ijhsa464373

Research on the Application of Reinforcement Learning in the Optimization of Digital Resource Allocation in the Cultural and Tourism Industry

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Abstract With the rapid development of the smart cultural tourism industry, how to rationally allocate digital resources to improve the overall operational efficiency has become an urgent problem to be solved. In this paper, a deep reinforcement learning (DQN)-based digital resource allocation optimization model for cultural and tourism industry is proposed. The model estimates the Q-value function by deep neural network, which solves the resource allocation problem of cultural and tourism industry in a complex cloud computing environment. The experiments use the Google Trace dataset to simulate different sizes of cloud environments for task scheduling. The experimental results show that the proposed model significantly outperforms traditional algorithms in terms of task execution success rate and resource utilization. For example, in a cluster of 75 servers, the task execution success rate reaches 0.742, which is higher than DRL (0.593) and AIRL (0.646). In addition, the model exhibits a higher success rate when dealing with low latency tolerant tasks, proving its advantage in dealing with urgent task scheduling. The study shows that the application of the DQN-based resource allocation model in the cultural tourism industry effectively improves the resource utilization efficiency and system throughput capacity.

Index Terms Deep Reinforcement Learning, DQN, Resource Allocation, Cultural Tourism Industry, Task Scheduling, Cloud Computing

I. Introduction

Culture and tourism industry is the development mode in which culture industry and tourism industry interpenetrate and cross each other, and through optimizing the allocation of resources, new forms and new products are formed to enhance the source of industrial competitiveness and comprehensive benefits [1], [2]. It is no longer a simple cultural display plus travel and tourism, but a deep integration to create more attractive and experiential products and services [3]. And with the advent of the digital era, the application and development of digital technology promotes a new era of digital cultural and tourism industry development [4]. Digitization of the cultural and tourism industry is the use of digital technology to transform the cultural and tourism industry in an all-round, multi-angle, full-chain transformation process, aiming to break the boundaries of the culture and tourism industry, and realize the deep integration of the cultural and tourism industry, and the rational allocation of digital resources in this digitalization process is of great significance for the sustainable development of the industry [5]-[8].

Digital resources of cultural tourism industry mainly include cultural heritage digitization, cultural IP digitization, immersive experience content, intelligent management platform, data sharing platform, etc. Reinforcement learning as an optimization algorithm helps to realize the optimization of digital resource allocation in cultural tourism industry [9]-[12]. Reinforcement learning is a machine learning method that learns optimal behavioral strategies through the interaction of intelligences with the environment [13]. In the digital resource allocation optimization problem of cultural tourism industry, reinforcement learning is widely used to solve the problem of rational allocation and utilization of digital resources, where the intelligent body can regard different behaviors as the selection of different digital resource allocation schemes, and obtain rewards through the interaction with the environment, so as to learn the optimal digital resource allocation strategy [14]-[16].

The research in this paper is mainly divided into two parts: on the one hand, the DQN algorithm is utilized to design a resource allocation model and combine it with the actual demand for dynamic resource scheduling in cloud computing and edge computing environments; on the other hand, experiments are conducted to verify the effectiveness and superiority of the proposed model. In this paper, by constructing an experimental environment based on Google Trace dataset, we compare the performance of traditional algorithms (e.g., Round Robin, DRL, AIRL) and the proposed DQN algorithm, and evaluate their performances under the conditions of different task requests, the number of edge servers, and so on. The results show that the DQN algorithm has significant advantages in improving resource scheduling efficiency and task execution success rate. Ultimately, this paper provides a new deep reinforcement learning-based resource allocation scheme for the cultural tourism industry to promote the efficient development of smart cultural tourism systems.

II. Cloud-side system design for an intelligent cultural and tourism resource platform

As a new technology model, the system platform using "cloud computing + edge computing" technology architecture has been applied in many scenarios, and has achieved relatively good results. In this paper, it is used in the construction of the cloud side system of the intelligent cultural tourism resource platform, and the cloud side of the intelligent cultural tourism system platform serves as a unified portal entrance to provide a variety of accurate and intelligent SaaS services (software as a service) to tourists, scenic spots, merchants, supervision and other departments.

