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Article

Intelligent Scheduling Algorithms and Resource Allocation Methods in Library Digitization Management

Jiaojiao He and Yu Zhao *

Library, Zhongkai University of Agriculture and Engineering, Guangzhou, Guangdong, 510225, China; lovesusanne0501@163.com

Abstract: Addressing the issue of intelligent scheduling and resource allocation optimization for library digital resources, this paper first designs a cloud-service-based library database resource model framework and studies the required multi-objective combinatorial optimization system based on the knapsack model. Then, an optimization configuration model based on a multi-agent genetic algorithm is designed, combining a multi-agent system with local perception characteristics with a globally efficient genetic algorithm. The fitness of individuals is selected as the energy of the multi-agent system to achieve multi-objective collaborative optimization of digital resource allocation. Finally, library digital resource data from X University Library from 2016 to 2024 is selected for empirical analysis. The empirical analysis results indicate that the proposed model can reasonably perform multi-objective collaborative optimization of resource allocation quantities for X University Library. The multi-objective evaluation value of digital resource allocation at the library increased by 0.22 between 2016 and 2024. Additionally, the proposed model demonstrates significant advantages in terms of digital library resource allocation efficiency, enhancing the collaborative level and efficiency between multi-objective evaluations of digital resources. This lays the foundation for future research on digital resource allocation in other domains of higher education institutions.

Keywords: knapsack model; multi-agent genetic algorithm; multi-objective coordination; resource allocation optimization; library digitization

1. Introduction

As an important hub for cultural heritage, libraries bear the important mission of preserving culture and facilitating information exchange. In the era of rapid information technology development, readers have set higher standards for accessing and utilizing information resources, presenting new opportunities and challenges for library resource management [1-2]. Currently, to ensure that library operations keep pace with the demands of the times, integrating information technology into library operations, establishing a digital management system, and providing intelligent services have become key measures to support the high-quality development of libraries [3-6].

Compared to traditional libraries, digital libraries offer unparalleled advantages, breaking the constraints of time and space and allowing readers to access a wealth of book resources from across the country and even around the world without having to visit the library in person [7-10]. As long as there is an internet connection, readers can access the library system anytime, anywhere to conduct information searches and reading, greatly satisfying their personalized reading needs [11-12]. Additionally, smart libraries encompass various forms such as mobile libraries and digital libraries, and also utilize advanced artificial intelligence technology to provide readers with more convenient and intelligent services [13-15]. Meanwhile, intelligent question-answering systems can promptly address issues encountered by readers during the reading process, thereby enhancing their reading experience [16]. However, relying solely on resource development efforts is insufficient to achieve satisfactory results in library management. To ensure that digital library resources meet the needs of various stakeholders, efficient resource scheduling algorithms and allocation methods are crucial [17-19].

To meet the diverse resource needs of different stakeholders, the application of digital library management technology must demonstrate comprehensiveness and holistic integration. Yang, X., and Lin, X. integrated a heuristic utility management algorithm into the library management system, using mathematical modeling and standardized programming calculations of book codes to achieve tracking and management of library resources, thereby reducing the workload of librarians while improving library management efficiency [20]. Liu, Y. designed a collaborative filtering algorithm aimed at improving library management and service efficiency. By conducting data mining on library resources, they generated accurate book recommendation results, providing valuable insights for university library management methods [21]. Zhang, F. proposed a library resource management model integrating Long Short-Term Memory (LSTM) neural networks, which played a significant role in classifying the practical application value of book resources [22]. Shi, Y. explored the application of the fuzzy C-means (FCM) clustering algorithm in library resource management. The resource management system supported by this technology can perform clustering analysis on user borrowing records and behavioral information, thereby providing technical support and recommendations for library resource scheduling and allocation processes [23]. Yang, X. indicated that recommending information of interest to users is an urgent task for library resource management systems, and proposed a library digital resource aggregation quality prediction model that integrates an improved genetic algorithm with a BP neural network to facilitate the efficient organization and management of library information resources [24]. Wang, J. et al. developed a library information management system comprising two modules—a mining algorithm and a management system—and combined a feature clustering algorithm to achieve intelligent information retrieval and resource sharing of library resources, providing an effective path for promoting the modernization of library resource management [25]. Therefore, with the support of intelligent algorithms, library administrators can effectively coordinate existing resources across libraries and establish information exchange and sharing channels in the process, providing convenience for readers and their own work.

Addressing the challenges of intelligent scheduling and resource allocation optimization in the management of digital library resources, this paper proposes an optimization configuration model based on a multi-agent genetic algorithm. This model integrates a multi-agent system with local perception capabilities and a genetic algorithm with efficient global search capabilities. It maps the fitness of individuals to the energy source of agents, driving agents to learn in the environment to solve the problems of intelligent scheduling and resource allocation optimization for library digital resources. Through empirical quantitative evaluation of the model's actual configuration effects and optimization performance, it provides a new method for the efficient management of library digital resources.

2. Intelligent scheduling and resource allocation optimization for digital library management

2.1. Integration of library database resources based on cloud services

Based on the library database resource integration requirements and management objectives, the cloud service-based library database resource integration model architecture is shown in Figure 1.

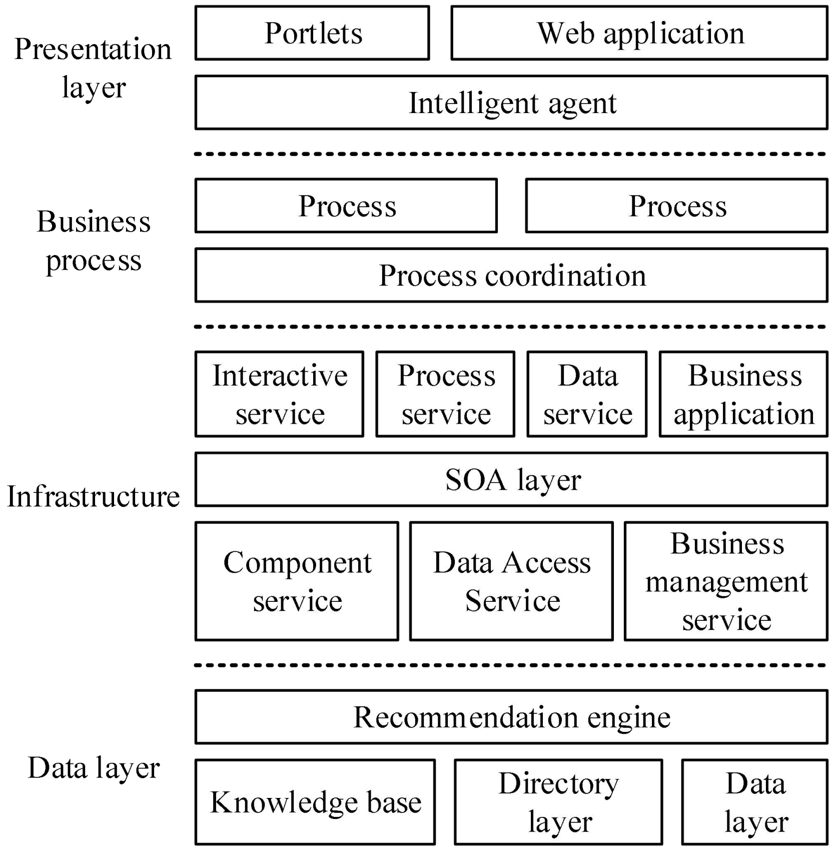


Figure 1. Library database resource integration system based on cloud services.

