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Optimization Method of Higher Education Resource Allocation Combined with DQN Algorithm

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Abstract: - At present, there are problems of low efficiency and serious waste of resources in the allocation of higher education resources. The aim of this study is to explore the potential and effectiveness of the DQN (Deep Q-Network) algorithm in higher education resource allocation, verify the advantages of the DQN algorithm in resource allocation through simulation experiments, and compare the differences in effectiveness between traditional methods and DQN methods. The study first analyzes the demand and current situation of higher education resource allocation, establishes a resource allocation model suitable for DQN algorithm, then designs the DQN algorithm framework and conducts algorithm training and testing, and finally, analyzes the performance of DQN algorithm and proposes optimization suggestions based on experimental data. The study observed that the usage rate of experimental equipment reached 90% in autumn, indicating that certain resources may face high load usage during specific time periods. This study introduces deep reinforcement learning technology into the field of higher education resource allocation, especially using DQN algorithm to optimize the decision-making process, which can achieve dynamic optimization and self adjustment of resource allocation.

Keywords: Allocation of Higher Education Resources; Deep Reinforcement Learning; Deep Q-Network; Resource Optimization; Improving the Quality of Education

1. Introduction

In today's higher education system, precise allocation of resources has become a core issue in improving educational efficiency and quality. The traditional resource allocation strategy that relies on empiricism is inadequate in the face of increasingly complex and changing educational demands. With the leap of computer technology, especially the breakthrough progress in the field of deep reinforcement learning, a new path has been opened up for the intelligent transformation of educational resource management. Deep Q-Network (DQN), as a leader in the field of DRL, has demonstrated outstanding performance in areas such as game strategy and autonomous robot navigation, indicating its enormous potential in optimizing the allocation of higher education resources.

This study focuses on exploring the innovative application and potential benefits of DQN algorithm in the field of higher education resource allocation. We have carefully designed a state space, action set, and reward

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mechanism closely related to the allocation of educational resources to adapt to the core framework of DQN algorithm. By elaborating on the customized adjustment, implementation details, and training process of the DQN algorithm, this study conducted in-depth experiments in a simulated educational environment. The experimental results not only strongly validated the effectiveness of DQN algorithm in dynamically adapting to changes in educational needs and optimizing resource allocation, but also highlighted its significant advantages in dealing with complex and changing resource allocation challenges through comparative analysis with traditional methods, providing strong support for the intelligent upgrading of higher education resource management.

The structure of this article is as follows: Firstly, introducing the research background and the basic principles of DQN algorithm, as well as the current challenges in educational resource allocation; then providing a detailed explanation of the research methodology and experimental design, including model establishment, algorithm implementation, and experimental setup; finally, analyzing the experimental results and discussing the performance and potential improvement directions of DQN algorithm in practical applications. Through these studies, this article not only enhances the understanding of the application of DQN algorithm in the field of education, but also provides a new technical solution for higher education resource management.

2. Related Work

The rational allocation of educational resources directly affects the quality of teaching and student satisfaction. Recent studies have shown that the use of modern technological means can significantly improve the scientific and precise allocation of resources. Especially the application of machine learning and optimization algorithms in the field of education has been proven to effectively solve the problem of resource waste, optimize teacher allocation and equipment utilization. Luo Jianghua believes that digital educational resources play an important role in promoting high-quality development of education. In the era of artificial intelligence, the key issue that urgently needs to be addressed in the construction of digital education resources is how to transform them from being adaptable to people to actively adapting to them. With the continuous expansion of application scenarios for artificial intelligence generated content, cross modal understanding and reconstruction technology provides feasible technical support for solving the adaptability problem of digital educational resources. Specifically, it advocates for "human environment machine object" multi-agent collaboration, utilizing cross modal understanding and reconstruction techniques to intelligently mine and couple multimodal teaching behaviors and digital educational resources in complex educational contexts, and achieve educational resource recommendations suitable for human-machine collaborative environments[1]. Li Fengliang conducted a sustainability analysis of the development of open educational resources in higher education institutions from the perspective of cost efficiency[2]. Li Xin believes that the spirit of the red school history and culture is carried by excellent traditional culture, fully tapping into the spiritual resources of the red school history and culture, which greatly affects the thinking and construction of ideological and political education and collaborative education[3]. Zhang Xuemin studied the spatiotemporal pattern and evolutionary plan of the efficiency of graduate education resource allocation based on provincial panel data from 2003 to 2018[4]. Ochieng V O explored the potential and impact of productivity research in higher education institutions from the perspective of open educational resources and social justice [5]. However, most of these studies rely on static data and lack real-time response capabilities to environmental changes, which is clearly insufficient in rapidly changing educational environments.