The cloud-side system of the intelligent cultural tourism resource platform is constructed according to the three-layer system of cloud services, which is divided into multiple levels such as multi-dimensional front-end access, e-government network, physical resource pool, data and business support platform, and application service portal.

The external portal of cloud side can provide services to the outside world by way of portal, WeChat public number, WeChat small program, etc. Its service objects include business application objects for tourists, scenic spots, merchants, and supervision, etc., and it provides a full range of tourism services, scenic spot management and scheduling, e-commerce management, marketing management, public service, supervision and management and other functions.

The support platform part includes the part of support module for realizing relevant business and application, and the data management service platform for providing support for the business module. Among them, the support modules include emergency command management application module, ticketing management module, tour guide service module, navigation service module, portal service management module, digital exhibition service management module, etc., as well as data open interfaces for service docking with other relevant units (or third-party service providers), data sharing and information exchange, data analysis and mining based on big data, etc., to complete the functions of intelligent transportation, e-payment, intelligent government, car rental service, and e-payment. The data analysis and mining based on big data accomplishes the business support of intelligent transportation, e-payment, intelligent government affairs, car rental service, GIS information, digital audio-visual, and cultural and creative transactions.

The data management and service platform provides basic fundamental data, thematic data and application data to each business support module, including the storage and management of relevant data such as ticket information database, tourist information database, travel agency information database, hotel information database, employee information database, e-commerce information database, geographic information database, emergency plan information database, digital audio-visual information database and so on. At the same time, the data management platform collects relevant data information through vertical communication with the side (different cities and municipalities, cultural and tourism venues system platforms) and horizontal communication with the cloud platforms of human society, public security, environment, safety supervision and other systems, and exchanges and shares the data through data categorization, audit, algorithms, quality management, data cleansing and conversion, and data correlation and coupling.

Resource pool is a physical hardware carrier and software management platform that provides resource and data management to cloud-side systems, and is used to realize deployment and management of resource scheduling, module deployment, virtual containers, mirror management, network security, load balancing, redundant backups and other deployment and management under the collaborative approach of the cloud and cloud-side.

III. Reinforcement learning-based model for optimizing resource allocation

Aiming at the cloud-side system of the intelligent cultural and tourism resource platform designed by using cloud technology and edge computing technology, the research on the digital resource allocation of the cultural and tourism industry in it is carried out, and the digital resource allocation optimization model of the cultural and tourism industry is constructed based on the DQN reinforcement learning algorithm.

III. A. Description of the problem

There are three roles involved in the Smart Literature and Tourism Resource Platform: the user, the IaaS (Infrastructure as a Service) provider and the SaaS provider. The user purchases the cultural and tourism resources cloud service from the SaaS provider, i.e., the task is submitted to the SaaS provider for execution, and the number of requests from the user ($\mathrm{Re}\,q_u^r$ denotes the first r request from the user u) is continuous and fluctuating.

An SLA violation (SLAV) occurs when a SaaS provider fails to guarantee the predefined SLA for a user request Req_u^r. FT_u^r and DL_u^r represent the completion date and deadline of the r th request of user u, respectively, and SLAV occurs if the completion date exceeds the deadline.SLAV is defined as:

$$SLAV(\mathrm{Re}\,q_u^r) = \begin{cases} Yes\ (1) & FT_u^r - DL_u^r > 0 \\ No\ (0) & otherwise \end{cases} \tag{1}$$

The total spend is the total cost incurred by the SaaS provider in providing the cloud service for cultural and tourism resources, which includes the cost incurred in renting VMs and the compensation cost incurred due to the violation of SLAs, which can be described as:

$$TC = VCs + CP \tag{2}$$

where TC represents the total cost, CP represents the compensation cost, VCs represents the cost incurred by renting VMs, and VCs is the sum of the cost incurred by renting all VMs:

$$VCs = \sum_{n=1}^{N} VC_n \tag{3}$$

where VC_n represents the cost incurred by the n th VM, which is denoted as:

$$VC_n = (VP_m \times VT_n) + IPr_m \quad \forall n \in N; m \in M \tag{4}$$

where VP_m denotes the rental price of a VM of type m, VT_n denotes the length of time for which this VM is rented, and IPr_m denotes the cost incurred in starting this VM.

