International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 5242-5251

https://doi.org/10.70517/ijhsa463451

Dynamic Planning and Allocation of Continuing Education Resources Dynamic Planning

Yuting Li[1,*] and Yisheng Xue[1]
[1] Development and Planning Division, Shandong Open University, Jinan, Shandong, 250064, China
Corresponding authors: (e-mail: sdoulyt@126.com).

Abstract Optimize the allocation of community continuing education resources to improve the community humanistic environment. This paper counts the amount of community continuing education resources, analyzes the efficiency objective and equity objective of resource allocation. And design the continuing education resource system based on optimization algorithm. Select the genetic algorithm as the optimal configuration scheme solving algorithm, use the genetic principle to be configured resources to solve the unknown real number form coding. Find the optimal solution of the configuration scheme through the process of generating the initial population and defining the fitness function. Integrate adaptive mutation and small habitat technology to improve the genetic algorithm and improve the performance of the algorithm. The results show that the improved genetic algorithm achieves the convergence of the objective function value at 90 iterations. The convergence time of the algorithm is no more than 1500s in all three community resource allocation solutions. The results of the five characteristic indexes are high, high, low, high, and high, respectively. The average configuration cost is only 78.215*103 yuan, which is lower than the comparison algorithm, and it has performance advantages such as fast convergence speed and low solution cost.

Index Terms continuing education resource allocation, genetic algorithm, optimization algorithm, fitness function, small habitat technology

I. Introduction

Community education is a kind of educational activity for community residents, and its core objective is to improve the comprehensive quality of community members and enhance the cohesion and vitality of the community [1]. Community education emphasizes tailored education so that residents of different age classes and cultural backgrounds can participate in and benefit from it [2]. For example, adult education programs can help middle- and low-age workers learn new skills, organize multicultural experience activities to enhance neighborhood communication, and offer parent-child seminars to promote family education [3]-[5]. It is undeniable that in today's era of education for all, community education plays a prominent role in enhancing the comprehensive quality of all people and ensuring the harmonious and stable development of the community [6], [7].

However, the healthy development of community education cannot be separated from the input of a large amount of educational resources, otherwise the development of community resources will be limited [8]. Due to the influence of the urban-rural dualistic system and the imbalance between urban and rural economic development, some regional communities are currently facing a serious resource allocation imbalance in educational practice [9], [10]. That is, there is a lack of community education resources that can be utilized in community education work, which makes it impossible for community education work in some areas to be carried out smoothly [11], [12]. By optimizing the allocation of continuing education resources in areas with a lack of educational resources, it can ensure that the community education work in the region has educational resources that can be adequately utilized, which can avoid limiting the smooth development of community education work due to the lack of community education resources [13]-[16]. Therefore, combining the optimization algorithm to strengthen the optimal allocation of community education resources can effectively clear the obstacles to the development of community education in the region and greatly promote the fairness of community education [17], [18].

Based on the results of the analysis of the importance of the optimal allocation of community continuing education resources, this paper establishes a resource allocation system containing six modules to achieve the orderly allocation of resources at all levels of the community. Genetic algorithm is introduced to solve the system resource allocation optimization scheme. Real number coding is applied to the unknown number of resource allocation to solve the problem of upper and lower limits of allocation ratio. Define the fitness function to improve the efficiency of allocation optimization, and calculate the individual fitness to find the optimal solution through the steps of selection, crossover and mutation. Under the premise of variable and parameter restriction, adaptive mutation and small habitat improvement of genetic algorithm are carried out to improve the algorithm's effect of finding the optimum. The performance of the improved algorithm is verified by combining the case of continuing education resource allocation in specific communities.

II. Analysis of community continuing education resource allocation based on genetic algorithm

This part constructs a resource allocation system from the specific objectives of community continuing education resources and introduces a genetic algorithm to solve the resource allocation scheme.