Since the integration of library database resources requires the fusion of multiple data sources into a cohesive whole, a four-layer architecture based on cloud services has been established for the library database. As shown in Figure 1, the bottom layer of the model is the data layer, which primarily contains structured and unstructured data from the database; the middle layer consists of the infrastructure and business processes, where all relevant business operations within the database are unified and integrated at this level, and cloud services are utilized to establish a unified data standard to enable information sharing; the top layer is the presentation layer, which enables users to access the database in a convenient and efficient manner.

2.1.1. Identification of library database resource attributes

Obtain resources based on user needs and use cloud services to integrate library database resources into a unified platform. To better integrate library database resources, first identify the attributes of the database resources. Use cloud services to share information from the library database, then use the FHO theorem to identify the resource attributes in the library database based on the shared information, calculate the weight vector of the resource attributes, and then use the FHO operator to aggregate multiple attributes.

The specific steps are as follows: 1) Construct the decision matrix:

$$Z = A_n * d(a_j) \tag{1}$$

In the formula: A_n represents the number of library servers; $d(a_j)$ represents the attributes of a_j.

2) Normalize the database resources using the following formula:

$$S = \frac{f * g}{\max(a_j)} \tag{2}$$

In the formula: S represents the normalized result of the database resources; $\max$ represents the maximum eigenvector of a_j; f represents the attribute weight; g represents the weight vector.

3) Combine multiple attributes using the FHO operator, as shown below:

$$D = \frac{P}{\sum_j a_j * T} \tag{3}$$

In the formula: D represents the attribute combination factor; T represents the attribute value; P represents the attribute size.

Based on the above definitions, the identification of database resource attributes is completed, providing a foundation for the integration of library database resources.

2.1.2. Integration of Library Database Resources

Based on the identification of database resource attributes mentioned above, cloud services are used to match database resources.

On this basis, cloud services are used to allocate database resources. Under the technical architecture support of cloud computing, various parameters in the database are classified into different levels. The specific calculation steps are as follows:

Step 1: Based on cloud services, establish unified data standards, assign different weights to different information in the database, calculate the database request volume, and classify it into large, medium, and small categories based on the average number of database requests submitted per second by users.

Step 2: Utilize cloud computing within cloud services to uniformly manage and schedule a large number of computing resources connected via networks, and calculate the request complexity. Calculations are based on key factors influencing database load resource consumption, with the formula as follows:

$$K = \frac{p \Rightarrow o}{\sum_j a_j * m * F} \tag{4}$$

In the formula: $p \Rightarrow o$ represents that p and o request an event simultaneously; F represents the complexity of the database request; m represents the database resources consumed.

Step 3: Check the database response time, which is the time required from the submission of the request to its completion and return to the client.

Step 4: Database connection count, which represents the maximum number of connections established when users make requests.

Allocate physical resources using different strategies based on the type of database objects to be allocated. Select the server for resource allocation based on the amount of resources accessed by users and the amount of available database resources. Assume that there are m system databases on server i in the library, the number of available connections for the k th system database is $SDGH_j$, $j \in (1,m)$, the database schema allocatable to users is $AADG_j$, $j \in (1,m)$, and there are q system schemas in the j th system database, then the data allocated to the user for the n th database is expressed as ASA_{qn}^j, $n \in (1,q)$. The problem to be solved is to select which server to allocate database resources to the user based on the amount of database resources required by the user and the amount of available resources on the server.

When the database object to be allocated is a database schema, the following formula is used to express the number of schemas that can be allocated in the library database:

$$Q = \sum_j a_j * \frac{e}{V} Sh \tag{5}$$

In the formula: e is the system database traffic; h is the number of connections accessed by users; V is the database objects to be allocated.

By using the above formula to allocate physical resources, and then combining the database resource allocation results with the physical resource allocation results, a computing resource pool is constructed using cloud services to provide on-demand services to users, thereby completing the integration of library database resources.

2.2. Issues related to the optimal allocation of digital resources

2.2.1. Overview of Digital Resources in University Libraries

Currently, university libraries primarily acquire digital resources through database procurement, which involves bundling electronic journals, e-books, and other resources into integrated databases for bulk purchasing. Based on research needs and library procurement documents, digital resources are categorized into eight types: Chinese journal full-text databases, foreign language journal full-text databases, Chinese and foreign language e-book databases, search tool databases, Chinese and foreign language thesis databases, discovery system platforms, multimedia resource databases, and other comprehensive Chinese and foreign language databases. When procuring digital resources, decisions are subject to various constraints, which can be broadly categorized into qualitative and quantitative constraints. Typical quantitative conditions include the school's annual procurement budget, which typically sets a maximum budget limit, and based on the school's disciplinary development, disciplinary evaluations, consideration of the diverse needs of various readers, and research requirements, each category of digital resources is assigned a procurement threshold, typically setting a minimum threshold for the number of resources to be procured.

Typical qualitative constraints include the decision-making body's preference for selection, as well as the white list formed by policy red lines stipulated by the Ministry of Education and other relevant departments. The white list refers to databases or system platforms that must be included in the annual procurement plan. Thus, the optimization of digital resource allocation is a resource combination optimization problem that must be considered under multiple quantitative constraints such as procurement budget and resource category allocation ratios, while also taking into account qualitative constraints such as the decision-making body's preferences and relevant policies.

2.2.2. Definition of digital resource allocation based on the backpack model

The knapsack problem is a typical combinatorial optimization problem in the field of operations research. Depending on the number of knapsacks, it can be classified into single-knapsack problems and multi-knapsack problems. The traditional 0-1 knapsack problem refers to placing n items of different types, each with a certain volume and value, into a knapsack of finite capacity, such that the total value of the items in the knapsack is maximized. Depending on the constraints, it is further subdivided into single-constraint knapsack problems and multi-constraint knapsack problems. The knapsack problem has significant theoretical research and application value and has been widely applied in many fields. However, it is not commonly used in the procurement and optimal allocation of digital resources. This paper addresses the problem of optimal allocation of digital resources, aiming to maximize the total value of electronic databases under multiple constraints. A mathematical model for the multi-constraint 0-1 knapsack problem is established to explore the quantitative solution process for digital resource allocation.

Based on the requirements of this paper, the mathematical description of the multi-constraint knapsack problem is established as follows:

$$\max f(x) = \sum_{j=1}^{n} x_j p_j \tag{6}$$

$$\begin{cases} \sum_{j=1}^{n} w_{ij} x_{j \le b_i} & i = 1, 2, \cdots, m \\ \sum_{j=1}^{n} c_{ij} x_{j \le C} & i = 1, 2, \cdots, m \\ x_j = 0 \text{ or } 1 & j = 1, 2, \cdots, n \end{cases} \tag{7}$$

Among these, n is the number of the electronic database, m is the number of the type of digital resource, x_j represents database j , p_j is the comprehensive evaluation value of database x_j , b_i represents the constraint conditions (such as quantity) of the i th type of digital resource, and c_{ij} represents the purchase price of database x_j . C is the total budget for digital resource procurement,

$w_{ij} \geq 0$ denotes the weight of database x_j in the i th type of resource, and x_j is a 0-1 decision variable (when database j is selected, $x_j = 1$; otherwise, $x_j = 0$).