CP is the compensation cost incurred by all users requesting Req_u^r due to SLA violations, i.e., whenever $SLAV$ occurs, and it is denoted as:

$$CP = \sum_{u=1}^{U} \sum_{r=1}^{R_u} Pe(Req_u^r) \tag{5}$$

where Pe represents the penalty fee for a user requesting Req_u^r, and Pe can be defined as a linear function:

$$Pe(Req_u^r) = \lambda_u^r \times \frac{FT_u^r - DL_u^r}{\Delta t} \tag{6}$$

where λ_u^r is a penalty rate determined by the type of failed user request and Δt is a fixed time interval.

III. B. DQN algorithm

Deep Reinforcement Learning (DRL) is a combination of Reinforcement Learning (RL) and Deep Learning (DL), which optimizes Reinforcement Learning algorithms by means of neural networks for solving sequential decision-making problems in complex environments.DQN algorithms are well suited to solve the problem of “explosion” of the state-action space that prevents algorithms from executing in traditional Reinforcement Learning. At the core of DQN is the use of deep neural networks as functional approximators to estimate a Q-function that represents the expected future cumulative reward for performing an action in a given state. The following are the main components of the DQN algorithm and their detailed description:

III. B. 1) Network structure

At the heart of a DQN is a deep neural network, usually consisting of a multilayer perceptron (MLP) or for visual inputs a convolutional neural network (CNN) may be employed. The network accepts the state of the environment as input and predicts the Q-value for taking each possible action in each state. The size of the output layer corresponds to the size of the action space, and each output node corresponds to an estimate of the Q-value of an action.

III. B. 2) Experience playback buffer pools

When building the DQN model, an experience replay buffer pool is introduced. This is a data structure that stores recently experienced quaternions (state, action, reward, next state). Each time an intelligent body interacts with the environment, the experience of this interaction is added to the buffer. During training, instead of sampling the training data one by one in the order of experience, small batches of data are randomly sampled for training, which helps to reduce the correlation between data, improve the learning efficiency and stabilize the convergence.

III. B. 3) Target networks

DQN also introduces a target network (also known as a fixed target network or shadow network) whose parameters are periodically copied from the main Q-network for computing the TD target. The objective network remains constant for a certain period of time and is used to compute the objective Q-value in Bellman's expectation equation, which helps to stabilize the Q-value learning process and avoids unstable training caused when the objective function is dynamically updated.

III. B. 4) Q-valued iterative functions

In DQN, the core expression for Q-valued iterations is still based on Bellman's expectation equation for Q-learning, and unlike reinforcement learning, here a neural network is utilized for approximation:

$$\text{Target} = R + \gamma \max_{a'} Q(S', a'; \theta^-) \tag{7}$$

$$Q(S, A; \theta) \leftarrow Q(S, A; \theta) + \alpha(\text{Target} - Q(S, A; \theta)) \tag{8}$$

where $Q(S, A; \theta)$ is the main Q network's estimate of the Q value of taking action A in state S based on the current parameter θ. R is the reward obtained instantly after performing action A. γ is the discount factor used to adjust the importance of future rewards obtained under the state action. $\max_{a'} Q(S', a'; \theta^-)$ is the maximum Q value output by the target network according to the parameter θ^- in the next state S'. That is, the action a' corresponds to the maximum Q value; α is the learning rate, which controls the magnitude of change to the old Q value at each update.

III. C. DQN-based resource allocation algorithm

The digital resource allocation algorithm for cultural and tourism industry consists of two sets of control MAPE-K loops. The first group of MAPE-K consists of monitoring phase A, analyzing phase A, planning phase A and execution phase A. The second group consists of monitoring phase B, analyzing phase B, planning phase B and execution phase B. The loops are looped once every minute, and vertical expansion is achieved through resource sharing, collaborative work and adaptive management.

III. C. 1) Monitoring phase

In the monitoring phase A, for the cloud service provided by the SaaS provider, the monitor will collect the number of VMs $NumVM_i(\Delta t)$ rented by the SaaS provider from the IaaS provider, the number of user requests to the cloud service $NumReq_i(\Delta t)$, the number of unanswered requests by the cloud service $NumWait_i(\Delta t)$, and also the monitor will detect the utilization rate of the cloud service $Utili_i(\Delta t)$. In the monitoring phase B, for each cloud service offered by the SaaS provider, the monitor collects the amount of remaining resources $NumSur_i(\Delta t)$ for the VMs in each cloud service tenancy and the number of user requests that have not yet started $NumWait_i(\Delta t)$. The information obtained in the monitoring phase is stored in the database and will be used in other phases.

