International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 7136-7145

https://doi.org/10.70517/ijhsa464618

Functional Spaces Integrating English Language Learning and Housing Design: A Feasibility Study of Creating Diverse Learning Environments

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Abstract Modern housing design is experiencing a shift from single residential function to diversified functional space, especially in the context of globalization, the demand for English learning is increasing, and the traditional housing layout can no longer meet the diversified needs of modern families for learning space. In this paper, a housing functional layout model based on improved adaptive genetic algorithm is proposed for the design of diversified living environments integrating English learning spaces. The spatial point cloud data are collected by Kinect device to establish a three-dimensional spatial feature geometric model, which is combined with the improved adaptive crossover and variance probability formulas to realize the intelligent optimization of housing layout. Multi-user interactive genetic algorithm is used for indoor layout frame extraction, coordinate transformation and visualization. The experimental results show that the algorithm converges after 6810 generations of iterations, and the average fitness is maintained near 0.147; the Pareto-optimal solution set contains 34 solutions, of which the student satisfaction level of the optimal solution reaches 73.005 points and the English improvement level is 78.58 points; the user satisfaction score of the minimalist style objective reaches 4.72 points, and the system reliability is respectively 94% and 98% confidence level The reliability of the system was verified at 94% and 98% confidence levels, respectively. The results of the study proved that the method can effectively realize the functional integration of English learning space and housing design, which provides a scientific basis and technical support for the diversified design of modern housing.

Index Terms Improved Adaptive Genetic Algorithm, Housing Functional Layout, English Learning Space, Diversified Learning Environment, Spatial Point Cloud Data, Multi-User Interactive

I. Introduction

In the traditional learning model, the main teaching purpose is to cultivate specialized talents, focusing on the teaching of professional skills and related knowledge [1]. The model is teacher-centered and the main learning behavior of students is collective learning based on the curriculum [2]. And under the influence of the development of educational technology as well as the development of disciplines and policy requirements, the diversified transformation of students' learning mode has become inevitable for the development of education [3], [4]. The concept of “student-centered” education has given rise to new learning modes, and teaching strategies, teaching methods and specific learning behaviors have also shown the trend of richer content and more complex forms, including curriculum-based group learning, small group learning, independent learning, blended learning, collaborative learning, problem-based or project-based learning, and collaborative learning. , problem- or project-based learning, informal learning, etc. [5]-[8]. Research has shown that students generally perceive learning to be closely related to the environment and consider the relevant functional services that learning spaces can provide to be very important [9]. Therefore, the new learning model also puts new demands on the space of related teaching buildings.

Under the diversified learning model, learning behaviors are characterized by complexity and dynamism, which requires teaching architecture to be more “adaptive” [10]. The meaning of “adaptability” is dynamic and refers to the ability to adjust to new conditions, requirements and situations in the process of existence of the subject [11]. Under the new educational requirements, specific spatial needs can be analyzed. Carrying out research on the adaptability of the functional space of university teaching buildings is conducive to the realization of the long-term utilization of teaching buildings in the new educational context [12]-[14]. It is necessary to pay attention to the spatial design within teaching buildings, such as size and form, in order to realize the provision of places for different learning behaviors [15]. Attention should also be paid to the organization and connection between teaching buildings to realize the need for school-enterprise integration and cross-disciplinary research. Attention should also be paid to the updating of supporting facilities within the teaching buildings so as to realize the need for smart learning and collaborative and shared learning [16].