As described above, the problem of optimizing resource allocation [26] is a feasible solution to a multi-constraint 0-1 knapsack combination optimization problem that maximizes the comprehensive evaluation value of digital resource allocation while satisfying the constraints.

2.3. Optimization Configuration Model Based on multi-agent genetic algorithm

2.3.1. Multi-agent genetic algorithm

Multi-agent systems (MAS) [27] are a type of computer model and framework technology that supports intelligent decision-making. Since the 1970s, they have developed rapidly based on complex adaptive systems theory and distributed artificial intelligence (DAI) technology, and have now become a research frontier in the field of artificial intelligence. As an important conceptual approach and tool for addressing issues related to the operation and simulation of complex systems, MAS offers two key advantages: first, its robust intelligence overcomes the limitations of traditional artificial intelligence methods in adapting to environmental changes; second, its bottom-up modeling approach enables the decomposition of a large-scale complex problem into multiple smaller problems, thereby addressing issues that are difficult to solve or computationally intensive under traditional methods. Against this backdrop, the interaction between agents and the environment has a very broad meaning. When the type, direction, and characteristics of the problem to be solved differ, the meaning and expression of agents and the environment also vary. Based on the research content of this paper, the primary problem to be addressed can be summarized as a multi-objective combinatorial optimization problem, and a multi-agent-based genetic algorithm is selected for its solution. Therefore, referencing relevant literature, the agent type selected for function optimization is adopted as the agent type in this paper, and agent design is conducted for the constructed model in the subsequent sections. The abstract mathematical model of the function optimization problem is shown in Equation (8), and the formalized description model of the agent α and its energy is shown in Equation (9):

$$\min f(x), x = (x_1, x_2, \cdots, x_n) \in S \tag{8}$$

$$\alpha \in S, Energy(\alpha) = -f(\alpha); Energy(\alpha) = \frac{1}{f(\alpha)} \tag{9}$$

Among these, $f(x)$ is the objective function for finding the minimum value, x_i represents the function variable, S represents the n-dimensional search space with boundaries $x_i \leq x \leq \overline{x_i}, i = 1, 2, \ldots\ldots, n$, i.e., $S = [\underline{x}, \overline{x}], \underline{x} = (\underline{x_1}, \underline{x_2}, \ldots\ldots, \underline{x_n})$, $\overline{x} = \overline{x_1}, \overline{x_2}, \ldots\ldots, \overline{x_n}$. α represents an agent, each of which contains information related to a function solution. Multiple agents collectively form a set of function solutions. $Energy(\alpha)$ represents the energy possessed by the agent, indicating the quality of the solution, which can be characterized by the opposite or inverse of the objective function.

Genetic algorithms (GA) [28] are global search optimization algorithms that simulate biological genetic and evolutionary processes. Their research abstracts the concepts of search, selection, elimination, inheritance, mutation, and optimization from the natural selection process, and summarizes them into a parallel, efficient, and adaptive pseudo-natural random global optimization search algorithm.

As a computational method inspired by natural genetics, genetic algorithms are based on the laws of biological inheritance and evolution. They analogize a population to a set of solutions to a problem, with individuals within the population analogous to individual solutions; genetic phenomena such as inheritance, crossover, and mutation are analogized to algorithmic optimization operations, leading to the design of selection, crossover, and mutation operators; the manner and medium of carrying genetic information are analogized to the structure and representation of solutions, and the design of encoding forms. The adaptability of organisms to their environment is analogous to the quality of solutions, and fitness functions are designed to evaluate and represent the quality of individuals. The higher the fitness, the more outstanding the individual is in the population, and the closer the solution represented by that individual is to the optimal feasible solution in the solution set.

As can be seen from the above, genetic algorithms (GA) and multi-agent systems (MAS) have different advantages and complementary disadvantages. Therefore, the Multi-Agent Genetic Algorithm

(MAGA) [29] effectively combines the two, treating individuals in the population as agents and the population as a multi-agent system. It uses the local perception characteristics of the multi-agent system and the operators and parameter requirements of the genetic algorithm as the system environment, and uses the fitness of individuals as the energy of agents, thereby achieving genetic algorithm operations and solutions under the constraints of a multi-agent system.

The multi-agent genetic algorithm can enhance the population update rate while maintaining population diversity, overcoming the issues of premature convergence or local optima that simple genetic algorithms often encounter. As a result, it imposes no restrictions on problem types or search spaces and is not hindered by complex problems such as high-dimensional functions. It has been applied across various fields and proven effective in solving diverse function-solving problems. This paper focuses on the site selection model for emergency material reserves in coastal high-density cities. Combining the main content of multi-agent genetic algorithms and the applications of multi-agent genetic algorithms by domestic and international scholars, this paper designs a multi-agent genetic algorithm suitable for the model, including the meaning and purpose of agents, the construction of a multi-agent grid system, process steps, and the design of operators that determine agent behavior.

2.3.2. Library Digital Resource Optimization Configuration Model

The framework of the digital resource optimization allocation model based on multi-agent systems and genetic algorithms is shown in Figure 2. Multi-agent systems are used to simulate decision-making entities involved in digital resource planning and procurement, and genetic algorithms are used to calculate the Pareto optimal digital resource allocation plan with the assistance of multi-agents.

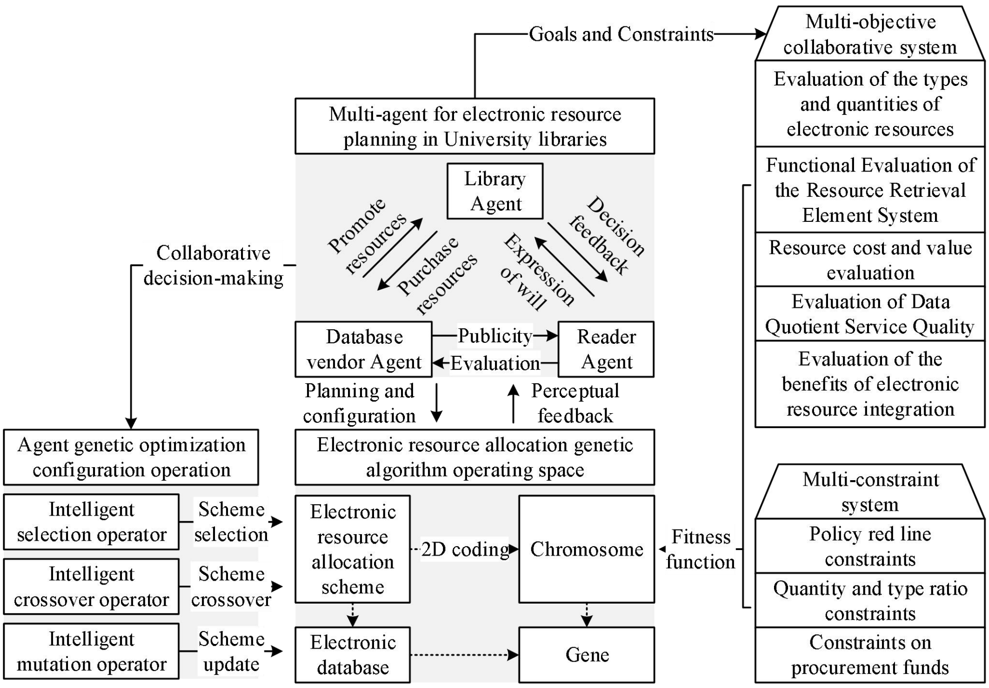


Figure 2. Digital resource allocation model.

