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

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ABSTRACT

This paper intends to introduce the multi-intelligence of digital resources in cultural and tourism industry in reinforcement learning. In order to scientifically evaluate digital resource allocation, the index system characterizing resource allocation is constructed using hierarchical analysis. From there, a multi-objective collaborative optimization allocation model of digital resources in cultural and tourism industry based on reinforcement learning and multi-intelligent body system is established. Through empirical analysis, it can be seen that referring to the observation of the development of the comprehensive level of digital resource allocation, there is an imbalance in the development level of N province. The indicator system is refined to consist of 4 guideline level indicators and 26 indicator level indicators. Before and after the multi-objective synergistic optimization, the total amount of digital resource procurement for the cultural and tourism industry in province N was reduced by 460,742 yuan. After optimization, the comprehensive efficiency of resource allocation in area a improves by 0.03136, area b improves by 0.03275, and area h improves by 0.02799. Moreover, all of them tend to be in equilibrium. Therefore, the multi-objective synergistic optimization allocation model in this paper can improve the efficiency of digital resources in cultural tourism industry and reduce the differences between districts and counties.

Keywords: reinforcement learning, digital resources, multi-intelligence, hierarchical analysis, multi-objective optimization

1. Introduction

In today's society, cultural tourism, as an emerging industrial model that integrates cultural connotation and tourism experience, is increasingly favored by people, and the rapid development of the digital economy, digital technology and cultural tourism in-depth integration [1-3]. This has led

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to the continuous emergence of high-quality digital cultural and tourism resources, further releasing the potential of digital cultural and tourism consumption, and the emergence of a number of new consumption formats, consumption modes and scene applications [4-5]. However, due to the problems of limited and uneven distribution of digital resources, the optimal allocation of digital resources in the tourism industry is particularly important, and reinforcement learning plays a role in the optimization of resource allocation in the cultural tourism industry [6-8]. Reinforcement learning, as one of the popular research directions in the field of artificial intelligence, maximizes returns by learning how to act in an environment [9-10]. In the of digital resource allocation in the cultural tourism industry, reinforcement learning enables an intelligent body to gradually learn the optimal action strategy based on the reward signals given by the environment by establishing a way of interaction between the intelligent body and the environment [11-13]. In the problem of resource allocation, the intelligent body can be regarded as the decision maker of the resource allocation system, and the environment is the resources to be allocated and the related constraints [14-15].

This paper combines the multi-intelligence body of digital resources of cultural and tourism industry with reinforcement learning algorithm, and establishes a multi-objective synergistic evaluation index system of digital resource allocation using hierarchical analysis method, so as to construct a multi-objective optimization model of digital resource allocation of cultural and tourism industry. The digital resource allocation of cultural and tourism industry in 22 districts and counties in N province is selected as the research object, and the quantitative analysis method is used to calculate the development index of digital resource allocation of cultural and tourism industry, and to compare and analyze the spatial gap of digital resource allocation of cultural and tourism industry. Carry out simulated empirical research work based on the problems existing in the digital resource allocation of cultural and tourism industry in 22 districts and counties of N province. Compare the overall situation and comprehensive efficiency of resource allocation before and after optimization, and verify the correctness and usability of the model.

2. Optimized allocation of digital resources for cultural tourism industry

The optimal allocation of digital resources in the cultural and tourism industry is a process of adjusting the current distribution and allocation expectations of information resources. Its configuration is based on the user's information resource needs, oriented to the efficiency and effectiveness of digital resource allocation, with the purpose of building a complete scientific collection resource protection system through the reasonable distribution of the collection resources to better meet the readers' needs, maximize the utility of the collection resources, and maximize the benefits of the input funds even if the benefits are value-added to make the service more efficient.

Issues such as the scale of funds, resource types, coverage, use effect and use efficiency related to digital resource allocation have gradually aroused the multi-dimensional attention and research of many scholars, which indicates that carrying out research related to resource allocation has important theoretical value and practical significance. International research on the evaluation of digital resources began in the 1990s, focusing on the selection criteria of digital resources, usage statistics, evaluation indexes and model construction of resource allocation. Comprehensive research at home and abroad shows that the planning and configuration of digital resources for the cultural and tourism industry is affected by national policies and regional economic and social development on a macro level, and depends on the positioning of regional development and the scale of the cultural and tourism industry level on a micro level.

In the construction process of digital resources for cultural and tourism industry, electronic books and periodicals, databases, network resources navigation library and self-built library is the core content, and the region in order to achieve their own development needs to be combined with the development of cultural and tourism needs, the structure of the digital resources to carry out a reasonable layout, highlighting the key points at the same time to achieve balanced development.

Such as ordering a certain number of databases, e-books, e-journals. Emphasis on the development of self-built library and network resource navigation. The number of foreign language literature can be appropriately increased.