The demand for residential functions in contemporary society shows a diversified development trend, and the traditional concept of living space design has been difficult to adapt to the composite living needs of modern families. As an international common language, the demand for English learning is becoming more and more prominent in modern families, especially under the promotion of family education and lifelong learning concept, family members' demand for specialized and personalized English learning space is growing. However, the constraints of limited urban housing area make it a design challenge to realize multifunctional composites within a given space. Traditional housing design tends to attach learning functions to the bedroom or living room without in-depth analysis of the characteristics of learning behaviors and spatial needs, resulting in poor learning effects and low space utilization. At the same time, there are significant differences in the English learning needs of different family members, including learning time, learning mode, and spatial privacy requirements, etc., and a single spatial design model cannot meet individualized needs. In addition, the multifunctional integration of housing space involves complex spatial relationship coordination, functional conflict elimination, use of time sequence arrangement and other issues, which requires systematic design methods and optimization tools. Therefore, it is of great theoretical value and practical significance to explore scientific and effective methods for optimizing the functional layout of housing to realize the organic integration of English learning space and residential function.

Based on the above problems, this study constructs a comprehensive research framework to solve the complex optimization problem of integrating housing design and English learning space. First, an improved adaptive genetic algorithm is used as the core optimization tool, and the convergence and global search ability of the algorithm is improved by dynamically adjusting the crossover and mutation probabilities. Second, the Kinect device is used to acquire 3D point cloud data of the real space and establish an accurate spatial geometric model, which provides a reliable data base for the subsequent layout optimization. Then, combined with the concept of multi-user interactive design, the user's subjective preferences and objective needs are incorporated into the optimization process to ensure that the design results comply with both technical standards and actual use requirements. Finally, through the establishment of a multi-dimensional evaluation system that includes investment cost, student satisfaction, English enhancement effect and social adaptability, the comprehensive assessment and optimization of design options are achieved.

II. Improvement of the functional layout model for housing by genetic algorithms

II. A. Improvement of genetic algorithm

II. A. 1) Principles of Genetic Algorithms

The basic principle of genetic algorithms is to simulate the phenomena of reproduction, hybridization and mutation in the process of natural selection and heredity, and it is a search method based on the mechanism of natural selection and population genetics. In solving practical problems, genetic algorithms start from a population of possible potential solution sets, which consists of a certain number of individuals genetically encoded, i.e., chromosomes with expressive characteristics [17]. In order to realize the mapping from expression to genotype, a coding exercise, such as binary coding, needs to be performed in advance. After randomly generating a population (i.e., the initial solution), each individual is evaluated according to a predetermined objective function and a fitness value is given. Based on this fitness value, the individuals used to generate the next generation are selected, and the selection operation reflects the principle of “survival of the fittest and survival of the fittest”, and then the selected individuals, after crossover and variation operations, generate a new generation. Then the selected individuals, after crossover and mutation operations, generate a new generation, which inherits some good traits from the previous generation and has better performance than the previous generation, and thus the evolution will continue to move towards the direction of the optimal solution.

II. A. 2) Adaptive genetic algorithms

The convergence of the genetic algorithm is mainly determined by the crossover and mutation operators, and the value of the two is the key to play the genetic role. Through the above analysis, we know that the standard genetic algorithm adopts fixed crossover and mutation values in simulating the biological evolution process, which obviously does not objectively consider the dynamic changes of the individual living environment in evolution, which is very unfavorable to the adaptation of individuals to the dynamically changing evolutionary environment. With the evolution of individuals, the fixed genetic operators can not meet the current requirements of population evolution, which seriously affects the performance and efficiency of the genetic algorithm. In view of the problems in the evolutionary process, experts and scholars have focused on the adaptive change of crossover and mutation operator values and proposed adaptive genetic algorithms.

Adaptive genetic algorithm compared to the basic genetic algorithm difference is mainly reflected in the dynamic adaptability of the crossover and mutation probability, the individual can according to the environmental changes in the evolution of the crossover, mutation probability values adjusted accordingly, not only to avoid the optimization results of the precociousness of the evolution, at the same time, more clear evolutionary direction is also conducive to speeding up the algorithm of the convergence of the later stages of the evolution of the significant advantages [18].