According to the basic process of digital resource planning and procurement, the main entities involved in digital resource planning decisions are divided into three types of agents: libraries, database vendors, and readers.

The library agent obtains data and requests and feedback from reader agents, and uses formula (10) to coordinate conflicts between them.

$$C_t(i,j) = U_d(i,j,t) + \alpha \cdot U_p(i,j,t) + P_t \tag{10}$$

$C_t(i,j)$ denotes the competitiveness of the t-type electronic database on cell (i,j), while $U_d(i,j,t)$ and $U(i,j,t)$ represent the utility functions of the t-type electronic database for the database vendor agent and reader agent, respectively. α denotes the reader participation rate [0, 1], with higher reader participation rates indicating stronger competitiveness of the database. When the utility function values of the database provider Agent or reader Agent are higher, the probability of the library Agent purchasing the database (i,j) from the t-class digital resources increases, reflecting the library's consideration of both data and reader preferences. The model simulates this process by adjusting the competitiveness, thereby achieving feedback among multiple agents.

$$C_t^{'}(i,j) = C_t(i,j) + n_d \cdot \Delta P_d + n_p \cdot \Delta P_p \tag{11}$$

$C_t(i,j)$ denotes the adjusted competitiveness, n_d is the number of times the database vendor promotes database (i,j,t), and ΔP_d is the increase in competitiveness each time the database is promoted; n_p is the number of times readers recommend database (i,j,t), and ΔP_p is the increase in competitiveness each time the database is recommended.

Database vendors act as agents or distributors for various electronic databases. They market digital resources to library agents, who coordinate efforts to promote these resources to readers through various channels, creating a competitive sales environment. This study employs a random dynamic model and a discrete choice model to simulate the competitive behavior among database vendors. The probability of selecting a specific electronic database (i,j) for promotion by a database vendor for a particular resource type t is expressed in Formula (12).

$$P(i,j,t) = \frac{\exp(U_d(i,j,t))}{\sum \exp(U_d(i^{'},j^{'},t))} = \frac{\exp(R_{neigh} \cdot S_{ljt})}{\sum \exp(R_{neigh} \cdot S_{ijt})} \tag{12}$$

In Formula (12), R_{neigh} denotes the number of databases competing for t-type resources, and S_{ijt} denotes the suitability (competitiveness) of digital resources (i,j) in t-type resources.

Reader Agents include full-time teachers, university students, and other readers, who are the primary users of digital resources. They recommend each digital resource to the library agent based on their own needs and preferences. The behavior of reader agents recommending each digital resource is simulated using a random dynamic model and a discrete choice model. The probability selection formula for digital resource (i,j) of type t being recommended by readers is:

$$P(i,j,t) = \frac{\exp(U_p(i,j,t))}{\sum \exp(U_p(i,j,t))} = \frac{\exp(Q_{ijt})}{\sum \exp(Q_{ijt})} \tag{13}$$

Q_{ijt} represents the reader's acceptance level of the electronic database (i,j) for resource type t.

The objective function formula F for the comprehensive evaluation of digital resources is calculated as follows:

$$F = \omega_a \cdot f_a + \omega_b \cdot f_b + \omega_c \cdot f_c + \omega_d \cdot f_d + \omega_e \cdot f_e \tag{14}$$

f_a denotes the evaluation function for the types and quantities of digital resources, followed by f_e representing the evaluation function for the usage of digital resources, ω_a represents the weighting coefficient for f_a, and $\omega_a + \omega_b + \omega_c + \omega_d + \omega_e = 1$.

The procurement, configuration, and optimization of digital resources in higher education institutions are subject to various constraints, primarily including the Ministry of Education's macro-level policy guidelines and subject evaluation indicators, institutional budgets and actual procurement funding controls, institutional subject configurations and the distribution of key disciplines, as well as institutional types and educational characteristics. The constraint framework for digital resources serves both as a macro-level guiding principle for the multi-objective evaluation function of resources and as a micro-level control mechanism.

First, the database vendor agent and reader agent observe and analyze the current state of digital resource configuration and optimization schemes. Based on the random utility model and discrete choice model, they provide resource configuration optimization recommendations and submit specific suggestions to the library agent. The library agent coordinates and updates the competitiveness of electronic databases according to the competitiveness function based on the plan. Based on the characteristics of genetic algorithms, the model designs three types of intelligent genetic optimization allocation operators: selection, crossover, and mutation, to achieve optimization of allocation schemes. The model evaluates the new generation of allocation schemes based on the digital resource optimization objective evaluation system and constraint system, repeats the above process for iterative calculation until the program termination conditions are met, and finally outputs a series of Pareto optimal allocation schemes for digital resources.

Among these, the model employs a two-level intelligent selection operator. The first-level selection operator uses the roulette wheel criterion to select chromosomes with higher fitness as the next generation after crossover and mutation in the chromosome population. The second-level selection algorithm compares chromosomes before and after crossover or mutation and retains only the superior chromosomes to enhance the algorithm's search efficiency. The intelligent crossover operator is primarily used to resolve conflicts between database agents and reader agents and the current digital resource allocation scheme, thereby avoiding contradictions between electronic database selection and the library's current digital resource planning. The intelligent mutation operator primarily addresses conflicts between electronic databases with similar functions under the same category of resources. It uses the competitiveness function $C_t(i, j)$ to construct the electronic database selection probability function $P_t(i, j)$, and employs the roulette wheel method to resolve competitive conflicts, as shown in Formula (15):

$$P_t(i,j) = \frac{C_t(i,j)}{\sum C_t^{'}(i,j)} \tag{15}$$

3. Performance testing of multi-agent genetic algorithms

3.1. Typical Algorithms

Multi-objective optimization is a common problem across various fields in real life, where it is impossible to achieve optimal results for all objectives simultaneously. There are numerous algorithms for addressing multi-objective optimization problems, among which the NSGA2 algorithm is one of the most effective. It employs the concept of dominance during the search process. This section will conduct comparative experiments with the NSGA2 algorithm, focusing on its non-dominated sorting method and crowding degree comparison method.