Deep learning techniques, especially deep reinforcement learning, have demonstrated excellent adaptability and optimization capabilities in the decision-making process of dynamic systems. The successful application of these technologies in the fields of finance, healthcare, and logistics provides a new perspective for addressing the dynamic and complex issues of educational resource allocation. Hilton III J conducted a review of research published between 2015 and 2018, as well as the relationship between open educational resources, student efficacy, and user perception[6]. Raja B S studied the allocation plan of online education resources for orthopedic residents [7]. Nipa TJ conducted an evaluation of open educational resources developed in an interactive learning environment [8]. Smirani L used the Unified Theory of Technology Acceptance and Use to investigate teachers' adoption of open educational resources [9]. Moon J conducted a review of the Shanghai Cooperation Organization's open educational resources to support interaction among disabled learners [10]. However, although existing research has explored the feasibility of these methods to some extent, there are still few specific application examples in the field of education, lacking in-depth analysis of the actual effects and implementation strategies in various educational scenarios.

3. Method

3.1 Adaptation and Adjustment of DQN Algorithm

In this study, we first adapted the Deep Q-Network (DQN) algorithm to meet the specific needs of higher education resource allocation. The DQN algorithm was originally designed to solve sequence decision problems, especially performing well in high-dimensional state spaces [11-12]. In the context of educational resource allocation, each type of resource (such as teachers, classrooms, equipment, etc.) and the state of each resource (such as usage rate, demand intensity, etc.) constitute a complex state space.

3.1.1 Definition of state space

Resource types and states: Quantifying the availability, current usage, and expected demand of various resources such as teachers, classrooms, and laboratory equipment as states.

Temporal dynamism: Incorporating different time points of each semester or academic year into state considerations to capture seasonal changes in resource demand. The data on the allocation of higher education resources is shown in Table 1.

Table 1. Data on resource allocation in higher education

Resource ID(Identifier)	Resource type	Current usage rate (%)	Demand intensity	Time (semester)
1	Teacher	75	High	Autumn
2	Classroom	60	Medium	Spring
3	Experimental equipment	90	High	Autumn
4	Teacher	50	Low	Spring

5	Classroom	85	High	Autumn
6	Book resources	40	Medium	Spring
7	Experimental equipment	30	Low	Spring
8	Classroom	70	High	Autumn
9	Teacher	95	High	Autumn
10	Book resources	55	Medium	Spring

There is a significant difference in resource utilization rate: the results show that the utilization rate of experimental equipment in autumn is as high as 90%, indicating that some experimental equipment may experience overload during a certain period of time. In sharp contrast, in spring, only 30% of experimental equipment is used. The correlation between demand intensity and time: There are significant differences in resource types such as teachers, classrooms, and books among different academic stages. For example, in autumn, the demand for classrooms will be higher, which may be closely related to the start time and class schedule of the new semester. Diversity of resource types: These resources include many types, from teacher materials to book materials, each with its own frequency of use and required density. This places higher demands on resource management systems, which require effective management of different types of resources. The importance of time dimension: The semester cycle has a significant impact on the utilization of resources, indicating that time is a necessary factor in resource allocation. For example, in autumn, teachers spend 95% of their time indicating that we should focus on students' learning.

Assuming our goal is to maximize resource utilization efficiency and meet educational needs, we can define a reward function as follows:

$$R(s,a) = \alpha \times U(s') + \beta \times D(s') - \gamma \times C(a) \quad (1)$$

s is the current state, s' is the new state after taking action a. $U(s')$ is the resource utilization rate in the new state, which is a ratio between 0 and 1, representing the efficiency of resource utilization [13]. $D(s')$ represents the degree of satisfaction of the requirements in the new state, which is also a value between 0 and 1, reflecting how the current resource allocation meets the teaching needs. $C(a)$ is the cost of taking action a, which may include quantifying resource adjustments, maintenance, or other related expenses. α, β, and γ are weight coefficients used to adjust the relative importance of utilization, demand satisfaction, and cost in the reward function.