II. A. 3) Improving adaptive genetic algorithms

In order to avoid the situation that the algorithm converges to a local optimal solution by too fast reproduction of superior individuals at the early stage of evolution, this paper proposes an improved adaptive crossover, mutation probability value formula as follows:

$$P_C=\begin{cases}\dfrac{P_{C\max}+P_{C\min}}{2}+\dfrac{P_{C\max}-P_{C\min}}{2}\sin\left(\dfrac{\pi}{2}+\dfrac{\pi(f'-\overline{f})}{f_{\max}-\overline{f}}\right), & f'\geq\overline{f}\\ P_{C\max} & ,f'<\overline{f}\end{cases} \tag{1}$$

$$P_m=\begin{cases}\dfrac{P_{m\max}+P_{m\min}}{2}+\dfrac{P_{m\max}-P_{m\min}}{2}\sin\left(\dfrac{\pi}{2}+\dfrac{\pi(f-\overline{f})}{f_{\max}-\overline{f}}\right), & f\geq\overline{f}\\ P_{m\max} & ,f<\overline{f}\end{cases} \tag{2}$$

where, $P_{C\max}$, $P_{C\min}$ - maximum and minimum values of crossover probability, $P_{m\max}$, $P_{m\min}$ - the maximum and minimum of the variation probability.

II. B. Characteristics of Housing Layout for Inclusive English Learning Spaces

II. B. 1) Spatial point cloud data acquisition

Use Kinect to acquire spatial point cloud data, Kinect in the scene scanning, due to occlusion or light reasons, there may be missing data, usually some of the scanning can not be located or the scanning angle is not correct. Therefore, it is necessary to adjust the position and angle of the Kinect device during the scanning process to establish a local coordinate system centered on Kinect, and collect indoor spatial data with the support of this coordinate system.

The main device of Kinect device in the process of data acquisition is the depth camera, which adopts the optical coding technology and mainly utilizes the depth sensor to collect indoor spatial location information, and its internal depth distance is represented by a 13-bit binary number. It is assumed that the individual pixel color information in the depth map collected from the Kinect device is parameter ξ, which is 16-bit data. According to the description of the pixel information in the SDK documentation, in the depth image pixel information, it is the first 13 bits of the data that contain the depth information and the last 3 bits of the data that contain the user index. When the raw depth data of Kinect is obtained, the obtained color information and user ID are segmented to ensure that the first 13 bits of the data remain unchanged, and the last 3 bits are returned to 0. After internal processing in the SDK, the depth data that can be obtained through the Kinect device ranges from 0 to 4095. In general, shifting the raw data of Kinect to the right by three bits is to obtain the depth information of the current pixel, and this depth information reflects the real-world distance of the pixel point.

The data collected by Kinect has some areas to be repaired, such areas are hollow areas, areas that cannot be monitored and shadow areas, for different areas, the corresponding repair measures are used to get more complete depth data. Repair completed data can not be used directly in the simulation model establishment, because in the process of repair will make the image edge at the depth of some continuous noise, need to use the filter processing point cloud data, the noise in the data to remove the noise, after completing the filtering process, the use of point cloud data to establish the indoor spatial feature collection model.

II. B. 2) Geometric modeling of spatial features

The spatial data obtained through the above process is mainly displayed in the form of depth images, which are two-dimensional maps, considering that spatial features are mainly composed of three-dimensional data, the depth maps need to be converted into the relationship of three-dimensional spatial points in the real world when obtaining depth images of indoor spaces. There is an auto-correction function inside Kinect that corrects the depth and color camera in real time, so the process of building a geometric simulation model of spatial features is actually completing the projection of spatial points onto the image plane. In order to quantitatively describe the geometric modeling process, the world coordinate system, camera coordinate system, image pixel coordinate system and physical coordinate system are established respectively. As shown in Fig. 1.