II. A. Analysis of continuing education resources

II. A. 1) Meaning of continuing education resources

Continuing education resources are an integral part of educational resources. Educational resources refers to the social and economic resources, input into the educational process of human resources, material resources, financial resources, information and time resources, including human resources, material resources, financial resources, information resources, time and space resources, power resources, cultural resources, policy resources, relationship resources, institutional resources and so on, which constitute a complete system of educational resources. Continuing education resources are at the same time an integral part of education resources, which is a new thing along with social development and the application of modern information technology in education. The understanding of continuing education resources in this paper is based on its origin with education resources. Like educational resources, continuing education resources can also be understood from two perspectives: broad and narrow.

Resources for continuing education in the broad sense can be understood as all human resources and non-human resources related to teaching and learning in continuing education, which not only refers to the information of teaching and learning in continuing education itself, but also refers to the human, material, financial and technological factors related to it, including the equipment and materials, personnel, information and facilities used in the process of teaching and learning.

Continuing education resources in a narrow sense refer to information resources directly used in continuing education teaching, including education and teaching management information resources, information resources related to education and teaching research, education and teaching basic information resources, and information resources of modernized education and teaching means.

In this paper, the broad concept of continuing education resources is mainly adopted. Because the broad concept of continuing education resources is more conducive to the “system” point of view to the configuration and management of continuing education resources, not only includes the information and its carrier, but also reflects the information collection, transmission, processing, storage and utilization of the capacity and development potential. However, when studying the configuration of continuing education information itself, the concept of continuing education resources in the narrower sense is still used.

II. A. 2) Objectives of resourcing continuing education

Like the goal of educational resource allocation, the goal of continuing education resource allocation is to maximize the welfare of social resources. For continuing education resource allocation, the maximization of resource welfare is manifested in two aspects: one is to achieve the efficiency goal of continuing education resource allocation, continuing education resource allocation should not only correspond to the user's educational needs but also correspond to the user's effective resource needs. This requires that continuing education resource allocation should be clustered around demand. Continuing education resources, whether it is time, space configuration, or variety, quantity configuration, need to maximize to meet the demand for continuing education at all levels, with as little as possible labor and material consumption to obtain more products in line with the needs of the community, continuing education resources to produce greater social and economic benefits to the group tilt. Secondly, to realize the fairness goal of the allocation of continuing education resources, the allocation of continuing education resources should ensure that everyone has the right to obtain continuing education resources on an equal basis. This requires that the allocation of continuing education resources should seek to serve everyone with all the continuing education resources created by mankind, to achieve a balance in the per capita possession of continuing education resources, and to ensure that community users have the opportunity to access continuing education resources.

II. B.Overall System Architecture Design

Figure 1 shows the overall structure of the continuing education resource allocation system. Among the modules in Figure 1, continuing education information resource allocation is the core module of the system. It mainly includes the following steps: 1) Community service center administrator logs into the main service center and submits resource demand information; 2) the main service center searches for resources according to the demand information and returns the resource list; 3) the community service center administrator selects the required resources; 4) the main service center generates the resource allocation plan according to the required resources of the community service center; 5) the administrator of the main service center audits the resource allocation plan If the audit passes, the corresponding resources will be packaged (the resource package includes the resource entity and the XML file containing the resource details), and the community service center administrator is authorized to notify the community service center administrator to download or copy the configured resources; 6) the community service center administrator batch exports the configured resources and batch imports them into the community service center.

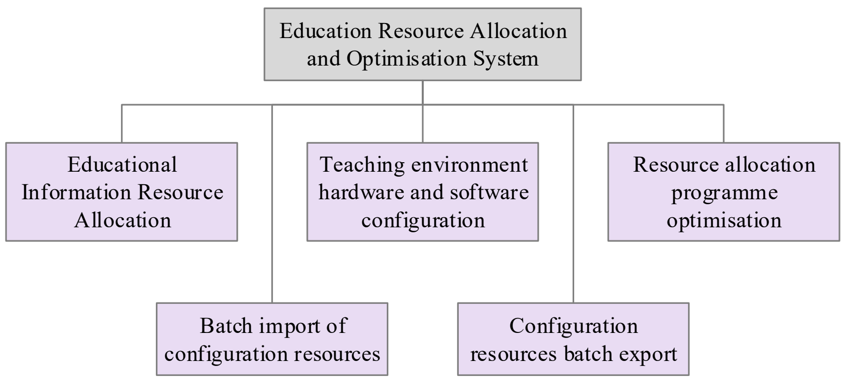

Figure 1: Overall Structure of the system

II. C.Genetic Algorithm Adaptation Analysis

Figure 2 shows the genetic algorithm process. It specifically includes the following steps:

1) Real number coding

Genetic algorithm is the use of the principle of heredity after a series of processes such as recombination, mutation, etc., the generation of offspring from the parent generation, and ultimately get the optimal result of the process. In order to complete the genetic process, the need to solve the unknown number of coding, so that it has the nature of the chromosome, the unknown number of the actual form of the phenotype, coding to give its genotype, to be established through the coding of the phenotype to genotype mapping. Genetic algorithm coding in various forms, such as binary coding, Gray coding, symbolic coding, real number coding and so on. In this paper, the unknown is the asset's resource allocation ratio x_{it}, in order to simplify the coding process and improve the efficiency of the solution, real number coding is chosen. The genotype of real number coding is expressed by the real value, i.e., the real value of the resource allocation proportion, and it can also set upper and lower limits for the decision variables, which can better solve the problem of upper and lower limits of the resource allocation proportion.

2) Population initialization

The genetic algorithm generates an initial population based on the selected coding form, and a population contains the values of decision variables generated by real number coding. In order to maintain the richness of the initial population and ensure the convergence speed, this paper chooses to use 25 initial populations for evolution.

3) Fitness function

The genetic algorithm needs to define the fitness function to judge the advantages and disadvantages of different decision variables, and if the solution objective contains constraints, the penalty function should be set at this stage to penalize the decision variables that do not comply with it.

Assuming that there are constraints in this paper: $\sum_{i=1}^{10} x_{it} = 1$, but there are a total of 10 decision variables in this paper, and if 10 decision variables are randomly generated, the constraints will be unsatisfied in most of the cases, which will make the algorithm less efficient, and the probability of finding the global optimum will be reduced. Therefore, in order to solve this part of the situation, this paper chooses to change the decision variables to 9, then the last random variable will be derived from $1-\sum_{i=1}^{9} x_{it}$. At this point, the constraint of the fitness function will change from the harsh equality constraint $\sum_{i=1}^{10} x_{it} = 1$ to the loose inequality constraint $1-\sum_{i=1}^{9} x_{it} > 0$, which will substantially improve the optimization efficiency.

At the same time, due to the specificity of the process of resource allocation accumulation, the process of resource allocation accumulation will have the problem of not being of the same order of magnitude as the semi-absolute deviation. If a single coefficient is used for weighting, there will be the same situation that the objective is too much concentrated on the total allocation objective. Therefore, when performing bi-objective weighting, the weighting cannot simply be performed using a single coefficient θ_t, but should be optimized after eliminating the order of magnitude difference. The approach adopted in this paper is to normalize both s_{it} and ω_t using the following formula so that both indicators are within the range of $(0,1)$. At the same time, when maximizing the allocation, it is assumed that each inflow of resources is equally scaled down to 1 category, which is only included in the calculation of W_t after the optimal resource allocation is finally arrived at, and is covered to the next optimization period. By applying the above method, this paper eliminates the order-of-magnitude inconsistency problem that occurs in bi-objective weighting. In this case, the fitness function will become:

$$\max \sum_{t=1}^{a} \left[\begin{array}{l} (1-\theta_t)*\left\{ \sum_{i=1}^{9} \frac{s_{it}}{\sum_{i=1}^{10} s_{it}} * x_{it} + \left(1-\sum_{i=1}^{9} x_{it}\right) * \frac{s_{10t}}{\sum_{i=1}^{10} s_{it}} \right\} - \theta_t * \\ \left\{ \begin{array}{l} \frac{\frac{1}{b}\left|\min\left\{0, \sum_{i=1}^{n} x_{it}\left[\sum_{j=1}^{b} r_{it}^{j} - r_{it}\right]\right\}\right|}{\omega_t} \\ + \frac{\frac{1}{b}\left|\min\left\{0, \left(1-\sum_{i=1}^{9} x_{it}\right)\left[\sum_{j=1}^{b} r_{10t}^{j} - r_{10t}\right]\right\}\right|}{\omega_t} \end{array} \right\} \end{array} \right] \tag{1}$$