III. C. 2) Analysis phase

The analysis phase A obtains the number of current user requests $NumReq_i(\Delta t)$ in the monitoring phase A, and predicts the number of user requests for the cloud service in the next time interval $(t+1)$. The ARIMA model is used to predict the number of user requests in the next time interval.

The $ARIMA(p, d, q)$ model firstly takes the non-smooth user request history data X_t, and preprocesses the smoothing by difference to get the new smooth sequence $\{Z_1, Z_2, \ldots, Z_{t-d}\}$, and the general expression for difference calculation:

$$\Delta y_{X_t} = y_{X_{t+1}} - y_{X_t} \quad t \in Z \tag{9}$$

The $ARMA(p,q)$ model is then fitted and a d th difference reduction is performed to obtain Y_t for the X_t prediction data, and the general expression for $ARMA(p,q)$ is:

$$X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \quad t \in Z \tag{10}$$

where the first half is the autoregressive part, non-negative integer p is the autoregressive order, $\phi_1,\ldots,\phi_p$ are the autoregressive coefficients, and the second half is the sliding average part, non-negative integer q is the sliding average order, and $\theta_1,\ldots,\theta_q$ are the sliding average coefficients. X_t is the sequence of user request data correlation, and ε_t is the sequence of independent and identically distributed random variables that satisfy $Var\varepsilon_t = \sigma_\varepsilon^2 > 0$.

The analysis phase B determines whether the cloud service satisfies the execution of the planning phase B according to the proposed threshold value, and the cloud service that satisfies the condition is subject to the operation of the planning phase B.

III. C. 3) Planning phase

In the planning phase A, decisions are made using the DQN resource elastic provisioning method for horizontal scaling of resources and the whole process is categorized into three states: normal resources, lack of resources and wasted resources. First, the predicted value of the number of user requests in the next time interval is obtained from the analysis phase using the prediction technique, and the CPU load situation after the predicted number of user requests in the next moment is added to the current cloud service is calculated based on the predicted value. Then, the current resource state is determined from the load situation and an action is randomly selected with probability ε according to the resource allocation algorithm, otherwise the action with the largest Q value in the network is selected. The action is then executed to direct the user to request access to the cloud service, request access to the cloud service, and observe the reward r_k and store the data pair (s_k, a_k, r_k, s_{k+1}) to the knowledge base D. Finally, a certain amount of data is taken out from the knowledge base D, and a gradient descent algorithm is used to compute the loss function and optimize the parameters of the network θ.

In the planning phase B, first, a resource sharing pool is created, which consists of a certain amount of unused resources in each VM. Then, user requests that are blocked due to insufficient resources during the operation of all cloud services are transferred to the resource pool for execution. Finally, a certain number of VMs are released by calculating the time from the current moment to the next scheduled phase A and the average number of user requests per minute in order to anticipate the resources reserved for the next scheduled phase A.

III. C. 4) Implementation phase

In execution phase A, the virtual machine manager component performs the actions determined in planning phase A. The virtual machine manager creates new VMs for the cloud service or releases the least utilized VMs. in execution phase B, based on the actions determined in planning phase B, the resource manager performs the task migrations and releases the VMs based on the criteria determined in the planning phase.

IV. Analysis of experimental evaluations

In this chapter, a series of experiments based on Google Trace are conducted to evaluate the performance of the proposed DQN digital resource allocation optimization model for the cultural and tourism industry and to compare it with other resource scheduling algorithms, all the presented experimental results are taken from the optimal value of the 15 results, and all the experiments were conducted using a single NVIDIA TITAN XP GPU with 12 GB of memory pytorch 2.0 executed in a Python 3.7 environment.