3.1.2 Action space design

Resource allocation decision: Specific operations include increasing or decreasing the allocation quantity of a certain resource, adjusting the usage time of the resource, etc.

Strategy adjustment: During the teaching process, teachers can make corresponding adjustments to the teaching plan based on the specific situation of the teaching activities.

3.1.3 Construction of reward function

Efficiency optimization: The design of the reward function is mainly aimed at better utilizing resources, such as calculating rewards based on maximum classroom utilization and teacher satisfaction.

Requirement satisfaction: While balancing the allocation of educational resources and teaching quality, it is also necessary to reflect students' academic achievement and satisfaction.

3.1.4 Model training and algorithm optimization

This article utilizes the "experience replay" mechanism of reinforcement learning to store the "memories" (states, actions, rewards, new states) during the learning process, in order to optimize resource allocation, break through temporal correlations between samples, and improve learning stability.

3.2 Training Data Preparation

Simulation environment establishment: Creating a simulated higher education environment that includes various course requirements, classroom conditions, and teacher availability.

Data generation: Generating training data by simulating different teaching activities and resource allocation situations.

The detailed information on the demand for educational resources in different teaching activities is shown in Table 2.

Table 2. Detailed information on the demand for educational resources in different teaching activities

Activity ID	Activity type	Resource type	Quantity of required resources	Activity duration (hours)	Activity frequency (per semester)
A1	Lecture	Classroom	1	2	30
A2	Experimental class	Laboratory	1	3	15
A3	Workshop	Conference room	1	4	10
A4	Large scale lecture	Lecture hall	1	2	5
A5	Computer courses	Computer laboratory	1	2	20
A6	Foreign language lesson	Language laboratory	1	1.5	25
A7	Physical Education class	Gymnasium	1	2	18
A8	Art Workshop	Art studio	1	3	8
A9	Music Practice	Music room	1	1	20
A10	Academic Reports	Auditorium	1	2	12

Diversified resource requirements: The data table shows that there are various types of teaching activities, from lectures to physical education classes, each requiring specific types of resources. For example, computer courses require a computer laboratory, while music practice requires a music room. This diversity requires resource management systems to be able to flexibly handle multiple resource requirements and ensure that each resource meets the specific needs of related activities. Time sensitivity of resource utilization: Data on activity duration and frequency indicate significant differences in resource demand for each activity over time. For example, although the frequency of large-scale lectures is not high, they usually require larger venues such as lecture halls. The prediction and scheduling of such demands are key to optimizing resource utilization.

Optimizing potential mining shows that by analyzing resource types and activity frequencies, low utilization areas such as art workshops and academic reports can be identified, and usage plans can be adjusted to improve efficiency. These data lay the foundation for developing efficient resource allocation strategies, such as adjusting predetermined strategies based on activity duration and frequency. Fine analysis helps to accurately predict resource demand, balance teaching quality and resource efficiency, and provide empirical data support for advanced algorithms such as deep reinforcement learning.

In the design of neural networks, a multi-layer perceptron architecture is constructed, with corresponding state spaces as inputs and action spaces as outputs. The middle layer strengthens feature extraction and transformation, and fine tunes learning rates, loss functions, and optimizers through cross validation to ensure model performance. Implementing experience replay strategy, utilize historical data for small batch training, and enhance generalization ability. Regularly updating the target Q network weights, stabilize the learning process, and ensure accurate and stable decision-making.

4. Results and Discussion

4.1 Experimental Environment and Parameter Settings

The experimental environment is set as follows:

Test scenario construction: Multiple educational resource allocation scenarios have been constructed, including schools of different sizes and resource restrictions of different types. Definition of evaluation indicators: Multiple performance indicators are defined, including resource utilization, satisfaction, educational outcomes, etc.

The performance comparison analysis is as follows:

Quantitative analysis: Collecting and analyzing performance data of DQN algorithm and other methods in various scenarios; Qualitative evaluation: obtaining subjective evaluations of algorithm effectiveness from feedback from educational administrators and teachers; the experiment was conducted in a simulated educational institution environment with complete curriculum arrangements, classroom distribution, teacher and student databases. This simulation environment can reflect the variability and complexity of school schedules in the real world.