For the scientific and reasonable distribution of digital resources funding for the cultural and tourism industry, that is, lies in the reasonable distribution of traditional paper resources, digital resources funding, foreign language, Chinese digital resources acquisition costs. To this end, the acquisition cost of digital resources must be increased, and the acquisition cost of traditional paper resources needs to be appropriately reduced, so as to ensure that the informationization needs to be effectively met. In addition, great importance should be attached to the construction of online resource navigation libraries and self-built libraries, so as to provide diversified ways for the development of digital resources.

3. Multi-objective optimization model based on multi-intelligent body reinforcement algorithm

The optimal allocation of digital resources in the cultural tourism industry is a complex multi-objective optimization problem, based on the hierarchical nature of the optimal allocation of digital resource utilization in the regional cultural tourism industry, the planning decision-making body is divided into 3 levels: library Agen is the macro-decision-making body model sets up these 3 types of intelligences, which do not occupy the geospatial unit, but participate in the planning decision-making process. Multi-intelligence body reinforcement learning algorithm model framework is shown in Figure 1.

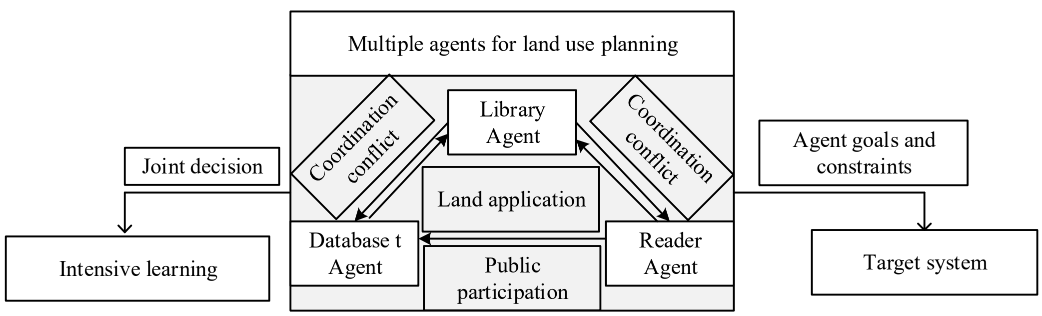

Fig. 1. Multi-agent genetic algorithm model frame diagram

3.1. Overview of reinforcement learning algorithms

Reinforcement learning is concerned with learning a control strategy that optimizes performance for a certain value through staged decision making. In this, the intelligent body acts as a decision maker interacting with an unknown dynamic environment in a trial-and-error manner and wants to maximize the cumulative positive feedback given by the environment. Reinforcement learning defines the standard formulation of such sequential decision making as a Markov Decision Process (MDP), and a Markov Decision Process G is defined as follows:

$$G = < S, A, P, R > \tag{1}$$

Define G as a quaternion, where S and A denote the state space and action space, respectively, $P(s,a): S \times A \to S$ is the state transfer function describing the probability of state transfer, and $r(s,a): S \times A \times R$ is the reward function providing immediate feedback to the intelligent body. At each time step of the MDP, the intelligent body selects an action $a \in A$ to interact with the environment based on the current state $s \in S$, and then obtains the next state $s \in S$ with the current behavioral reward based on the state transfer function and the reward function $r \in R$. Reinforcement learning with multi-intelligent body interaction is shown in Fig. 2.

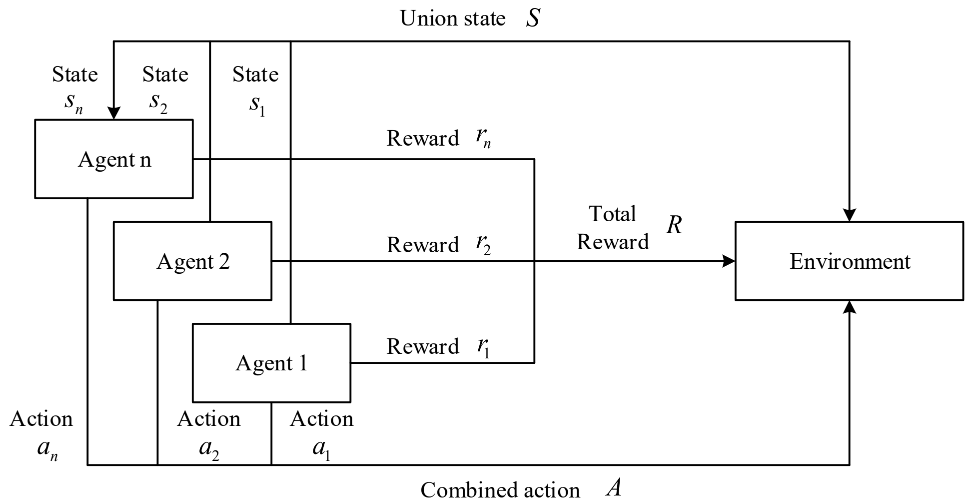

Fig. 2. Multi-agent reinforcement learning "agent-environment" interaction

The goal of the intelligent body is to find a way to act that maximizes the expected reward in the long term, given that the state transfer function is unknown. The desired reward is defined as the expectation of obtaining the reward at each time step in the time series, multiplied by the corresponding time decay factor γ. Thus, the intelligent body learns a behavioral strategy π that optimizes the cumulative discounted reward 1 throughout the learning process, defined as:

$$J = E_{a\sim\pi}\left[\sum \gamma^k r_{t+k+1}\right] \tag{2}$$

To evaluate the performance of the current policy, reinforcement learning designs the state-value function V(s) and the state-action-value function Q(s, a) to describe the expected performance as a function of the policy. The state-value function V(s) describes the expectation of future cumulative rewards from state s. The state-action-value function Q(s, a) denotes the expected reward that the MDP receives from executing an action in the current state when following the policy π. It is defined as follows:

$$V_\pi(s) = E_\pi\left[\sum \gamma^k r_{t+k+1} \mid s_t = s]\right] \tag{3}$$

$$Q_\pi(s,a) = E_\pi\left[\sum \gamma^k r_{t+k+1} \mid s_t = s, a_t = a]\right] \tag{4}$$

During the learning process, the intelligent body iterates through constant interactions by sampling in the environment, and reinforcement learning uses the Bellman equation to iteratively update V(s) and Q(s, a):

$$V_\pi(s) = \sum_a \pi(a \mid s) \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma V_\pi(s')\right] \tag{5}$$

$$Q_\pi(s,a) = \sum_{s',r} p(s', r \mid s, a)\left[r + \gamma V_\pi(s')\right] \tag{6}$$

Through iterative updating, the intelligent's policy π will eventually converge to the optimal policy π^*. Traditional reinforcement learning represents V(s) and Q(s, a) in the form of a table, and then this approach cannot be applied when the state space dimension is very high or even continuous, which restricts the applicability of traditional reinforcement learning to complex tasks.

3.2. Multi-intelligent body reinforcement learning

Many real-world scenarios involve multiple intelligences interacting and affecting a common environment, e.g., autonomous driving, sensor networks, robotics, and gaming, and in these scenarios, in this paper, intelligences are viewed as individuals with autonomy that need to learn strategies to achieve their goals. Multi-intelligent body environments can be formalized in several ways, depending on whether the environment is fully observable, how relevant the goals of the intelligences are, etc. Based on the premise that in cooperative scenarios the intelligences have the same reward function and have the same goal, the multi-intelligent body problem can be modeled as a distributed observation-constrained Markov decision process (Dec POMDP), defined by a heptad:

$$< S, A, P, R, Z, 0, N > \tag{7}$$

where S is the set of environment states denoted as the global state space, A is the set of available actions of the intelligences denoted as the action space, and N is the number of intelligences. In a distributed observation-constrained Markov decision process, an intelligent body $i \in N$ at each time step, in its current state, has access to only a portion of its own observations about the environment $o_i \in 0$, which depends on the state mapping function designed in the simulation environment:

$$Z(s,a): S \times N \to 0 \tag{8}$$

Next, the intelligent body selects the next action $a_i \in A$ based on its own observation o_i All the actions selected by the intelligent body form a joint action a, which interacts with the environment based on the joint action. The environment expresses the transfer probability from state S to a new state through the environment state transfer function based on the current intelligent body state S and the joint action:

$$P(s,a): S \times A_1 \times A_2, \ldots, A_N \to S \tag{9}$$

The reward value r for performing this action is returned to the intelligent body i according to the designed reward function $R(s,a): S \times A^N \to R$. In this setting, the multi-intelligent body needs to learn the strategy for generating joint actions to maximize the cumulative discounted rewards, where π_t is the strategy of the intelligent body i:

$$J = E_{a_1 \sim \pi_1, \ldots, a_N \sim \pi_N} \left[\sum \gamma^k r_{t+k+1} \right] \tag{10}$$

4. Empirical study on digital resource allocation optimization in cultural tourism industry

4.1. Analysis of the development level of digital resource allocation in the cultural tourism industry

4.1.1. Development level of digital resource allocation for the cultural tourism industry. The data in this paper comes from two sources: first, it is based on the survey questionnaire, which is conducted in the form of online questionnaire, and 530 valid questionnaires were recovered in 2024. The second is based on the real-time dynamic collection data of N province in the informationization work progress system in 2024. In order to explore the degree of coordinated development of digital resource allocation in the cultural and tourism industry in each district and county, relying on the "online questionnaire" research and the "information system for the progress of informatization in the cultural and tourism industry" to obtain the data of each district in N province, and calculate the comprehensive development index of digital resource allocation in the cultural and tourism industry. The development of digital resource allocation in the cultural and tourism industry is divided into 5 levels, including high level resource allocation (0.8, 1], high level resource allocation (0.6, 0.8], medium level resource allocation (0.5, 0.6], low level resource allocation (0.4, 0.5], low level resource allocation [0.3, 0.4]. Instructional application development was categorized into five levels, including high level of application (0.8, 1], higher level of application (0.6, 0.8], medium level of application (0.5, 0.6], lower level of application (0.4, 0.5], and low level of application [0.3, 0.4].