3.2. Typical test functions for multiple objectives

To validate the effectiveness of the algorithms presented in this chapter, this section conducts simulation experiments using six commonly used high-dimensional multi-objective optimization problems. Among the six test functions, four are two-objective test problems, namely ZDT1, ZDT2, ZDT3, and ZDT6, while the other two test functions are three-objective optimization problems, namely DTZL1 and DTZL2. The specific formulas are as follows:

$$\text{ZDT1} \quad \begin{aligned} & f_1(x) = x_1 \\ & f_2(x) = g(x)[1 - \sqrt{x_1 / g(x)}] \\ & g(x) = 1 + 9(\sum_{i=2}^{n} x_i) / (n-1) \end{aligned} \tag{16}$$

$$\text{ZDT2} \quad \begin{aligned} & f_1(x) = x_1 \\ & f_2(x) = g(x)[1 - (x_1 / g(x))^2] \\ & g(x) = 1 + 9(\sum_{i=2}^{n} x_i) / (n-1) \end{aligned} \tag{17}$$

$$ZDT3 \quad \begin{aligned} & f_1(x) = x_1 \\ & f_2(x) = g(x)[1 - \sqrt{x_1 / g(x)} - x_1 / g(x) \sin 10\pi x_1] \\ & g(x) = 1 + 9(\sum_{i=2}^{n} x_i) / (\mathrm{n}-1) \end{aligned} \tag{18}$$

$$ZDT6 \quad \begin{aligned} & f_1(x) = 1 - \exp(-4x_i)\sin^6(6\pi x_1) \\ & f_2(x) = g(x)[1 - (x_1 / g(x))^2] \\ & g(x) = 1 + 9[(\sum_{i=2}^{n} x_i)/(n-1)]^0.25 \end{aligned} \tag{19}$$

$$DTZL1 \quad \begin{aligned} & f_1(x) = (1 + g(x))x_1 x_2 / 2 \\ & f_2(x) = (1 + g(x))x_1(1 - x_2)/2 \\ & f_3(x) = (1 + g(x))(1 - x_1)/2 \\ & g(x) = 100(n-2) + 100\sum_{i=3}^{n}\{(x_i - 0.5)^2 - \cos[20\pi(x_i - 0.5)]\} \end{aligned} \tag{20}$$

$$DTZL2 \quad \begin{aligned} & f_1(x) = (1 + g(x))\cos(x_1\pi/2)\cos(x_2\pi/2) \\ & f_2(x) = (1 + g(x))\cos(x_1\pi/2)\sin(x_2\pi/2) \\ & f_3(x) = (1 + g(x))\sin(x_1\pi/2) \\ & g(x) = \sum_{i=3}^{n} x_i^2 \end{aligned} \tag{21}$$

3.3. Comparison of simulation experiment results

In this paper, the algorithm is compared with the classical algorithm NSGA2, and the two-objective optimization problem of the test functions ZDT1, ZDT2, ZDT3 and ZDT6 is tested in 30 dimensions, and the optimization problem of three objectives of DTZL1 and DTZL2 is tested in 10 dimensions. The experiment was conducted in the following environment, operating system: Windows 7 ultimate, processor: Intel®Core™i5-3470CPU@3.2GHz3.2GHz installation memory: 6.00GB, software: Microsoft Visual Studio 2017, language: C.

In order to better evaluate the performance of the algorithm, this paper introduces a comprehensive performance evaluation metric for multi-objective optimization problems, namely the inverse generation distance evaluation metric (IGD). It primarily evaluates the algorithm's convergence performance and distribution performance by calculating the sum of the minimum distances between each point (individual) on the true Pareto front and the set of individuals obtained by the algorithm. The smaller the IGD value, the better the algorithm's overall performance, including convergence and distribution performance. The formula for IGD is as shown in Equation (22):

$$IGD(P,Q) = \frac{\sum_{v \in P} d(v,Q)}{|P|} \tag{22}$$

Among these, P is a set of points uniformly distributed on the true Pareto surface, and $|P|$ is the number of points distributed on the true Pareto surface. Q is the set of optimal Pareto optimal solutions obtained by the algorithm. $d(v,Q)$ is the minimum Euclidean distance from individual v in P to population Q.

The experiments in this section were run independently 30 times, with the IGD distance calculated each time and the best value, worst value, average, and standard deviation recorded. The experimental results were compared, with the results shown in Table 1.

For the four two-objective test problems and two three-objective test functions, the experimental results of the MAGA algorithm are slightly better than those of NSGA2. For the test function ZDT1, MAGA outperforms NSGA2 in terms of best value, average value, worst value, and standard deviation, with the best value being only 0.3839. For the test function ZDT2, MAGA slightly outperformed NSGA2 in terms of best value and average value, but it was not as good as NSGA2 in terms of worst value and average value. For the piecewise function ZDT3, MAGA was inferior to NSGA2 in terms of best value, average value, worst value, and standard deviation, indicating that MAGA has some limitations in handling piecewise functions. However, for the test function ZDT6, the test results were the opposite of ZDT3, with MAGA slightly outperforming NSGA2 in terms of best value, average value, worst value, and standard deviation. The results for the three-objective test function DTZL1 show that MAGA is far superior to NSGA2 in terms of best value, slightly superior in terms of average value, but inferior to NSGA2 in terms of worst value and standard deviation, indicating that the algorithm is less stable than NSGA2 when testing DTZL1. In the comparison of the results for the test function DTZL2, the two algorithms are similar.

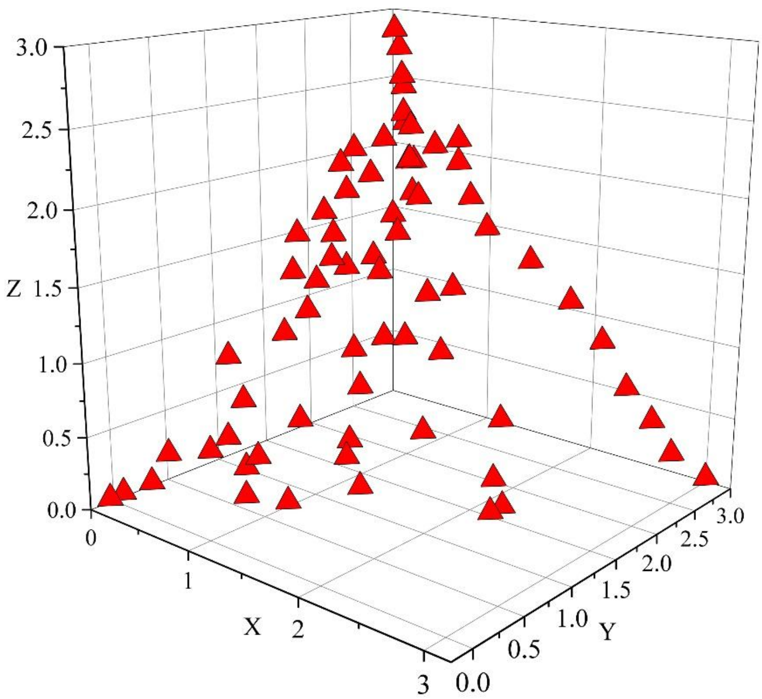
Table 1. The IGD value of MAGA and NSGA2 for six test functions.

Test function	Algorithm	Best value	Mean value	Worst value	Standard deviation
ZDT1	NSGA2	0.4719	0.5352	0.5889	0.0284
	MAGA	0.3839	0.4905	0.5561	0.0188
ZDT2	NSGA2	0.5369	0.5898	0.6294	0.0249
	MAGA	0.5003	0.5652	0.7117	0.0408
ZDT3	NSGA2	0.6012	0.6814	0.7376	0.0377
	MAGA	0.7492	0.7797	0.8203	0.0512
ZDT6	NSGA2	0.6275	0.6695	0.7321	0.0309
	MAGA	0.5288	0.6123	0.6941	0.0265
DTZL1	NSGA2	1.1667	2.7972	6.1905	1.3312
	MAGA	0.0768	2.4845	7.5205	1.7636
DTZL2	NSGA2	0.4542	0.4894	0.5012	0.0109
	MAGA	0.4699	0.4740	0.4968	0.0081