The constraint function becomes:

$$\left(1-\sum_{i=1}^{9} x_{it}\right) \geq 0 \tag{2}$$

$$-\sum_{i=1}^{9} x_{it} * \ln(x_{it}) - \left(1-\sum_{i=1}^{9} x_{it}\right) * \ln\left\{\left(1-\sum_{i=1}^{9} x_{it}\right)\right\} \geq 2 \tag{3}$$

4) Selection

In order to carry out the cross mutation from parent to offspring more efficiently, the genetic algorithm does not take all the individuals of the initial total population as the parent, but selects some of the excellent populations as the parent. In this paper, we adopt the “roulette” selection method, which uses individual fitness to judge whether the parent is excellent or not, and the probability of an individual being selected as the parent for cross-mutation is determined by the proportion of its fitness to that of the individuals in the total population. Assuming that an individual is i, its fitness is F_i, and there are a total of n individuals in the population, the probability that it is selected is:

$$P_i = \frac{F_i}{\sum_{i=1}^{n} F_i} \tag{4}$$

5) Crossover

After selecting the parents of the initial population, the genetic algorithm allows the parents to crossover, i.e., to exchange genotypes in some way to generate offspring. In this paper, we use a crossover operator suitable for real number coding - discrete crossover recombination, i.e., the amount of parental individual change is randomly selected proportionally from the changes in the offspring to form the number of independent offspring.

6) Variation

Like the laws of nature, the new individual genes after crossover will be deformed. Genetic algorithms have a variety of mutation operators, such as basic bit mutation, balanced change, boundary deformation, unbalanced mutation and so on. In this paper, we use balanced deformation, which is to replace the original gene position of each locus in the genotype with a probability of 0.06 in the $(0,1)$ interval random number.

A new population is obtained by selection, crossover, and mutation, and individual fitness is recalculated. If the result converges and reaches the optimum value, the genetic algorithm stops; if it does not converge, selection, crossover, and mutation are repeated until an optimal solution is found.

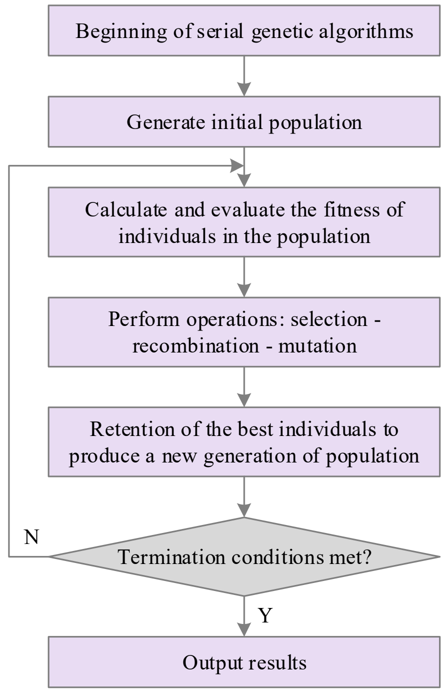

Figure 2: Genetic algorithm process

II. D.Improvement of the genetic algorithm

II. D. 1) Adaptive mutation

The improvement of the genetic algorithm in this paper is to utilize the existing variables to achieve the adaptive effect. Adaptive variation usually implies dynamically adjusting the probability of variation (P_m) according to certain conditions, but without the restriction of adding new variables and parameters, the probability of variation is influenced by pre-existing information, such as the index (i) of an individual. Adaptive methods assume that individuals in a population are ordered according to a certain quality or fitness, which can be such that individuals at the front of the list (usually assumed to be the more fit individuals) have a lower probability of variation, while those at the back of the list (the less fit individuals) have a higher probability of variation. Such adaptive tuning can encourage more mutation attempts on less well-adapted individuals, using the existing i and NSel (total number of individuals) to adjust the mutation probability. The specific adaptive scheme may be adjusted according to the actual genetic algorithm and problem requirements.