In order to more conveniently analyze the development level of digital resource allocation for the cultural and tourism industry in all districts and counties of Province N, the districts and counties are ranked from low to high in accordance with the comprehensive development level of digital resource allocation in terms of prefecture and city, and the specific situation is shown in Fig. 3. The comprehensive development index of digital resource allocation for the cultural and tourism industry in all districts and counties of Province N ranges from 0.33 to 0.56, with a large undulation and a high level of development in general, the digital resource allocation index of cultural and tourism industry is small, with a large difference between prefecture and city. The overall development level of the digital resource allocation comprehensive index of the cultural and tourism industry is on the small side, with large differences between cities and districts, and large gaps between districts and counties belonging to the same city and district. The development level of digital resource allocation for cultural and tourism industry in district o is the lowest, and the development level of digital resource allocation for cultural and tourism industry in county h is the highest. The difference in the level of digital resource allocation for cultural and tourism industry in each district and county is obvious, and the level of development of digital resource allocation for cultural and tourism industry in the province presents an unbalanced phenomenon. Based on the phenomenon presented by the province of N as a whole, the research is carried out from the perspective of local municipalities, combining the survey data of the questionnaire, the policy documents on the development of digital resource allocation for cultural and tourism industry in local municipalities, and the organization of informatization activities.

The gap in the digital resource allocation development index of the cultural and tourism industry in the urban area is the smallest, with the comprehensive development index ranging from 0.45 to 0.54, and the difference in the comprehensive development index is 0.09, indicating that the digital resource allocation of the cultural and tourism industry in the county is relatively balanced. The level of digital resource allocation of the cultural and tourism industry in County C is the highest, while the level of digital resource allocation of the cultural and tourism industry in District A is the lowest. From the point of view of the policy documents of the cultural and tourism industry informatization of the district and county, County C has established the goal of "3 priority development, 5 objectives and tasks, and 20 construction contents" of the informatization of the cultural and tourism industry, and actively corresponds to the policy of the informatization development of the cultural and tourism industry in N Province in terms of the allocation of digital resources in the cultural and tourism industry, and makes full use of the network resources of the cultural and tourism industry to carry out the innovation of the cultural and tourism industry model under the background of "Internet + cultural and tourism industry", and the number of online resources exceeds 20,000, and gradually forms a situation of co-construction and sharing of high-quality cultural and tourism industry resources. The six measures in Zone A promote the innovative development of "Internet + cultural tourism industry", focusing on the construction of an efficient cultural and tourism industry network, the construction of a perfect cultural and tourism industry environment, the innovation of high-quality application resources, and the building of a comprehensive information team. In terms of digital resources, more emphasis is placed on the construction of high-quality resources and innovative literacy resources, and the number of resources uploaded by the public service platform for cultural and tourism industry resources is concerned, and the allocation and development of digital resources are not comprehensive.

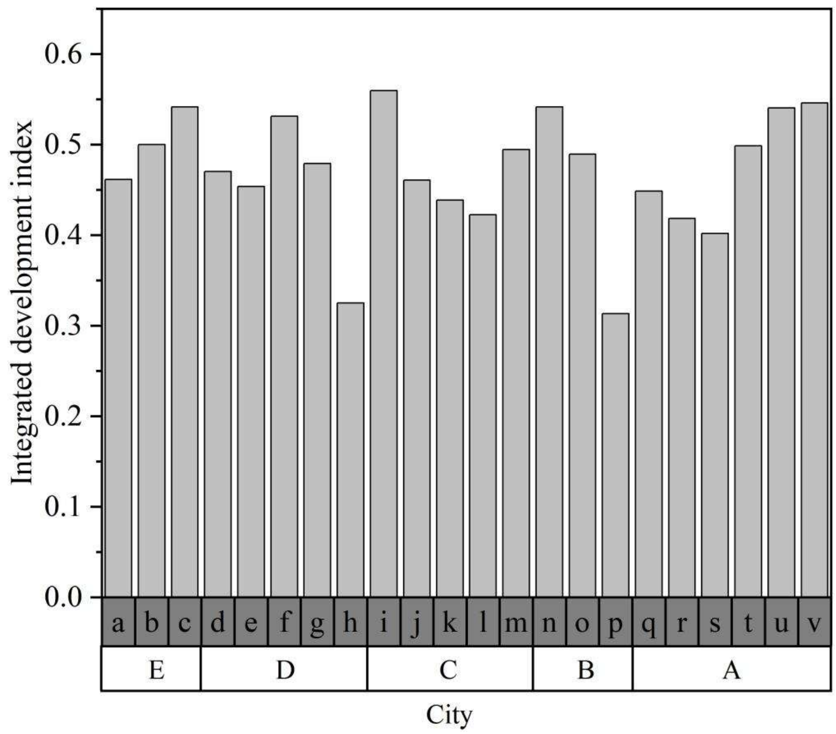

Fig. 3. Digital resource configuration development level

4.1.2. Comparative analysis of digital resource allocation space in cultural tourism industry. In order to make the development of the comprehensive level of digital cultural and tourism industry resource allocation in N province more detailed and clear presentation in space, Arc GIS software is used to visualize the level of digital resource allocation of cultural and tourism industry in each district and county as shown in Figure 4.