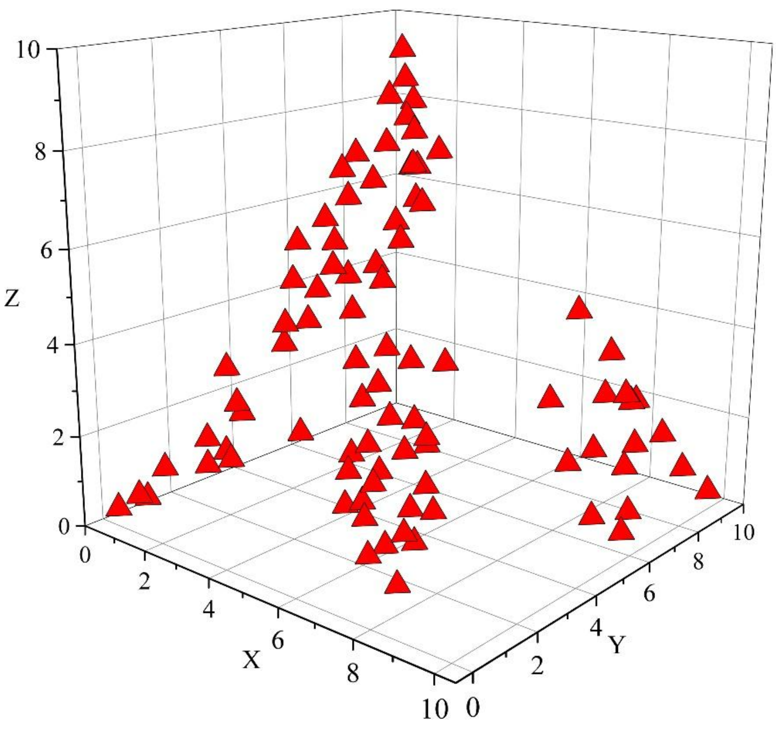
Test function	Algorithm	Best value	Mean value	Worst value	Standard deviation
ZDT1	NSGA2	0.4719	0.5352	0.5889	0.0284
	MAGA	0.3839	0.4905	0.5561	0.0188
ZDT2	NSGA2	0.5369	0.5898	0.6294	0.0249
	MAGA	0.5003	0.5652	0.7117	0.0408
ZDT3	NSGA2	0.6012	0.6814	0.7376	0.0377
	MAGA	0.7492	0.7797	0.8203	0.0512
ZDT6	NSGA2	0.6275	0.6695	0.7321	0.0309
	MAGA	0.5288	0.6123	0.6941	0.0265
DTZL1	NSGA2	1.1667	2.7972	6.1905	1.3312
	MAGA	0.0768	2.4845	7.5205	1.7636
DTZL2	NSGA2	0.4542	0.4894	0.5012	0.0109
	MAGA	0.4699	0.4740	0.4968	0.0081

To provide a more intuitive visualization of the experimental results, this section selected 50 individual test results for each of the DTZL1 and DTZL2 functions to plot the experimental results. The test results of the two algorithms on the functions are shown in Figures 3 and 4, respectively. Group (a) consists entirely of NSGA2 test results, while group (b) consists entirely of MAGA test results.

In Figure 3, it can be observed that the distribution in Figure (b) is broader than that in Figure (a), with more solutions distributed along the edges in Figure (a). Through graphical comparison in Figure 4, it is evident that Figure (b) exhibits superior uniform distribution compared to Figure (a). From the images, it can be seen that MAGA slightly outperforms NSGA2 in terms of solution uniform distribution. However, for piecewise functions, NSGA2 is more efficient in searching for the Pareto optimal solution frontier.

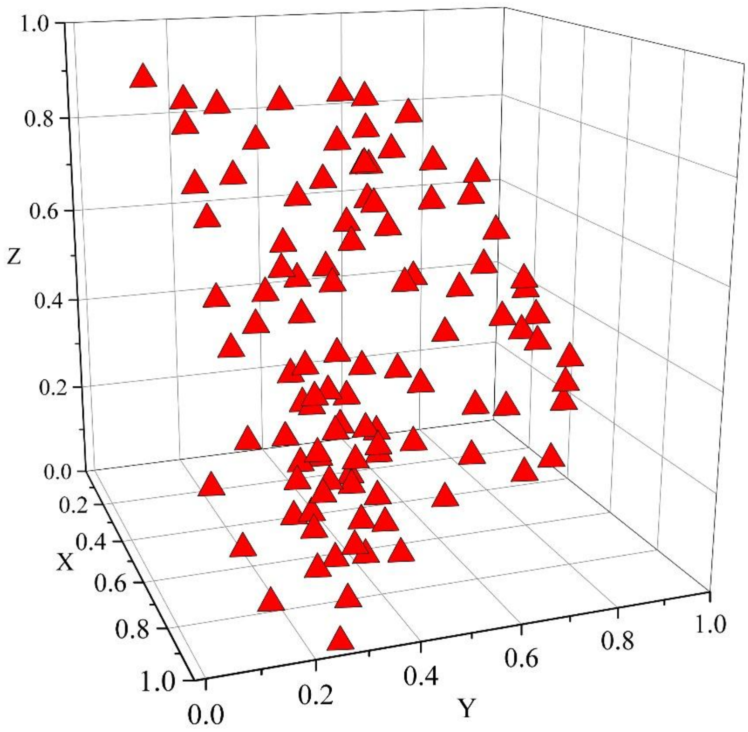


(a)NSGA2

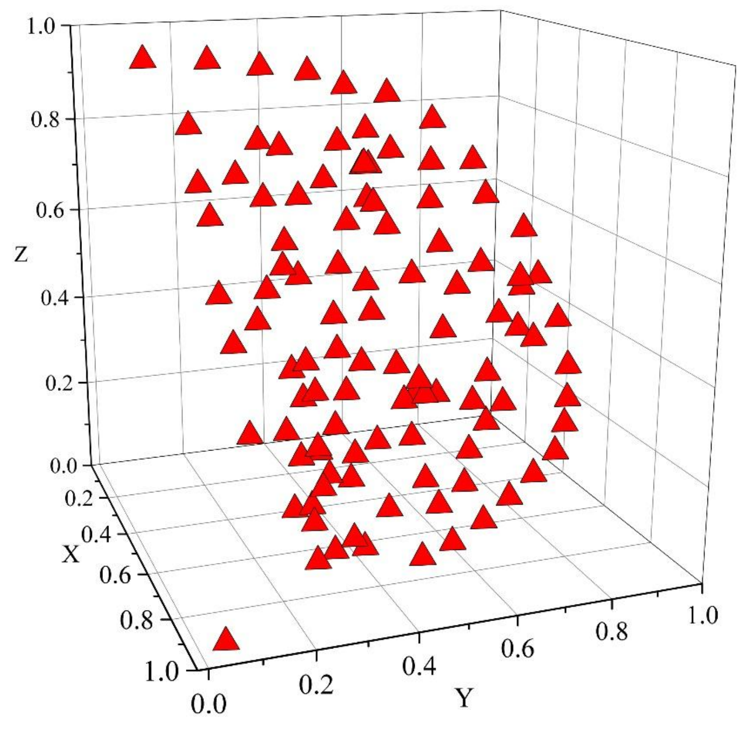


(b)MAGA

Figure 3. DTZL1 test results.



(a)NSGA2



(b)MAGA

Figure 4. DTZL2 test results.