IV. A. Data sets

All the experiments in this paper use GoogleTrace, a real-world cluster trace dataset from Google Cloud Data Center, to explore the performance performance and adaptability of the algorithms proposed in this study.There are 25 million tasks and 12,500 machines (servers) in the Google Cloud Data Center, and during a period of about one month in May 2011, the Google Cloud Data Center collects information about the cloud environment every Five minutes, the Google Cloud Data Center collects the cloud environment information and records it into Google Trace, which includes task information and server information, etc. The reason for choosing Google Trace is that it is the best choice for the cloud environment. Google Trace is chosen because it is the most representative real dataset, and it is the most widely used dataset for evaluating the performance of cloud computing task scheduling (or resource management). Therefore, Google Trace is also used in this paper in order to make an experimental comparison with many other methods.

IV. B. Baseline Algorithm

In this section, the results of comparative experiments between the DQN digital resource allocation optimization model for the cultural and tourism industry and some baseline algorithms will be presented, and three representative algorithms are used here as baseline algorithms for comparison.

Round Robin (RR): uses a round-robin approach to select appropriate servers for tasks.

DRL: directly applies Actor-Critic networks to task scheduling without two modules, offline and online imitation learning, and is chosen as a representative of traditional DRL-based methods.

AIRL: An Adversarial Imitation Learning based on Deep Reinforcement Learning is proposed to optimize the task scheduling problem, using a pre-trained expert network to confront the intelligences online, thus transforming the expert knowledge into the intelligences' knowledge.

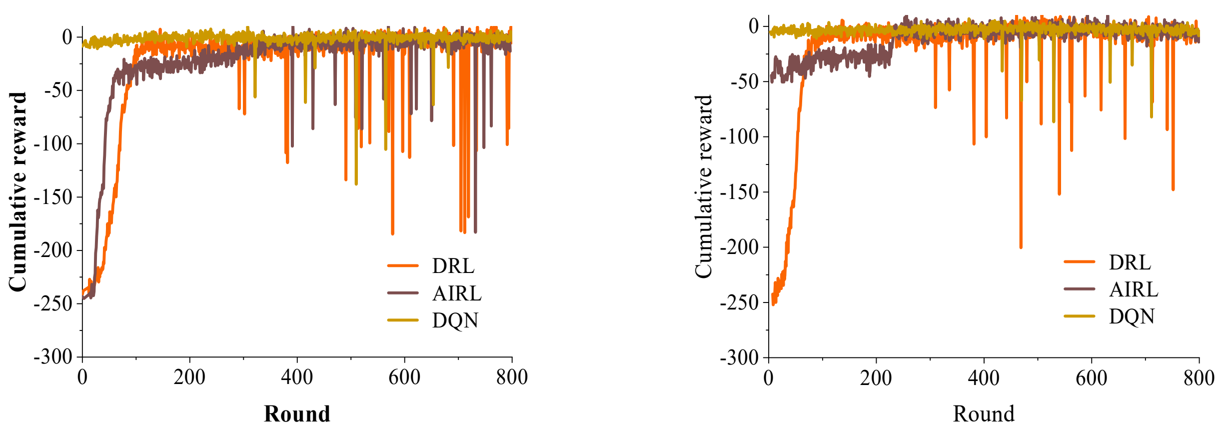
IV. C. Experimental results

IV. C. 1) Convergence analysis

The DRL and AIRL algorithms are used for convergence comparison with the model in this paper, and the convergence curves between the baseline algorithms and DQN at different cloud sizes are shown in Fig. 1, where it can be seen that the rewards returned by both DRL and AIRL in the initial phase are lower than those of DQN, and the cumulative rewards refer to the sum of all the rewards in a round. The reason is that in the initial scheduling phase of both DRL and AIRL, they use randomly initialized network parameters to make decisions, which means that the intelligences have no scheduling experience (samples) to learn in this case. Afterwards, they learn the policy by interacting with the environment, so the rewards of both algorithms slowly increase until they reach their maximum value.

As an example of the results for a cluster of 75 servers, DRL converges around 120 rounds and AIRL converges around 50 rounds, this is because DRL learns only from the online interactions of the cloud environment, whereas AIRL is able to converge faster with the help of additional expert experience beyond the online interactions. In this case, AIRL converges faster than DRL in the initial scheduling phase, and as an example, the cumulative reward of AIRL grows faster than the cumulative reward of DRL within 60 rounds (one round contains 300 time slots) as a result of the 75-server cluster, due to the fact that AIRL learns with the help of additional expert experience in addition to the online interactions, while DRL learns only from the intelligentsia's and the cloud environment's learning from online interactions. However, after 60 rounds, AIRL always converges slower than DRL due to the fact that the experts used by AIRL are obtained through pre-training and do not provide effective real-time knowledge, which makes the optimal learning direction difficult to be explored.