(1) Parameter setting: semester length: 15 weeks; resource types: classroom, teacher, experimental equipment; action selection interval: once a week; discount factor: 0.9; learning rate: 0.05; exploration rate: gradually decreases from 1 to 0.01.

(2) Evaluation indicators: evaluation indicators include resource utilization, satisfaction, cost-effectiveness, and system stability. Resource utilization is calculated as the total time spent on resources divided by the total time available; Satisfaction: based on feedback from teachers and students, data is collected through a

questionnaire survey, with a rating range from 1 to 5; Cost effectiveness: considering the costs required for changes in resource allocation, including material, manpower, and time costs; System stability: evaluating the frequency of resource allocation changes and the responsiveness of the system. Experimental environment E can be defined as a tuple, including state space S, action space A, and transition function T:

$$E = (S, A, T)(2)$$

To evaluate the performance of the DQN model, we define a set of evaluation metrics M, including resource utilization U, satisfaction D, and cost-effectiveness C [14]:

$$M = \frac{1}{N}\sum_{i=1}^{N}\left(\alpha \cdot U(s_i) + \beta \cdot D(s_i) - \gamma \cdot C(a_i)\right)(3)$$

N is the total number of decisions considered during the testing period. s_i is the state after the i-th decision. a_i is the i-th decision.

4.2 Result Analysis

(1) High demand period experiment

Scenario description: Considering the final exam week, there is a high demand for resources, especially classrooms and invigilators.

Objective: To maximize resource utilization while maintaining high satisfaction.

The experimental results during the high demand period are shown in Figure 1 (Figure 1 (a) is the classroom utilization rate, Figure 1 (b) is the teacher availability rate, Figure 1 (c) is the experimental equipment utilization rate, and Figure 1 (d) is the book resource utilization rate).

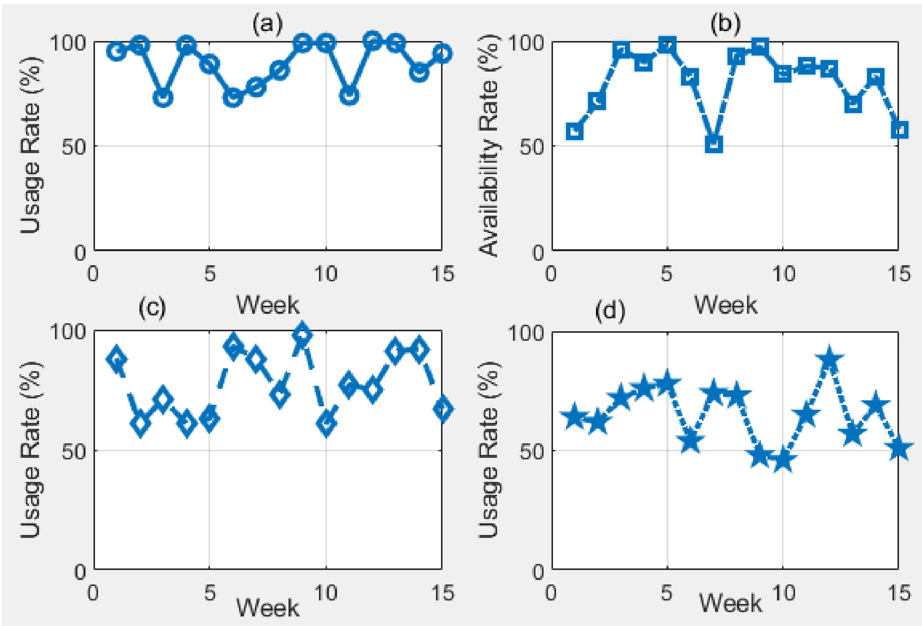

Figure 1. Experimental results during high demand period

Classroom utilization rate: The utilization rate of classrooms is relatively high, usually above 70%, indicating that classroom resources are actively used during the demand period. High utilization may indicate good resource allocation or potential overload risk. Teacher availability: The availability of teachers fluctuates greatly, with a minimum of 50%, which may reflect shortages of teacher resources during certain weeks or adjustments during holidays and training periods. The low availability rate requires further analysis of the reasons to ensure that teaching quality is not affected. Experimental equipment utilization rate: The utilization rate of experimental equipment also shows high fluctuations, but remains above 60%, and even approaches 100% during peak hours. This fluctuation may be related to the arrangement of specific courses, indicating that additional equipment investment may be required during the week of concentrated experimental courses. Book resource utilization rate: The utilization rate of book resources is relatively low compared to other resources, with a peak of only about 90%. This may indicate that the allocation of book resources is relatively sufficient or the utilization efficiency is not particularly high.