Based on the geographic characteristics of N province and combined with the spatial division characteristics of N province, it is divided into the northern Sichuan district and the southern mountainous area. The northern Chuan district includes 15 districts and counties, including q city, d district, a district, r county, s county, t district, n district, o district, h county, v district, c county, f city, p county, u district and e district, and the southern mountainous area includes 7 districts and counties, including l county, k county, j county, i county, m district, b county and g county. By analyzing the space of digital cultural and tourism industry resource allocation in each district and county, it can be seen that the overall digital cultural and tourism industry resource allocation in N Province is unevenly developed, and there are three types of low level districts, lower level districts and medium level districts. The distribution of districts and counties of each level is uneven, most districts and counties belong to lower level districts and multiple districts and counties are adjacent to each other, individual districts and counties located in the north belong to lower level districts and districts and counties are not adjacent to each other, while districts and counties belonging to medium level districts are surrounded by districts and counties that are adjacent to districts and counties of other level levels.There are still obvious regional differences among the five cities of City A, City E, City D, City C, and City B.

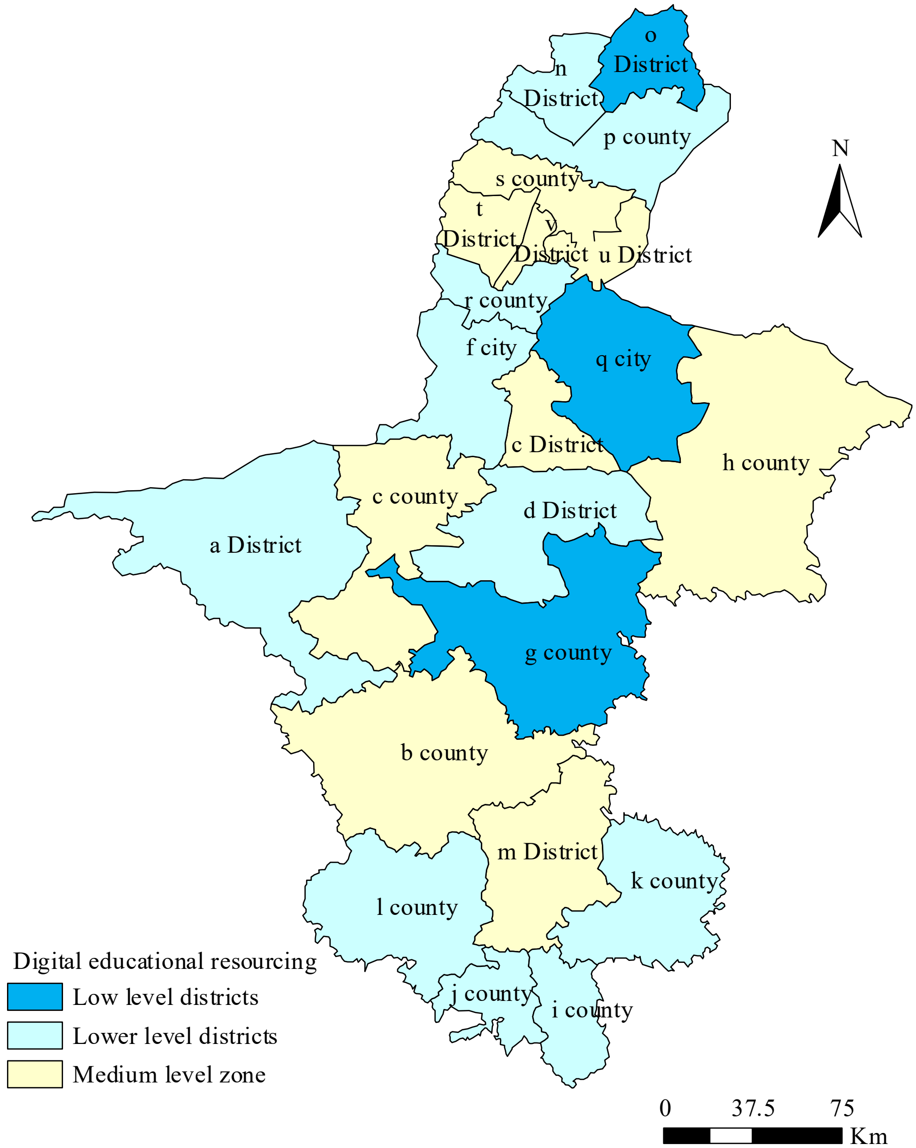

Fig. 4. The level of resource allocation of the wen brigade industry

4.2. Analysis of multi-objective collaborative optimization results

This paper uses the research to establish a digital resource optimization allocation model based on multi-intelligent body system and reinforcement learning algorithm for experimental testing, and the test data comes from the N province cultural and tourism industry digital resource statistical basic database reporting platform. Reinforcement learning algorithm is applied to solve the digital resource allocation optimization model of cultural and tourism industry proposed in this research.