II. D. 2) Small habitat improvements

The goal of integrating small habitat techniques in genetic algorithms is to increase the diversity of the algorithm and to prevent premature convergence while maintaining the algorithm's search capability. One approach, without introducing new variables and parameters, is to apply the concept of microhabitats in the selection and reinsertion phases to maintain intra-population diversity. The improvement of the genetic algorithm in this paper will be adapted within the existing framework, especially in the implementation of Select and Reinsertion.

For the Select and Reins functions, there is a need to ensure that these functions maintain diversity. This typically involves favoring the selection of diverse individuals in the Select process and maintaining diversity between old and new populations in the Reinsert process. In order to enhance the implementation of the microhabitat technique, this paper requires details of the internal implementation of the functions, such as implicitly increasing diversity during the selection and reinsertion phases, but the exact implementation still relies on the internal details of the functions.

Selection phase: ensure that the selection process is not only based on fitness, but also takes into account the variability between individuals. This is done by including diversity judgments in tournament selection, or by adding additional selection probabilities for individuals with high variability in roulette selection.

Re-insertion phase: when re-inserting new individuals into the population, consider the variability between individuals to ensure that the new population maintains a certain level of diversity. For example, first compare the differences between old and new individuals, then prioritize the retention of those individuals that bring new characteristics to the population.

III. Community Continuing Education Resource Allocation Practice Based on Improved Genetic Algorithm

In this part, the proposed improved genetic algorithm is applied to the allocation of continuing education resources in different communities to compare the performance advantages of the algorithm and its practical application effects.

III. A. Statistics on resources for continuing education infrastructure

III. A. 1) Statistics on the value of fixed assets and teaching equipment

Continuing education resource allocation in 12 communities in T city is taken as the research object. The continuing education resources of each community are counted to provide a data basis for the subsequent allocation of continuing education resources based on the results of genetic algorithm optimization. Figure 3 shows the values of fixed assets and teaching equipment owned by the 12 communities. The total value of fixed assets of continuing education resources in the 12 communities in T city is 1606*104 yuan, of which teaching equipment is worth 120.8*10^4 yuan. Community 1 invested the most in fixed assets and instructional equipment in continuing education resources at 170*10^4 yuan and 14*10^4 yuan, respectively. Community 12 invested the least in continuing education resources, with fixed assets of only 115*10^4 yuan and teaching equipment valued at 7.1*10^4 yuan. The differences in fixed assets and teaching equipment among the 12 communities in continuing education resources are related to the resident population as well as the foreign population of each community, and the actual level of development of the community.

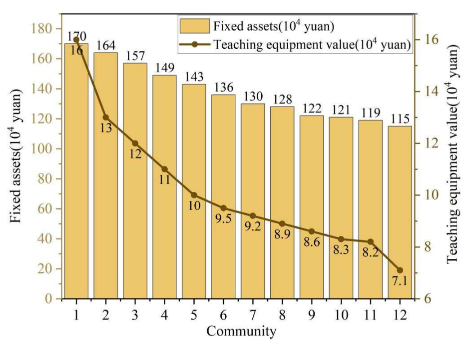

Figure 3: The value of community fixed assets and teaching equipment

III. A. 2) Statistics on the size of schools and school premises

The area of continuing education schools and the area of school buildings in the 12 communities are summarized in Figure 4. Of the 12 communities in T, Community 3 has the largest continuing education school area and school building area at 13.2km² and 3.34km². This is followed by Community 2 with 12.1km² and 2.78km². Again, Community 1 with 10.3km² and 2.31km². The higher demand for continuing education resources in Communities 1, 2, and 3 may be related to the size of these three communities as well as their larger populations.

III. A. 3) Statistics on the number of books in the collection

Figure 5 shows the statistical results of the number of books in the collections of continuing education schools in 12 communities. Community 1 has a collection of 6.11*10^4 books, while the remaining 11 communities have collections ranging from 5.97*10^4 to 5.57*10^4 books. In general, the number of books in the collections of the continuing education schools in the 12 communities does not vary much, which may be related to the fact that the schools mainly purchase books according to the book list given by the Ministry of Education.