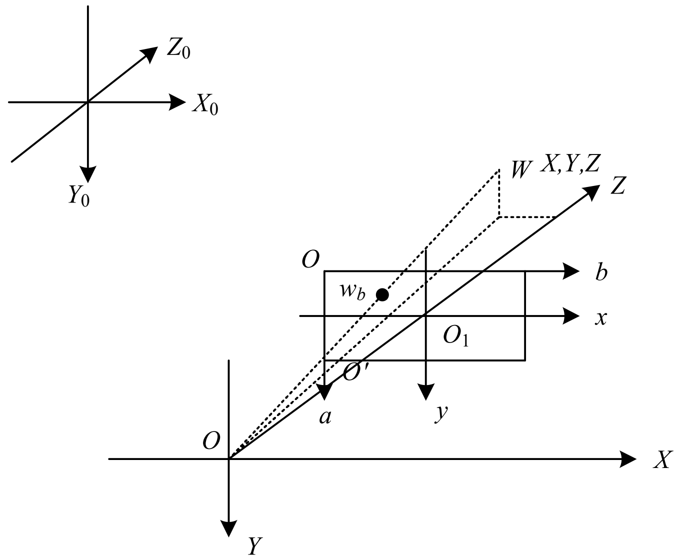


Figure 1: Camera imaging model

The figure shows $(O_s - X_sY_sZ_s)$ denotes the camera coordinate system, $(O_1 - xy)$ denotes the physical coordinate system, $(O_0 - X_0Y_0Z_0)$ is the world coordinate system, and $(O' - ab)$ denotes the image pixel coordinate system. In the image pixel coordinate system, the coordinates of each point are represented by (a,b) in pixel units; in the camera coordinate system, Z_s represents the camera optical axis, and the origin of O_s is the camera optical center. The default O_1 is (a_0, b_0) in pixel coordinates, and O_1 is the center of the image and the origin of the physical coordinate system. The x and y axes are parallel to the camera coordinate system X_s and Y_s respectively. The coordinates of the object point W in the world coordinate system are $W(X_s, Y_s, Z_s)$ in the camera coordinate system, and $w_b(x_b, y_b)$ in the physical coordinate system under the simulation model. Assuming that the physical dimensions of the image pixels obtained through Kinect are l_x in the a direction and l_y in the b direction, respectively, it can be seen that the transformation relationship between the image pixel coordinate system and the physical coordinate system is as in Eq. (3) and Eq. (4):

$$b = \frac{x}{dx} + b_0 \tag{3}$$

$$a = \frac{y}{dy} + a_0 \tag{4}$$

The transformation relationship between the world coordinate system and the camera coordinate system is shown in equation (5):

$$\begin{bmatrix} X_s \\ Y_s \\ Z_s \end{bmatrix} = Q \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} + T \tag{5}$$

where Q denotes the rotation matrix of 3×3 and T denotes the translation vector. In the ideal condition, the perspective projection transformation under the simulation model is the change from the camera coordinate system to the physical coordinate system, and its transformation relation is:

$$x_b = g \times \frac{x_s}{z_s} \tag{6}$$

$$y_b = g \times \frac{y_s}{z_s} \tag{7}$$

where g denotes the transformation vector, according to the correspondence between the coordinate systems, the transformation relationship between the object point w in the world coordinate system and the image pixel coordinate system is obtained, in the process of calculation, the camera coordinate system is used as the world coordinate system to get the value on the world coordinate system corresponding to the target point in the Kinect data, and the final X_s, Y_s, Z_s values are obtained:

$$\begin{cases} X_s = (b - b_0) \times \dfrac{l}{\alpha} \\ Y_s = (a - a_0) \times \dfrac{l}{\beta} \\ Z_s = l \end{cases} \tag{8}$$

where α , β , a_0 and b_0 denote the internal parameters of the camera, the conversion of depth image pixel coordinates to spatial point 3D coordinates can be accomplished by utilizing Eq. (8), which uses the Kinect sensor as the origin of the world coordinate system. The simulation model corresponding to the indoor spatial depth image can be obtained by this conversion.