Through these analyses, managers can better understand the resource allocation situation during high demand periods, adjust strategies in a timely manner to optimize resource utilization, improve satisfaction, reduce costs, and maintain overall system stability. The visualization analysis in Figure 1 can also help educational institutions predict future resource demands, enabling more accurate resource planning and allocation.

(2) Teacher shortage experiment

Scenario description: Simulating a scenario where a large number of teachers are absent due to unexpected situations.

Objective: To minimize the impact on teaching quality by adjusting course schedules and alternative resources.

The results of the teacher shortage experiment are shown in Figure 2 (Figure 2 (a) is the classroom utilization rate, and Figure 2 (b) is the rating).

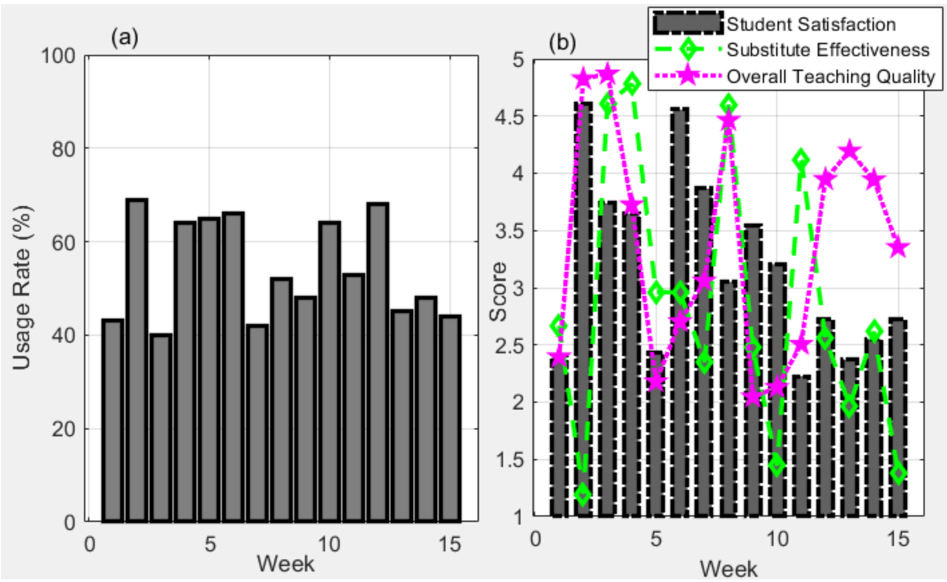

Figure 2. Experimental results of teacher shortage

It shows the trend of classroom utilization and three key teaching evaluation indicators (student satisfaction, effectiveness of alternative measures, and overall teaching quality). We can conduct the following analysis:

The fluctuation of classroom utilization rate: In the figure, the classroom utilization rate fluctuates between 40% and 70%, indicating that the optimal use of classrooms has not been achieved in the context of teacher resource shortage. The lower utilization rate may be due to a lack of sufficient teachers to teach courses or conduct teaching activities. Student satisfaction: The rating of student satisfaction fluctuates greatly throughout the entire cycle, ranging from nearly 2 points to 5 points. This fluctuation may reflect inconsistent effects of alternative teaching measures or other temporary adjustment measures, or individual differences in students' responses to changes.

The teaching effectiveness of alternative teaching measures has also fluctuated, but overall it remains at a medium to high level. This indicates that although there is a shortage of teaching staff, teaching activities can still be sustained and effectively maintained through available courses. The evaluation of overall education quality also shows fluctuations, which may be closely related to the effectiveness of other measurement methods and student satisfaction. When resources are insufficient, fluctuations in quality scores indicate unstable educational quality. This chart reveals the mutual influence between various teaching indicators from multiple perspectives under the condition of insufficient teaching staff. Through comparative analysis, it was found that insufficient school resources seriously affect the efficiency of school utilization and teaching quality. In addition, although alternative teaching can alleviate the shortage of teachers to some extent, the inconsistency of its effectiveness will have a greater impact on student satisfaction and overall evaluation of educational quality. Education administrators can comprehensively understand and evaluate current teaching resource management strategies, and explore ways to improve them in order to enhance the utilization of educational resources and teaching quality, ensuring the stability and sustainable development of educational quality.