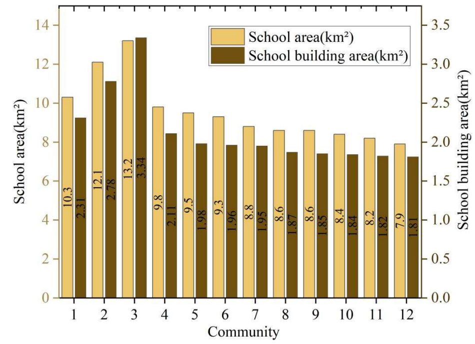

Figure 4: Statistics of school area and school building area

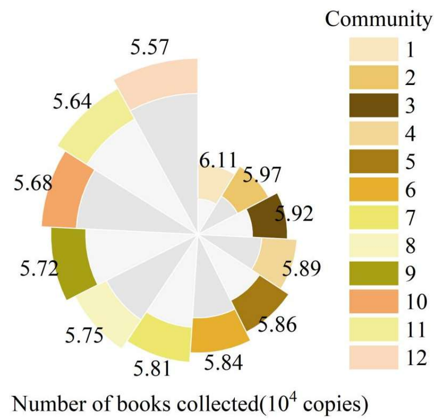

Figure 5: The number of books collected

III. B. Algorithm iteration number setting

Combining the continuing education resources in 12 communities and the proposed improved genetic algorithm, the continuing education resource allocation model is established. In order to test the performance of the improved genetic algorithm and determine the optimal number of iterations, this section utilizes the genetic algorithm to find the optimal solution for the allocation of continuing education resources in the communities. Figure 6 represents the change of the objective function value with the number of genetic generations during the training process of the algorithm. If the value is smaller, the algorithm performance is better, if the value is larger, the algorithm performance is worse. At 90 iterations, the objective function value has converged, indicating the effectiveness and feasibility of the algorithm. In the subsequent practical applications and calculations, setting the number of iterations to 90 can meet the requirements.

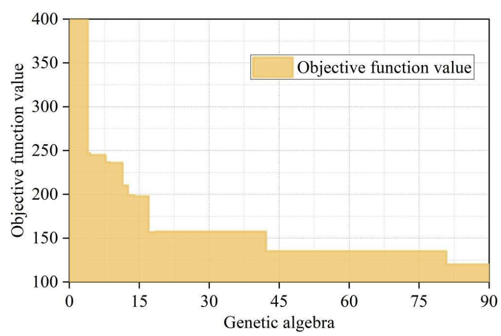

Figure 6: Variation of the objective function value with the number of inheritance

III. C. Algorithm Performance Comparison

III. C. 1) Convergence time comparison

Taking the allocation of continuing education resources in Communities 1, 2 and 3, which have the most continuing education resources and the highest demand, as a case study, we compare the performance advantages of the improved genetic algorithm proposed in this paper among different algorithms, and determine that it is able to play a role in optimizing the allocation of resources in the community education governance framework.

A total of nine algorithms, namely, Taboo Search (TS), Simulated Annealing (SA), Intelligent Algorithm (IA), Ant Colony Optimization (ACO), Ant Colony System (ACS), Particle Swarm Algorithm (PSO), Taboo Search with Genetic Algorithm (TS/GA), Simulated Annealing with Ant Colony Optimization (SA/ACO), and Genetic Algorithm with Ant Colony System (GA/ACS) were selected as comparison algorithms to be compared to the Improved Genetic Algorithm (IGA) proposed in this paper. Improved Genetic Algorithm (IGA) for convergence time comparison.

Table 1 summarizes the convergence times of the 10 algorithms in the allocation of continuing education resources in Communities 1, 2, and 3. In the allocation of continuing education resources in 3 communities, the convergence time of the 9 compared algorithms is between 1700s-1900s, which takes a long time. The convergence time of the improved genetic algorithm proposed in this paper is 1472s, 1455s and 1421s, respectively, and the convergence time in different sizes of resource allocation is not more than 1500s, with faster convergence speed.