II. B. 3) Basic layout features

The basic layout features are the description of the indoor visualization layout form, in order to adapt to the multi-user interactive genetic algorithm for the landscape node setup needs, the implementation of the layout, the requirements of the selected landscape node placement position and the coordinate axis must be in the same plane. The O' is used to denote the indoor landscape node placement coefficient based on the multi-user interactive genetic algorithm, and its solution expression is as follows:

$$O' = \frac{1}{q} \sum_{r=1} \left(\frac{\delta \left| e_{\max}^2 - e_{\min}^2 \right|}{\gamma^2 \cdot E} \right) \tag{9}$$

where: r denotes the derivative vector; $e_{\max}$ denotes the maximum value of the planar layout parameter; $e_{\min}$ denotes the minimum value of the planar layout parameter; δ denotes the indoor layout planning feature; E denotes the non-zero orientation vector in the layout plane; and γ denotes the indoor landscape node layout authority.

Let φ denote the scene vector in the indoor layout environment, $\dot{I}$ denote the planning coefficients, and associate equation (9) to derive the expression for solving the basic layout feature as:

$$U = \left(\varphi^2 - 1 \right) \cdot \sqrt{\frac{Q'}{\left\| \dot{I} \right\|}} \cdot \left| \Delta T \right|^2 \tag{10}$$

where ΔT denotes the unit layout period. The visualization of the indoor layout environment must be processed in accordance with the principle of multi-user interactive genetic algorithm to determine whether the actual placement position of the landscape is within the same spatial plane as the preset coordinate axes.

II. C. Design of housing layouts that incorporate English language learning spaces

II. C. 1) Indoor Layout Framework Extraction

The indoor layout framework extraction arranges landscape nodes in accordance with the connection form of the layout framework (spatial coordinate axes), and when extracting the node coordinates, there are more coordinate samples involved, and in order to avoid the emergence of misclassification behaviors, the nodes with the same x -axis coordinates are categorized as nodes of the same system of transverse coordinates, nodes with the same y -coordinates as nodes of the same system of longitudinal coordinates, and nodes with the same z -coordinates are categorized as nodes of the same system of spatial coordinates. The indoor layout frame extraction expression for the horizontal, vertical and spatial coordinate homology nodes is:

Horizontal coordinate homology node:

$$P_x = |U| \cdot \exp\left(-\left(\frac{A_x}{\varepsilon_x}\right)\right) \tag{11}$$

Vertical coordinates of homologous nodes:

$$P_y = U \Big/ \left(\frac{A_y}{\varepsilon_y}\right) \tag{12}$$

Spatial coordinate homology nodes:

$$P_z = \frac{U \cdot A_z}{\varepsilon_z} \tag{13}$$

where: A_x, A_y, A_z denote the results of layout node extraction in the x-axis, y-axis and z-axis directions, respectively; $\varepsilon_x, \varepsilon_y, \varepsilon_z$ denote the node categorization coefficients in the x-axis, y-axis and z-axis directions, respectively.

If an indoor landscape node simultaneously satisfies the layout frame extraction conditions in the x-axis, y-axis, and z-axis directions, the node is determined to be an omni-directional layout node when implementing the visualization process.

II. C. 2) Coordinate conversion

Coordinate transformation is the omnidirectional processing of the extraction conditions of the indoor layout framework, and in the multi-user interactive genetic algorithm cognition, only if the selected nodes fully satisfy the principle of coordinate transformation, it can ensure that the landscape placement position fully conforms to the indoor layout visualization design results. The so-called conversion can be understood as a kind of change processing to meet the operational requirements, in the case of the core node position remains unchanged, after the conversion of the coordinate axes system biased towards which fixed coordinate axis, it means the implementation of the visualization of indoor layout processing design direction is biased towards which fixed coordinate axis. Let f denote the core conversion coefficient, ϕ denote the bias parameter, s_x, s_y, s_z denote the value parameters of the interior landscape nodes in the direction of x-axis, y-axis and z-axis, respectively, and g_x, g_y, g_z denote the bias coefficients in the direction of x-axis, y-axis and z-axis, respectively. Combining the above physical quantities, the joint formula (13), the expression of the multi-user interactive genetic algorithm based on indoor layout coordinate transformation can be defined as:

$$D = \frac{P_x \cdot P_y \cdot P_z}{g_x \cdot g_y \cdot g_z} \cdot \left| \frac{f\sqrt{s_x^2 + s_y^2 + s_z^2}}{\phi} \right| \tag{14}$$