(3) Resource optimization and allocation experiment

Scenario description: Optimizing in a situation where resources are abundant but unevenly distributed.

Objective: To achieve higher resource utilization efficiency and reduce operating costs.

The experimental results of resource optimization configuration are shown in Figure 3 (Figure 3 (a) is the resource utilization efficiency field, and Figure 3 (b) is the efficiency status of each resource point).

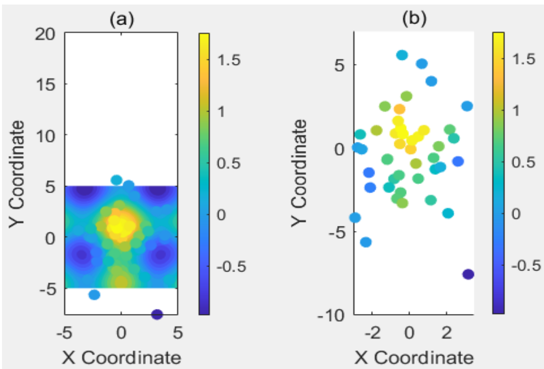

Figure 3. Experimental results of resource optimization configuration

From Figure 3, we can observe two different perspectives on resource optimization allocation. The first subgraph uses contour maps to display the entire resource utilization efficiency field, while the second subgraph visually indicates the efficiency status of each resource point through scatter plots. These figures together provide a detailed view of resource optimization, and this article presents the following key points:

The distribution of efficiency field: The contour map reveals the spatial distribution characteristics of resource utilization efficiency, where the changes in efficiency are represented by contour lines of different colors. This continuous spatial distribution map helps us understand the potential efficiency of resource utilization in different regions, thereby guiding the rational layout and optimized allocation of resources. Distribution and efficiency of resource points: Each point in the scatter plot represents a resource location, and the color intensity of the point indicates the efficiency of resource utilization. Through this representation, we can intuitively see which resources are efficiently utilized and which resources are underutilized. This provides direct visual evidence for adjusting resource allocation strategies, especially in areas that require optimization or reallocation of resources. The optimization potential of resource allocation: By comparing the two subgraphs, we can analyze the positional relationship of resource points in the efficiency field, identify abnormal points located in high-efficiency areas but with low actual efficiency, and identify excellent points that can maintain high efficiency even in low efficiency areas. This analysis helps identify the strengths and weaknesses in resource allocation, further promoting the scientific and precise allocation of resources. Decision support information: Graphics provide quantitative and visual support to assist in resource allocation decisions. By displaying the spatial distribution and status of efficiency, decision-makers can accurately plan resources, optimize utilization, and enhance overall efficiency. Figure 3 is a key tool for optimizing decision-making, analyzing the efficiency and effectiveness of resource allocation from multiple dimensions, providing scientific guidance for maximizing resource utilization.

(4) Long term stability testing

Scenario description: Observing the performance of DQN algorithm throughout the semester and evaluate its performance in continuous operation.

Objective: To evaluate the adaptability of algorithms to long-term changes and the stability of resource allocation.

The long-term stability test results are shown in Figure 4.