Table 1: The convergence times of 10 algorithms

Algorithm	Convergence time (s)		
	Community 1	Community 2	Community 3
TS	1782	1766	1731
SA	1769	1763	1754
IA	1892	1862	1893
ACO	1704	1711	1726
ACS	1823	1867	1833
PSO	1815	1829	1818
TS/GA	1713	1735	1735
GA/ACO	1785	1787	1725
GA/ACS	1816	1842	1810
IGA	1472	1455	1421

III. C. 2) Comparison of Algorithm Characteristics

The comparison of the specific characteristics of the different algorithms continues to provide a comprehensive understanding of the characteristics of the algorithms in the allocation of resources for continuing education in all types of communities. Table 2 shows the results of the comparison of the characteristics of the 10 algorithms. The characteristics of the improved genetic algorithm in this paper are high, high, low, high and high in the five indicators of optimization ability of simple configuration, optimization ability of complex configuration, computational cost, tuning complexity, and independence of the initial solution, respectively. That is, it has low computational cost while realizing the solution of optimal configuration scheme of different community continuing education resources. Overall, the improved genetic algorithm in this paper has good resource allocation capability.

Table 2: Comparison of Algorithm Characteristics

Algorithm	Ability to optimize simple configurations	Ability to optimize complex configurations	Calculation cost	Tuning complexity	Independence of the initial solution
TS	High	Low	High	High	Low
SA	High	High	Low	Middle	Middle
IA	High	Middle	Low	High	High
ACO	High	Middle	Low	High	High
ACS	Low	Middle	Low	Middle	High
PSO	High	Low	Middle	Middle	High
TS/GA	High	Low	High	Low	High
GA/ACO	High	Low	High	Middle	High
GA/ACS	High	High	Low	Low	High
IGA	High	High	Low	High	High

III. C. 3) Comparison of Algorithmic Cost Objective Functions

Multiple experiments on the allocation of continuing education resources for different types of algorithms were conducted for communities 1, 2, and 3 to obtain the allocation costs of the algorithms for different configurations (averaged over the 3 communities). Figure 7 compares the allocation costs obtained by different types of algorithms.

According to the average configuration cost comparison results, the average configuration cost of this paper's improved genetic algorithm in different configuration experiments is only 78.215*10^3 yuan, while the average configuration costs of the comparison algorithms are all over 80*10^3 yuan. Comparatively speaking, the improved genetic algorithm in this paper has a lower configuration cost and can save economic expenditure more significantly for the optimal allocation of community continuing education resources.

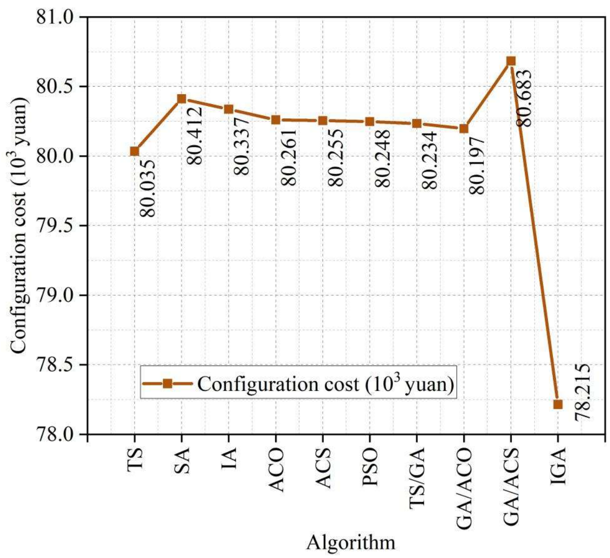

Figure 7: Cost objective functions of different types of algorithms

IV. Conclusion

In this paper, the improved genetic algorithm is introduced into the community continuing education resource allocation system to improve the resource allocation effect. In the practice of community continuing education resource allocation, the improved genetic algorithm has realized the effective convergence of the objective function value when it is iterated to 90 times. In the community 1, 2, 3 of continuing education resource allocation, the algorithm completes the convergence time of 1472s, 1455s, 1421s, which is significantly faster than the comparison algorithm's 1700s-1900s.The results of five characteristic indexes: optimization ability of simple configuration, optimization ability of complex configuration, computational cost, tuning complexity, and the independence of the initial solution are as follows: high, high, low, high, and high. The average configuration cost is only 78.215*10^3 yuan, which is lower than 80*10^3 yuan of the comparison algorithm. Using the improved genetic algorithm, it can quickly realize the optimization of multi-community continuing education resource allocation scheme. In the future, it can continuously access the community continuing education resources of different provinces and cities to realize the national resource integration and improve the quality of community continuing education.