Due to the indoor layout node placement coordinates can not completely follow the “horizontal and vertical” rule, so the implementation of the coordinate conversion process, allowing the existence of small values of the deflection angle.

II. C. 3) Visualization processing and fusion

The visualization treatment is a control design treatment of interior layout nodes according to a multi-user interactive genetic algorithm. The visualization processing expression is:

$$K = \frac{1}{\iota}|D|^2 + \lambda \sum_{l=1}^{+\infty} \overline{h}_l^2 \tag{15}$$

where ι denotes the visualization operation coefficient; λ denotes the node control parameter based on the multi-user interactive genetic algorithm; l denotes the initial value of the node labeling coefficient; and $\overline{h}$ denotes the cumulative mean amount of nodes in the layout plane. When Eq. (15) is satisfied, it indicates that the current indoor layout visualization design is reasonable, and conversely it needs to be further optimized.

Visualization fusion is to synthesize all the indoor layout nodes together, thus enabling the design host to quickly extract and process the nodes to be processed when completing the indoor landscape visualization layout. The visualization fusion expression satisfies the formula as follows:

$$M = \log_D b' + \sum_{v=1} \left(j_1 + j_2 + \cdots + j_v + \cdots + j_n \right)^2 \tag{16}$$

where b' denotes the standard fusion parameters; $j_1, j_2, \cdots, j_n$ denote the results of n different indoor layout node fetches; v denotes the initial fusion vector.

III. Experimental results and analysis

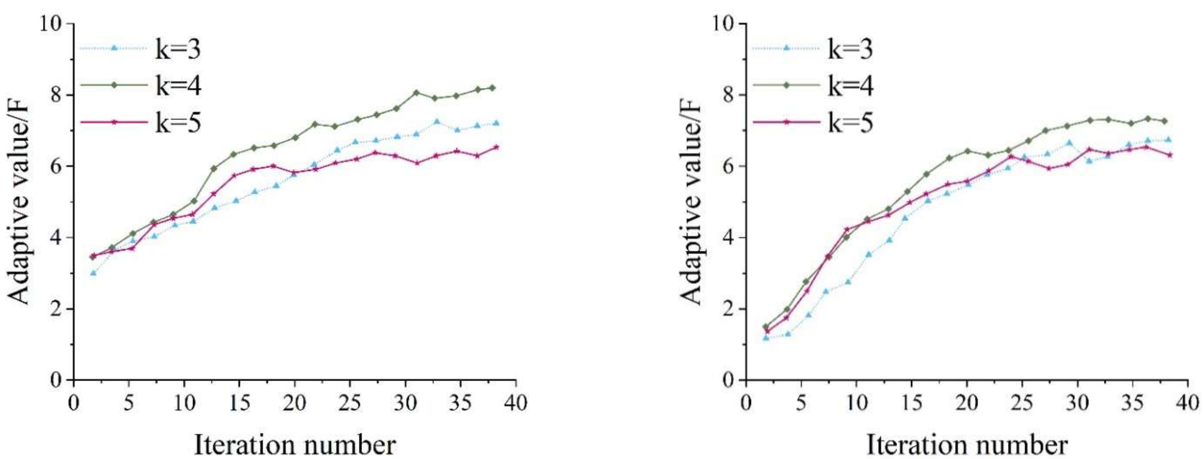
III. A. Parameterization

In order to reduce user fatigue while increasing the diversity of individuals during selection, for the experimental parameters, the population size was set to 13, the selection probability was set to 0.7, the variation probability was set to 0.06 so that genes were not confined to a certain range, k was set to 4 in the K-means method, and the roulette algorithm was used for the selection strategy.