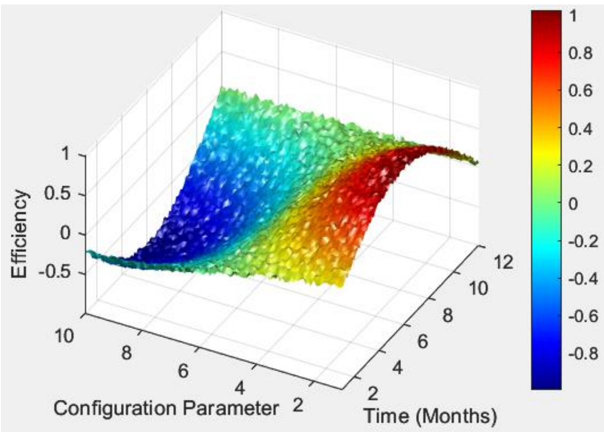

Figure 4. Long term stability test results

The data reveals a positive correlation between increasing configuration parameters and improving resource utilization efficiency, indicating that optimizing parameter settings is crucial for enhancing resource efficiency. The monthly efficiency has generally increased, indicating the role of operational optimization or seasonal factors. The peak efficiency under specific month and parameter combinations provides clues for determining the optimal resource allocation strategy. Based on this, the following strategic suggestions are proposed: Firstly, implementing dynamic configuration adjustment and flexibly adjust parameters according to monthly changes to maximize resource utilization. Secondly, deepening the detailed analysis of configuration parameters, clarify the specific contributions of each parameter to efficiency, and promote precise resource allocation. Finally, strengthening long-term monitoring and analysis mechanisms, regularly review data, and flexibly respond to environmental changes to ensure the effectiveness and adaptability of strategies. This analysis not only provides data support for resource allocation decisions, but also points out the direction of continuous optimization and improvement, helping to achieve efficient and stable resource management, and laying a solid foundation for the sustainable development of educational institutions.

4.3 Discussion

This study explores the innovative application of Deep Q-Network (DQN) algorithm in higher education resource allocation, focusing on improving resource allocation efficiency and utilization. DQN, with its powerful learning and decision-making abilities, has demonstrated significant advantages in dynamic educational environments, especially in response to peak resource demands. Through intelligent strategy optimization, it effectively reduces resource idle and improves teaching quality and student satisfaction.

However, DQN applications also face challenges: the diversity of educational resources and policy changes exacerbate decision-making complexity; data requirements and computational resource limitations have become practical obstacles; the quality of data directly affects the efficiency of algorithms. Future research should explore the integration of DQN with other machine learning techniques to improve decision-making accuracy and efficiency; meanwhile, developing lightweight algorithm variants to reduce resource consumption. In addition, strengthening the social responsibility of algorithms and ensuring that resource allocation balances efficiency and fairness are key to promoting technological applications.

At the social and policy levels, the implementation of DQN resource allocation strategies needs to be carefully considered to ensure that technology serves the overall goal of educational equity and quality improvement. Policy makers need to work closely with educational institutions to develop algorithmic application guidelines that meet social needs and promote the deep integration of technological ethics and educational values. This study not only opens up a new path for the application of DQN in the field of education, but also provides valuable reference and inspiration for subsequent research and practice. This will help achieve modernization of educational resource management, promote the dual improvement of educational equity and efficiency, and lay a solid foundation for future educational reforms and technological applications.

5. Conclusion

This study uses Deep Q-Network (DQN) to optimize the allocation of higher education resources, constructs a dynamic decision-making model, simulates the use of resources such as classrooms and teachers, and defines state, action, and reward mechanisms. Experimental results have shown that DQN significantly improves resource utilization, reduces idle, and enhances teaching satisfaction. Long term testing has shown that the model has high adaptability and stability, effectively responding to changing demands, achieving intelligent resource allocation optimization, and thus improving educational efficiency. Although the research has achieved positive results, there are still some limitations. Firstly, the practical application of the model relies on accurate and comprehensive data input, and in reality, data collection and processing may have delays and incompleteness. Secondly, the performance of DQN algorithm in handling extreme situations such as sudden large-scale demand changes still needs further validation. In addition, this study mainly focuses on the internal resource allocation of a single institution and has not yet addressed complex scenarios such as cross institutional resource sharing. Future research can be expanded and deepened from several aspects. Firstly, it is possible to explore incorporating a wider range of resources and complex decision-making factors into the model, such as students' learning preferences and teachers' professional expertise. Secondly, research can be extended to cross institutional resource sharing and collaborative configuration, exploring a wider range of educational resource optimization networks. In addition, further research will be conducted on the universality and adjustment needs of algorithms in different types of educational institutions to adapt to more diverse educational environments and policy changes. Through these studies, future educational resource allocation will be more intelligent, efficient, and adaptable, better meeting the needs of educational institutions and learners. This will bring revolutionary changes to educational management, promoting the maximum utilization of educational resources and the continuous improvement of educational quality.

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