Under different sizes of data centers, the DQN model in this paper always converges to the maximum cumulative reward throughout the online scheduling process. In addition, the DQN model overcomes oscillations due to load variations and learns steadily in the direction of maximizing rewards and scheduling tasks with optimal policies.



(a)75 server clusters (b)150 server clusters

Figure 1: Convergence comparison: baselines and DQN under different server number

IV. C. 2) Comparative experimental analysis

The success rates of task execution of the four algorithms under different numbers of requests are shown in Figure 2. With the increase in the number of requests, the problem of insufficient digital resources in the system culture and tourism industry begins to appear, the competition of tasks for computational resources intensifies, more and more tasks cannot be completed before the deadline due to the inability to obtain sufficient computational resources, and the corresponding task execution success rates of the four algorithms show a decreasing trend. In addition, all edge servers tend to schedule tasks to the edge server with the optimal resource allocation for execution, which will result in load imbalance and overloading of local edge servers.

The RR algorithm has the lowest task execution success rate among the four algorithms, and the mean task execution success rate in the experiments is 0.520. The DRL and AIRL algorithms are able to make decisions that are more favorable to the long-term task execution success rate improvement, and the two algorithms significantly outperform the RR algorithm, in which the AIRL algorithm corresponds to a slightly higher success rate than the DRL algorithm, and the mean task execution success rate of the two methods is 0.593 and 0.646. The method proposed in this paper performs the best, with an average task execution success rate of 0.742, which verifies the advantages of the DQN algorithm proposed in this paper in improving the utilization rate of digital resources in the culture and tourism industry, and enhancing the throughput rate of the intelligent culture and tourism resource system.

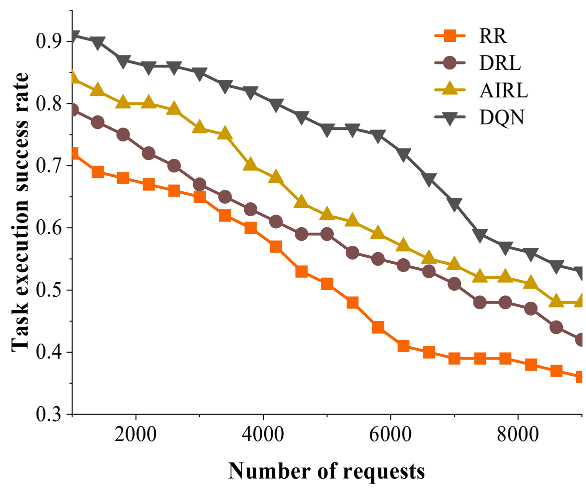


Figure 2: The task execution success rate of the four algorithms in different requests

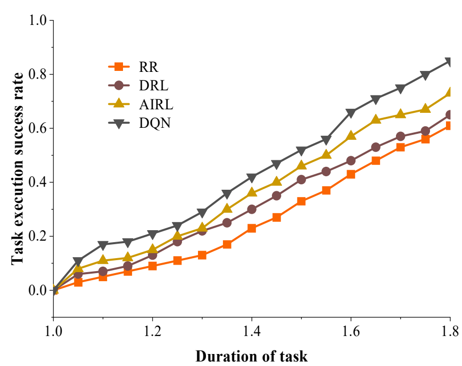


Figure 3: The task execution success rate change with the tolerance of the time

The time that each task actually occupies the computational resources for execution is calculated in constructing the service request dataset, and the latency tolerance is the ratio of the task's as-of-time to the execution time, the higher the latency tolerance, the higher the possibility that the task will be executed and completed before the as-of-time. The task execution success rate of the four algorithms with different task delay tolerance is shown in Figure 3. As the delay tolerance increases, the corresponding task execution success rates of the four algorithms show an upward trend, and the overall mean values of the corresponding task execution success rates are 0.262, 0.313, 0.362, and 0.430, respectively. The algorithm DQN proposed in this paper shows a significant advantage over the other three algorithms in the lower delay tolerance, which reflects the superiority of the algorithms in the scheduling of the urgent tasks. This shows the superiority of the algorithm proposed in this paper in dealing with emergency task scheduling.