III. B. Convergence test

In interactive algorithms, in addition to the influence of parameters on convergence, the user's subjective choice also plays a key role, the purpose of the convergence test is to study how the user's subjective choice affects convergence during the evolution process, and at the same time, in order to improve the effectiveness of the algorithms, the value of k in the K-means clustering method was taken as 3, 4 and 5 for comparison experiments. The design and art industry is biased towards subjective characteristics, it is difficult to quantitatively describe the convergence, so we use the scoring mechanism to convert the score into the adaptation value of the individual of the population.

In the test, 10 users used the system to score the individuals of each generation and obtain the average score, the higher the score, the stronger the convergence of the algorithm. Figure 2 shows how the score (convergence) changes depending on the user's subjective choice and the value of k. As can be seen from the figure, when the number of iterations is $t \in [0,12]$, the value of k has no obvious impact on the result, when t>12, k takes 4 will show stronger convergence, and we understand that the different subjective needs of users will have an important impact on the convergence of the algorithm, and different style choices will also have an impact on the subjective judgment of users, which in turn affects the convergence of the algorithm.



(a) Minimalist style (b) European-style

Figure 2: Convergence test

III. C. Generating results

The above genetic algorithm is implemented by a self-written Python program, which takes one generation result of the functional topological relationship generation experiment as the input condition of the in-set planar generation experiment, and controls the evolutionary direction of the population through the fitness function to finally generate multiple in-set planar layout schemes under the same functional topological relationship.

The connection relationship of each functional space is also used as one of the parameters of the fitness function to regulate the generation results, so that the average environmental resilience of the population will be increased generation by generation, but it may not be able to generate a perfect individual that meets all the design goals. Therefore the generated results may not always be able to fully comply with the functional topological relationships and other design requirements such as area and form, and the final floor plan layout will be an extremely optimal solution under this objective.

A class II set in the set layout generation result is chosen as the basis for the in-set planar generation experiment, and the planar layout optimization is carried out within the contour of the set, and the adaptability of the spatial planar layout generation experiment is shown in Fig. 3. As can be seen from the figure, with the increase in the number of iterations, the average fitness of the population gradually decreases, the average environmental adaptability gradually enhances, and after the number of iterations exceeds about 6810 generations, the average fitness maintains up and down in the neighborhood of 0.147, which indicates that even if the population continues to iterate, it is difficult to produce more excellent individuals, and the algorithm has converged.

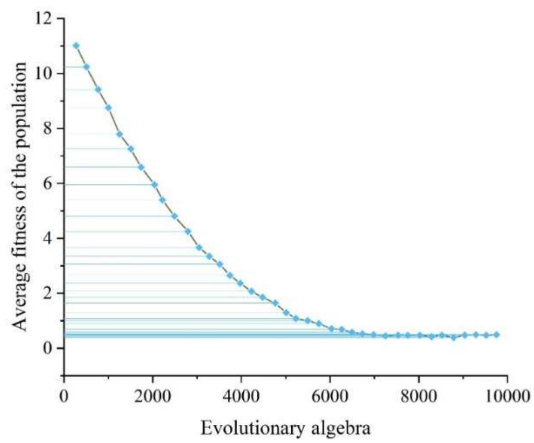


Figure 3: The fitness curve of the experiment in the inner plane layout

The residential space is limited by the 600*600 grid, most of the results of the spatial contour is relatively regular, and the area and size of the space are basically in line with the requirements of use.

Using genetic algorithms to generate the layout design within the limited residential contour can output a number of generation results that meet the preset design goals in a relatively short time, and the designer can deepen the plan according to the graphical expression of the generation results, and the drawing process of the plan can also be generated automatically. However, since the automatic plan generation system is not the content of this study, the plan deepening design is still completed by manual drawing.