4.2.1. Design of indicators for multi-objective computing. As the optimal allocation of digital resources is constrained by multiple conditions such as procurement funding and the allocation ratio of resource categories, the hierarchical analysis method is used to consider the multi-objective synergistic optimization of multiple evaluation indicators in an integrated manner. The first task of scientifically, comprehensively and objectively evaluating the multi-objective synergistic situation of digital resource allocation is to construct an indicator system that characterizes resource allocation. There is no uniform standard for the current research on the multi-dimensional evaluation index system of digital resources, therefore, this study refines the multi-objective evaluation index system required in the research based on the principles of hierarchy, scientificity, completeness, operability and accessibility that are followed in the multi-dimensional evaluation of digital resources, as shown in Table 1. The multi-objective collaborative evaluation index system of digital resources designed in this paper consists of 4 guideline-level indicators and 26 indicator-level indicators, which are then categorized according to the nature of the indicators, consisting of 11 qualitative indicators and 15 quantitative indicators. Considering that the multi-objective evaluation of digital resources is a kind of human subjective judgment, the subjective assignment method has scientific rationality and its practicality is stronger than the objective assignment method, so the AHP method is used to determine the weights of the criterion layer and each indicator layer, and the calculation process adopts the hierarchical analysis method auxiliary software YAAHP (v10.0).

Table 1. Multi-objective evaluation indicators and properties

	Target layer	Criterion layer	Index layer (xi)	Label quality	Index weight	Criterion layer weight
Digital resource evaluation index system	Digital resource content evaluation	X1 Resource type and data volume	Quantification	Effect type	0.048	0.2225
		X2 Time limit	Quantification	Effect type	0.0386	
		X3 School coverage	Quantification	Effect type	0.0502	
		X4 Authoritative publication ratio	Quantification	Effect type	0.0441	
		X5 Update frequency	Quantification	Effect type	0.0422	
	Digital resource retrieval system evaluation	X6 Retrieval function	Qualitative	Effect type	0.0238	0.1342
		X7 Retrieval effect	Qualitative	Effect type	0.0269	
		X8 Retrieval speed	Qualitative	Effect type	0.0221	
		X9 System stability	Qualitative	Effect type	0.0182	
		X10 Interface friendliness	Qualitative	Effect type	0.0140	
		X11 System extensibility	Qualitative	Effect type	0.0128	
		X12 Background statistics	Qualitative	Effect type	0.0178	
	Digital resource cost evaluation	X13 Hardware and software maintenance cost (yuan)	Quantification	Cost type	0.0455	0.2084
		X14 Resource price increases	Quantification	Cost type	0.0465	
		X15 Single use cost (yuan)	Quantification	Cost type	0.0632	
		X16 Reader per capita service cost (yuan)	Quantification	Cost type	0.0531	
	Database business service level	X17 Data transfer mode	Qualitative	Effect type	0.0172	0.1205
		X18 Trial time (month)	Quantification	Effect type	0.0191	
		X19 Use statistical reports	Qualitative	Effect type	0.0144	
		X20 Publicity training service	Qualitative	Effect type	0.02	
		X21 Service response time (day)	Quantification	Effect type	0.0253	
		X22 Customer access number (times)	Qualitative	Effect type	0.0293	
	Digital resource utilization evaluation	X23 System login times	Quantification	Effect type	0.044	0.3144
		X24 Retrieval frequency	Quantification	Effect type	0.0526	
		X25 The number of times per person per capita	Quantification	Effect type	0.0882	
		X26 Per capita full load	Quantification	Effect type	0.1347	

The iterative graph based on the multi-intelligent body system and the reinforcement learning algorithm is shown in Fig. 5, which shows that the experiment stabilizes at around 100-200 generations, indicating that at this point we get the optimal solution of the model.