The task execution success rates of the four algorithms under different numbers of edge servers are shown in Fig. 4, with the increase of the number of edge servers, the total amount of resources within the edge computing system is elevated, and the corresponding task execution success rates of the four algorithms show an upward trend. When the number of edge servers is 10, the task execution success rate of the proposed algorithm DQN is 0.524, which is significantly better than the comparison algorithm, and verifies the performance of DQN algorithm under the condition of shortage of digital resources in cultural industry. When the number of edge servers is greater than 17, the edge computing system overflows with resources, and the success rate of task execution under the four algorithms gradually approaches. When the number of edge servers is 30, the task execution success rate of the proposed algorithm DQN is 0.894.

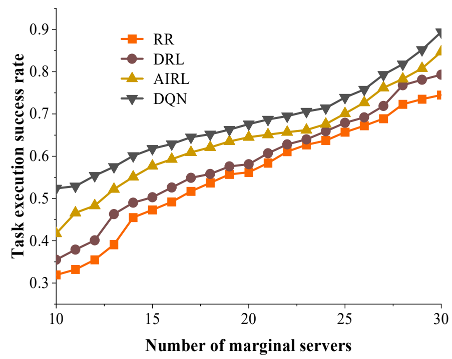


Figure 4: The task execution success rate varies with the number of marginal servers

To verify the scalability of the proposed algorithms, the inference time required to generate decisions for the four algorithms in this paper at different number of edge servers. The inference time is the time from data input into the neural network to the output generated by the neural network, and the inference time of the deep reinforcement learning algorithms depends on the matrix multiplication operation performed by the environmental observations with the parameters of the neural network. The variation of inference time with the number of edge servers is shown in Fig. 5. As the number of edge servers increases, the inference time corresponding to other algorithms is significantly higher than that of the DQN algorithm proposed in this paper, and the inference time grows in a linear trend, and the inference time is too long, which will lead to inefficient task scheduling, and it is difficult to expand to the request-intensive, large-scale network environment. The reasoning time of the DQN digital resource allocation optimization model for cultural tourism industry proposed in this paper is basically stable at 2~3ms, which has high scalability.

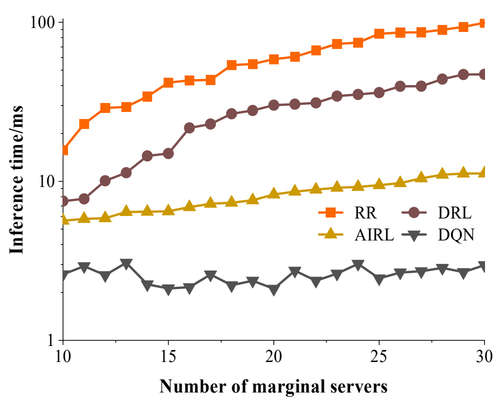


Figure 5: Inference time changes with the number of marginal servers

V. Conclusion

The application of DQN algorithm in digital resource allocation for cultural tourism industry in this study significantly improves the task execution success rate and resource utilization. The experimental results show that in a test environment of 75 servers, the proposed model has a task execution success rate of 0.742, which is significantly better than the traditional Round Robin algorithm (0.520) and other baseline algorithms (DRL: 0.593, AIRL: 0.646). In addition, the DQN algorithm shows good scalability with different numbers of edge servers, and the success rate of task execution reaches 0.894 when the edge servers are 30, which proves the advantage of the algorithm when the resources are sufficient. Compared with other methods, the DQN algorithm performs particularly well in handling low latency tolerance tasks, and can efficiently schedule tasks to ensure timely completion. Based on these experimental data, it can be concluded that the DQN algorithm provides a more efficient and flexible resource allocation solution for the cultural and tourism industry, and promotes the intelligence and efficiency of resource management in the cultural and tourism industry.

Funding

This work was supported by Project number 2023122946573: Project name Yuanzhou Tourism Industry's digital-real integration of professional talent supply and demand docking and employment education model construction.

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