4. Empirical Study on the Optimal Allocation of Library Resources

4.1. Empirical Subjects

Over the past 50 years since its establishment, the library of X University has developed into a multifunctional modern large-scale library. As of the end of 2024, the library has over 130 electronic databases (including free databases and open access OA resources), forming a professional literature resource system characterized by the integration of science and engineering, featuring multidisciplinary, multi-level, and multi-type resources.

Therefore, this empirical study selected relevant data from the digital resources of X University Library from 2016 to 2024. All data were sourced from the statistical data of the respective years. To mitigate potential risks, all research data underwent certain processing without affecting the conclusions of the study.

4.2. Results and Analysis of Resource Optimization

4.2.1. Multi-objective collaborative overall change analysis

The multi-objective evaluation values of library digital resources are shown in Figure 5 and Table 2. Between 2016 and 2024, the multi-objective evaluation values of digital resource allocation increased slowly, with evaluation values of 0.51, 0.57, 0.61, 0.65, and 0.73, respectively. This is because the period from 2016 to 2020 marked a critical transition phase for the research subject, shifting from a focus on print collections to prioritizing digital resource development. The library of X University implemented a phased approach, using procurement years as units, the library introduced a large number of digital resources and related resource optimization systems in phases. From 2020 to 2024, X University is in a critical period of optimizing its disciplinary layout and striving to achieve the national "Double First-Class" university construction goals. The library has optimized the content of digital resource construction from aspects such as resource construction content, search systems, and disciplinary analysis, targeting the school's disciplinary characteristics and disciplines it plans to prioritize. Therefore, the multi-objective evaluation level shows a trend of gradual improvement year by year.

The coordination among sub-objectives of digital resource evaluation has gradually strengthened. From 2016 to 2024, the levels of content evaluation, system evaluation, cost evaluation, service evaluation, and usage evaluation have all improved to varying degrees. Among these, content evaluation has maintained a rapid upward trend, system evaluation has shown a trend of initially rapid then gradual improvement, cost evaluation and service evaluation have maintained a slow upward trend, and usage evaluation has exhibited a trend of initially slow then rapid improvement.

Usage evaluation is a product of digital development reaching a certain stage and is also a key target for libraries to focus on to improve resource service efficiency and resource allocation benefits. The standard deviation and change advantage degree of multi-objective evaluation standards are shown in Table 3, with usage evaluation exhibiting a trend of slow growth followed by rapid growth. Additionally, the standard deviation calculation results indicate that the standard deviation of the multi-objective evaluation for the research subjects has been narrowing annually from 2016 to 2024, suggesting that the coordination among multi-objective evaluations of digital resources has gradually strengthened over the past decade.

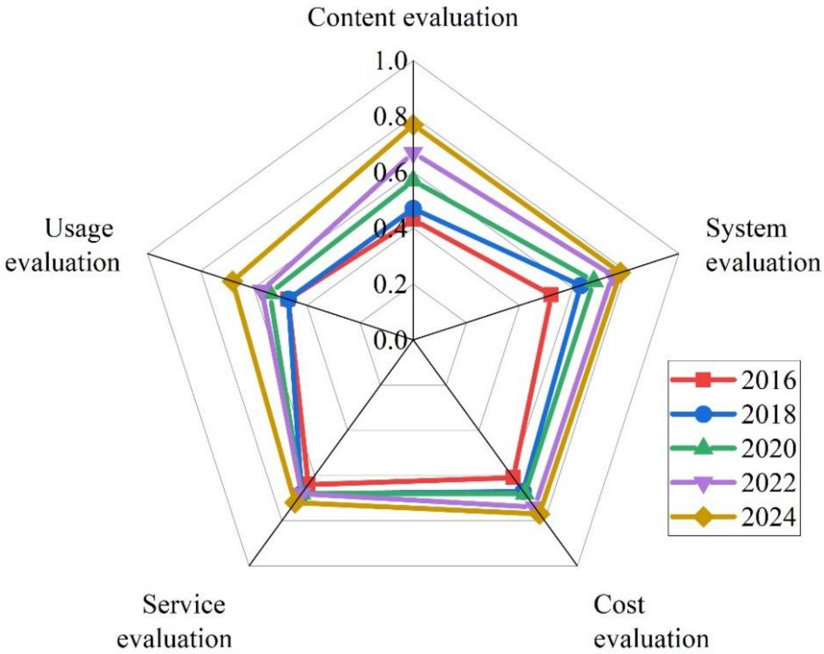


Figure 5. Library digital resource multi-target evaluation.

Table 2. Resource allocation multi-objective synergization.

Target	Target realization rate	Evaluation grade								
	2016	2018	2020	2022	2024	2016	2018	2020	2022	2024
Content evaluation	0.43	0.47	0.57	0.67	0.77	low	low	low	medium	medium
System evaluation	0.52	0.63	0.68	0.75	0.78	low	medium	medium	medium	medium
Cost evaluation	0.61	0.67	0.68	0.74	0.77	medium	medium	medium	medium	medium
Service evaluation	0.64	0.68	0.68	0.68	0.72	medium	medium	medium	medium	medium
Usage evaluation	0.47	0.47	0.54	0.57	0.68	low	low	low	low	medium
General purpose	0.51	0.57	0.61	0.65	0.73	low	low	medium	medium	medium

Target	Target realization rate	Evaluation grade								
	2016	2018	2020	2022	2024	2016	2018	2020	2022	2024
Content evaluation	0.43	0.47	0.57	0.67	0.77	low	low	low	medium	medium
System evaluation	0.52	0.63	0.68	0.75	0.78	low	medium	medium	medium	medium
Cost evaluation	0.61	0.67	0.68	0.74	0.77	medium	medium	medium	medium	medium
Service evaluation	0.64	0.68	0.68	0.68	0.72	medium	medium	medium	medium	medium
Usage evaluation	0.47	0.47	0.54	0.57	0.68	low	low	low	low	medium
General purpose	0.51	0.57	0.61	0.65	0.73	low	low	medium	medium	medium

Table 3. Evaluate the standard deviation and the change advantage.

Hierarchy	Multi-objective evaluation standard deviation					Target change dominance			
	2016	2018	2020	2022	2024	2016-2018	2018-2020	2020-2022	2022-2024
Single index	0.0778	0.0685	0.0517	0.0385	0.0347	0.6785	0.5974	0.4785	0.4456
Subscale	0.0865	0.0812	0.0716	0.0577	0.0473	0.3556	0.3795	0.3954	0.3675

4.2.2. Analysis of changes in each evaluation indicator

The dynamics and types of changes in resource allocation objectives are shown in Table 4. The evaluation of digital resource allocation is becoming increasingly diversified, with the focus gradually shifting from content construction and retrieval system evaluation to content quality and resource utilization effectiveness. Between 2016 and 2020, the sub-objectives with the most significant changes in evaluation were system evaluation and content evaluation, with sub-objective dynamics of 16.65% and 11.28%, respectively, and an advantage ratio of 0.3795, indicating that digital resource allocation during this period exhibited a diversified characteristic centered on retrieval systems and content development. From 2020 to 2024, the sub-objectives with the most significant changes in evaluation were content development and usage evaluation, with sub-objective dynamics of 15.16% and 13.78%, respectively, and an advantage ratio of 0.3675, which is slightly lower than in 2020. This indicates that resource allocation evaluation is becoming more diversified, with the focus gradually shifting toward a multi-objective collaborative evaluation centered on content and usage effectiveness.