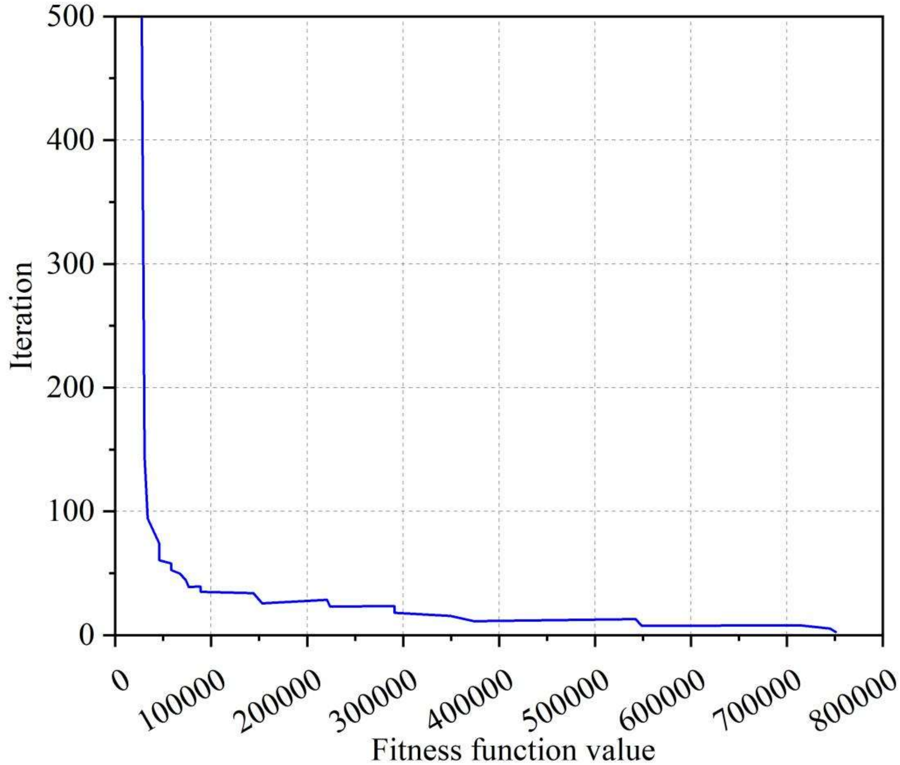

Fig. 5. The iteration graph of algorithm

4.2.2. Overall situation analysis after optimization. Experiment selected N province 2024 cultural tourism industry digital resources part of the relevant data, according to the optimization of the allocation of statistical results, optimization of the number of various types of digital resources and the amount of statistical changes as shown in Table 2. From the viewpoint of digital resources quantity ration, the number of dissertation databases, discovery system platforms and multimedia resources databases remain unchanged, Chinese periodical full-text databases and e-book databases are reduced by 8 each, foreign-language periodical full-text databases are reduced by 4, and other comprehensive databases are reduced by 5, while retrieval tools databases are increased by 10. From the perspective of changes in procurement funding, the total amount of digital resources procurement decreased from 9741482 yuan before optimization to 9280740 yuan after optimization, a total reduction of 460742 yuan.

From the perspective of the overall structure of the 8 types of resources constituting the digital resource allocation, the full text database of foreign language journals firmly occupies the first position regardless of the number of resources allocated for procurement or the amount of procurement funds. The quantity is 344 before optimization and 340 after optimization respectively, while the procurement funding accounts for about 60% of the overall funding for digital resources. The smallest proportion of the number of resources and procurement funding is the discovery system type platform, which is 319 before optimization and 320 platforms after optimization, and the procurement funding only accounts for 17% of the overall funding. The most stable ones are Chinese periodical full-text databases and multimedia resources category databases, which basically remain unchanged, no matter the procurement quantity and procurement funding, or even the composition of databases within the category. The most significant change is the search tool database. From the optimization effect, all types of resources have been optimized to different degrees, among which the more obvious ones are the full-text foreign language periodicals database and other comprehensive databases, as can be seen in the table, after the optimization, the foreign language periodicals database has been reduced by 4, and the other comprehensive databases have been reduced by 5, and the procurement expenses have been saved by 175780 yuan and 120840 yuan respectively. After optimization, there are 4 fewer foreign language journal libraries and 5 fewer other comprehensive databases.

Table 2. Overall analysis

Resource type	Before optimization		After optimization	
	N	Funds (yuan)	N	Funds (yuan)
Chinese text	328	68920	320	61540
Foreign text	344	6222870	340	6047090
Electronic book	331	379000	330	367450
Retrieval tool	322	1645892	332	1528420
dissertation	322	245690	325	230800
Discovery system	319	157280	320	144450
Multimedia	400	296240	400	296240
Other synthesis	417	725590	412	604750
Total	2783	9741482	2509	9280740

4.2.3. Combined efficiency of resource allocation in each district before and after optimization. Since this study is to optimize the resource allocation for the four evaluation indicators of cultural and tourism industry resources in each district and county of a city, in order to verify that the model improves the efficiency of the resources, the comprehensive resource efficiency of each district and county before and after the experiment is calculated separately as shown in Table 3. a district improves from 0.46117 to 0.49253, b district improves from 0.49992 to 0.53267, and h district improves from 0.32487 to 0.35286, and, all of them converge to the equilibrium state. It can be shown that this model improves the efficiency of digital resources of cultural and tourism industry and reduces the differences between districts and counties. By analyzing the above four aspects of digital resource content, digital resource retrieval system, digital resource cost, and digital resource utilization, it can be seen that the model has the effect of making the indicators meet the standards, improving the efficiency, and reducing the differences between districts and counties. The experiment shows that it is very necessary to optimize the allocation of existing resources in a city, and also verifies the correctness and usability of the model, as well as the importance of the optimization of the allocation of resources in the cultural and tourism industry, and also provides theoretical decision-making guidelines for the allocation of digital resources in the cultural and tourism industry in the city.