Funding

This work was supported by the Department of Culture and Tourism of Shandong Province: "Research on the Communication of Excellent Traditional Chinese Culture in the Context of Convergent Media" (24WL(Y)165).

References

[1] Djunaidi, D. (2024). Implementation of Community Governance in the Field of Education. JMKSP (Jurnal Manajemen, Kepemimpinan, dan Supervisi Pendidikan), 9(2), 961-972.
[2] Pechtelidis, Y., & Kioupkiolis, A. (2020). Education as commons, children as commoners: the case study of the little tree community. Democracy and Education, 28(1), 5.
[3] deWinter, J., Kocurek, C. A., & Vie, S. (2017). Managing community managers: Social labor, feminized skills, and professionalization. Communication Design Quarterly Review, 4(4), 36-45.
[4] Tjarve, B., & Zemīte, I. (2016). The Role of Cultural Activities in Community Development. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 64(6).
[5] Edwards-Fapohunda, D. M. O. (2024). The role of adult learning and education in community development: A case study of New York. Iconic Research And Engineering Journals, 8(1), 437-454.
[6] Lv, Y. (2019, March). On Construction of Lifelong Education Community from the Perspective of Community Education. In 2018 8th International Conference on Education and Management (ICEM 2018) (pp. 322-324). Atlantis Press.
[7] Zhang, J. (2020). Research on the Theoretical Framework and Practical Form of Provincial Lifelong Education Community. Open Access Library Journal, 7(04), 1.

[8] Pintilie, L. M., & Bedrule-Grigoruta, M. V. (2016). The effects of resource allocation on education system. In ICERI2016 Proceedings (pp. 8633-8643). IATED.

[9] Song, J. (2023). The Impact of Economic Development on Inadequate Education Resources in Rural China. Journal of Education, Humanities and Social Sciences, 23, 285-290.

[10] Henry, W. (2019). Identifying and allocating resources for learning improvement: A study of sustainably improving rural schools. Theory & Practice in Rural Education, 9(1), 61-73.

[11] Pan, M., Huang, Y., Qin, Y., Li, X., & Lang, W. (2022). Problems and strategies of allocating public service resources in rural areas in the context of county urbanization. International Journal of Environmental Research and Public Health, 19(21), 14596.

[12] Kithinji, C., Gakuu, C., & Kidombo, H. (2017). Resource allocation, evaluational capacity building M&E Results utilization among community based organizations in Meru County in Kenya. European Scientific Journal, 13(16), 283-304.

[13] Ghufron, M. I. (2024). Optimization of Educational and Economic Management Towards Community Advancement: A Service Study for Improving Quality, Educational Access, and the Economy in Berme Village, Krucil District, Probolinggo Regency. Ijocore: Indonesian Journal of Community Research & Engagement, 2(02).

[14] Papară, C. M. (2023). Enhancing Education Quality in Rural Settings through Steiner-Based Societal Partitioning Optimization. Journal of Innovation in Psychology, Education and Didactics ISSN, 2247-4579.

[15] Amaya, J., Peeters, D., Uribe, P., & Valenzuela, J. P. (2016). Optimization modeling for resource allocation in the Chilean public education system. International Regional Science Review, 39(2), 155-176.

[16] O'Hara, K. L., Guastaferro, K., Hita, L., Rhodes, C. A., Thomas, N. A., Wolchik, S. A., & Berkel, C. (2024). Applying the resource management principle to achieve community engagement and experimental rigor in the multiphase optimization strategy framework. Implementation Research and Practice, 5, 26334895241262822.

[17] An, X. F. (2023). Research on the complex construction and community education function of smart cloud platform. In 2023 International Conference on Economics, Education and Social Research.

[18] Li, Y., & Xue, Y. (2025). Computational Analysis of Resource Allocation Optimization and Dynamic Planning for Continuing Education under Community Education Governance Framework. J. COMBIN. MATH. COMBIN. COMPUT, 127, 5831-5849.