First, content evaluation. Over the past decade, the dynamic changes in digital resource content construction have evolved from a phase of quantitative growth to one of stabilizing quantities, adjusting structures, and improving quality. The number of electronic databases within the library has remained stable at around 130, with types becoming increasingly diverse and structures and ratios tending toward rationalization and scientific optimization. The library continuously optimizes database procurement plans based on the school's development goals and disciplinary dynamics, resulting in higher disciplinary coverage and stronger support for key disciplines.

Second, system evaluation. During the study period, the construction method of the retrieval system shifted from local mirroring plus remote services to a model primarily based on cloud services. Between 2016 and 2020, the library invested heavily in the system construction of digital resources, as evidenced by the annual increase in the number of library retrieval systems, the gradual completion of system types, and the transition from a single database retrieval system to an integrated discovery system platform combining multiple database platforms. The local mirror storage of digital resources also expanded annually. Macroscopically, this is reflected in the rapid rise in the dynamic level of system construction evaluation. The cloud computing model ensures the stability, concurrency, availability, and scalability of large-scale data center systems, objectively reducing the operational costs of database vendors while also saving libraries costs in terms of human resources, funds, and technology.

Third, cost evaluation. Cost evaluation is composed of indicators such as software and hardware maintenance costs, annual increases in resource prices, per-article usage costs, and per-reader service costs. As shown in Tables 2 and 4, the cost evaluation level of digital resources is slowly increasing, generally aligning with the price trends of other commodities in the market. The PAAS and SAAS models of cloud computing have gradually reduced hardware usage and maintenance costs, as well as saved human and time costs in software development, leading to a year-on-year decrease in libraries' software and hardware maintenance costs.

Fourth, service evaluation. The overall service evaluation level of digital resources shows a slow upward trend. The transmission method of electronic data has gradually shifted from local storage plus remote access in 2016 to a model dominated by cloud services in 2024, with other transmission methods as a supplement, making data transmission methods increasingly simple and access methods increasingly convenient.

Fifth, usage evaluation. During the study period, usage evaluation showed a trend of slow growth followed by rapid growth. Usage efficiency and effectiveness analysis and evaluation are inevitable outcomes of the development of library digital resources to an intermediate or advanced stage. Between 2016 and 2020, as the focus of library development was on digital resource content and platform construction, readers went through a process of exploration, familiarity, and habit formation in using digital resource platforms and content. The primary objective of this stage was to cultivate readers' habits of using resources, resulting in a slow overall increase in usage rates, with rates of 6.68% and 8.35%, respectively.

Table 4. The dynamic and the type of change of the target.

Target	Target variation dynamics	Change type						
	2016-2018	2018-2020	2020-2022	2022-2024	2016-2018	2018-2020	2020-2022	2022-2024
Con	14.25	16.65	17.8	15.1	Fast	Fast	Fast	Fast

tent evaluation			8	6	rise	rise	rise	rise
System evaluation	16.97	11.28	7.26	6.78	Fast rise	Fast rise	Slow rise	Slow rise
Cost evaluation	8.32	4.65	7.36	4.12	Slow rise	Slow rise	Slow rise	Slow rise
Service evaluation	1.55	3.02	1.45	1.46	Slow rise	Slow rise	Slow rise	Slow rise
Usage evaluation	6.68	8.35	11.55	13.78	Slow rise	Slow rise	Slow rise	Slow rise
General purpose	9.11	8.71	9.85	9.28	Slow rise	Slow rise	Slow rise	Slow rise

Target	Target variation dynamics				Change type			
	2016-2018	2018-2020	2020-2022	2022-2024	2016-2018	2018-2020	2020-2022	2022-2024
Content evaluation	14.25	16.65	17.88	15.16	Fast rise	Fast rise	Fast rise	Fast rise
System evaluati	16.97	11.28	7.26	6.78	Fast rise	Fast rise	Slow rise	Slow rise

on								
Cost evaluation	8.32	4.65	7.36	4.12	Slow rise	Slow rise	Slow rise	Slow rise
Service evaluation	1.55	3.02	1.45	1.46	Slow rise	Slow rise	Slow rise	Slow rise
Usage evaluation	6.68	8.35	11.55	13.78	Slow rise	Slow rise	Slow rise	Slow rise
General purpose	9.11	8.71	9.85	9.28	Slow rise	Slow rise	Slow rise	Slow rise

4.3. System Effectiveness Testing

The experimental platform is MATLAB, running on the Windows XP operating system. To verify the effectiveness and rationality of digital library resource allocation in a cloud computing environment, experiments were conducted. The experimental design involved configuring eight sets of digital library resources, with resource file sizes of 350k, 450k, 550k, 650k, 750k, 850k, 950k, and 1050k. The effectiveness of digital library resource configuration was tested using configuration time, with the test results shown in Table 5.

F represents configuration time, O represents the 8 groups of digital library resource configuration tasks, A represents the method proposed in this paper, J represents the method based on the particle swarm algorithm, and Y represents the method based on the genetic algorithm. The configuration time for the first group of digital library resources using the proposed method was 6 minutes. As the size of the digital library resource files increased, the configuration time also gradually increased. by the eighth group, the resource file size reached 1050k, corresponding to a configuration time of 21 minutes. In the method based on the particle swarm algorithm, the configuration time for the first group of digital library resources was 11 minutes, and the configuration time for the last group was 44 minutes. In the genetic algorithm-based method, the resource allocation time for the first group of digital library resources was 13 minutes, and the last group's resource allocation time was 52 minutes. Comparison shows that the proposed method has the shortest resource allocation time, indicating the fastest allocation speed and higher effectiveness, thereby verifying the applicability of multi-agent genetic algorithms in library resource intelligent scheduling and resource optimization allocation tasks.

Table 5. Validity test for digital library resource allocation.

O	F(min)		
	A	J	Y
1	6	11	13
2	9	22	26

3	11	24	29
4	13	33	32
5	14	26	38
6	18	42	43
7	19	43	47
8	21	44	52

O	F(min)		
	A	J	Y
1	6	11	13
2	9	22	26
3	11	24	29
4	13	33	32
5	14	26	38
6	18	42	43
7	19	43	47
8	21	44	52

5. Conclusion

This paper proposes a multi-agent genetic algorithm-based optimization model for the allocation of library digital resources, enabling intelligent scheduling and optimal distribution of library digital resources.

In terms of algorithm performance testing, the experimental results of the MAGA algorithm were overall slightly better than those of NSGA2 for six test functions. On the ZDT1 test function, MAGA outperformed NSGA2 in terms of best value, average value, worst value, and standard deviation, with the best value achieving an excellent IGD index value of 0.3839. The distribution analysis of solutions shows that MAGA also outperforms NSGA2 in terms of solution uniformity.

An evaluation of the multi-objective coordination level of digital resource allocation at X University Library from 2016 to 2024 indicates that the model accurately reflects the actual changes in the utilization of digital resources at the library. After applying the optimization allocation model based on the multi-agent genetic algorithm, the multi-objective evaluation value of the library's digital resource allocation from 2016 to 2024 showed an upward trend, increasing from 0.51 to 0.73.

In terms of allocation efficiency, the method proposed in this paper requires the shortest resource allocation time and the fastest allocation speed, fully demonstrating the practicality and feasibility of multi-agent genetic algorithms in library resource intelligent scheduling and resource optimization allocation tasks.

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