Table 3. Integrated efficiency of resource allocation

District		Before optimization	After optimization
E	a	0.46117	0.49253
	b	0.49992	0.53267
	c	0.5416	0.57234
D	d	0.47011	0.50023
	e	0.45363	0.48289
	f	0.53107	0.56162
	g	0.47898	0.50947
	h	0.32487	0.35286
C	i	0.55938	0.6284
	j	0.46041	0.49294
	k	0.43857	0.46189
	l	0.42232	0.45655
	m	0.49427	0.52277
B	n	0.54137	0.57174
	o	0.48921	0.51285
	p	0.3131	0.3424
A	q	0.44841	0.47269
	r	0.41822	0.44574
	s	0.40179	0.44763
	t	0.49859	0.52275
	u	0.54018	0.57027
	v	0.54601	0.57241

In order to observe the comparison before and after the experiment more intuitively, the comprehensive efficiency data of the districts and counties before and after the experiment are represented by line graphs, and the results are shown in Figure 6: the horizontal coordinates of the graphs represent the districts and counties, the names of the districts and counties are replaced by numbers, and the vertical coordinates of the graphs represent the comprehensive efficiencies of the corresponding resources of each district and county, which are obtained by the calculation. The gray line represents the comprehensive efficiency of resource allocation in the cultural and tourism industry before the experiment, and the blue line represents the comprehensive efficiency of resource allocation in the cultural and tourism industry after the experiment. It can be seen that before the experiment, the comprehensive efficiency of resource allocation among districts and counties is relatively low, except for some districts and counties. After the experiment, the comprehensive efficiency of the districts and counties have improved.

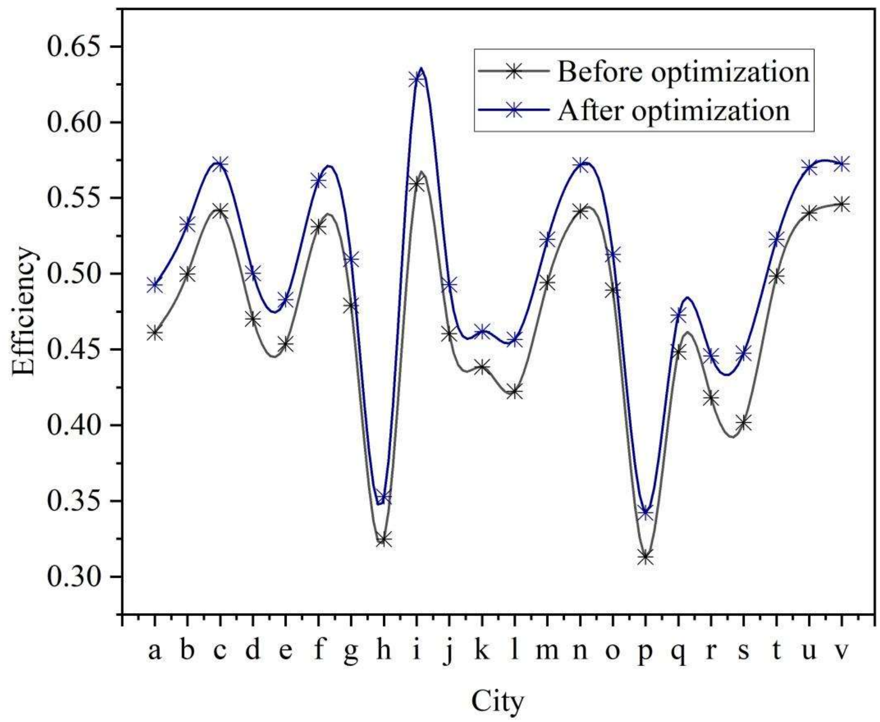

Fig. 6. Comprehensive efficiency data of each county

5. Conclusion

This paper uses multi-intelligent body system, hierarchical analysis method, reinforcement learning and other techniques to construct a multi-objective collaborative optimization allocation model of digital resources for cultural and tourism industry based on multi-intelligent body reinforcement learning. The paper selects 22 districts in N province to carry out example application research, and the experimental results show that considering the multi-objective co-optimization problem of multiple evaluation indexes, the digital resource optimization allocation model of cultural and tourism industry based on multi-intelligent body genetic algorithm can reasonably configure the quantity structure and procurement funds of the dissertation database, the discovery system platform, the multimedia resource database, which obviously improves the comprehensive efficiency of the utilization of resources, reduces the procurement funds, and reduces the differences between districts and counties. The model can reduce the procurement expenses and the differences between districts and counties, thus promoting the sustainable development of cultural and tourism industry.

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