Taking the optimal individual two-dimensional map floor plan layout of the in-suite floor plan layout generation experiment as an example, we simulate the change of English learning needs during the development of family life cycle, carry out the design of floor plan deepening and spatial modification of this suite floor plan layout in each family life stage, and analyze the spatial adaptability characteristics of the in-suite floor plan in each stage.

By running the program through MALAB, the final solution set contains 34 solutions. Table 1 shows the set of 34 optimal solutions. The table corresponds to an investment of 5.29 million dollars per set, a student satisfaction level of 73.005 points, an English enhancement level of 78.58 points, and a social adaptation of 76.37 points. This further reveals the concept of Pareto-optimal solutions, i.e., in multi-objective optimization, the Pareto-optimal solution provides the best trade-off between all objectives without being outperformed by any other solution on all objectives simultaneously.

Table 1: The pareto solution of the case builder case

Builder's case	investment	Student satisfaction level	English improves	Social adaptability
1	426	71.855	74.75	72.933
2	450	72.63	79.25	76.026
3	529	73.005	78.58	76.37
4	230	73.63	78.28	77.995
5	116	76.022	74.78	77.62
6	319	76.797	79.28	80.714
7	129	74.005	80.08	78.339
8	160	77.13	80.58	80.776
9	231	77.172	81.08	81.058

10	270	77.797	80.78	82.683
11	450	77.838	79.08	78.389
12	109	78.172	82.58	83.026
13	229	78.213	80.88	78.733
14	209	78.838	80.58	80.358
15	218	78.338	82.03	83.808
16	213	81.23	77.08	79.983
17	155	82.005	81.58	83.076
18	235	79.213	82.38	80.701
19	160	82.338	82.88	83.139
20	229	82.38	83.38	83.42
21	119	83.005	83.08	85.045
22	180	83.338	84.38	85.108
23	123	83.38	84.88	85.389
24	170	83.505	83.83	85.889
25	350	83.672	78.705	84.701
26	280	83.838	85.13	85.951
27	149	83.88	85.63	86.233
28	229	84.047	80.505	85.045
29	270	84.672	80.205	86.67
30	339	84.713	80.705	86.951
31	449	85.047	82.005	87.014
32	510	85.172	80.955	87.514
33	139	85.213	81.455	87.795
34	249	85.547	82.755	87.858

III. D. Subjective tests

People's subjective aesthetics will change over time, then the bias of these overly subjective test results may be larger. In this paper, Sheffe's two-point test (pair-test) is used. This test determines a criterion, and by comparing the model obtained from the evolution to this criterion, it results in a survey of the user's satisfaction with the experimental results.

First of all, we randomly selected 400 sample models from the entire search space and divided them into 4 equal parts, and selected 4 users, each of whom got 100 sample models, and asked them to score these 100 models (0-5) according to the two home styles of "simple" and "European", and finally according to the average score, each obtained 10 "simple" and "European" individual models as the reference standard for the next test. Next, we asked 10 users to use the system to find target individuals with a style of "simple" and "European", the evolutionary algebra was limited to 20, and the users selected the individuals they thought were the best from the last generation, compared them with the previously established criteria, and scored these individuals (0-5). Finally, after statistical analysis, it shows the user's satisfaction level under the reliability of 94% and 98%. On average, users rated the "simple" goal at 4.72 and the "European" goal at 3.35, which shows that users are very satisfied with the assessment. At the same time, compared with the "European" style goal, the "minimalist" style goal has higher satisfaction and a narrower confidence interval. Therefore, it can be considered that the application of improved adaptive genetic algorithm to interior design and assist students in learning English is promising.

IV. Conclusion

This study successfully realizes the effective integration of English learning space and residential design by constructing a housing functional layout model based on improved adaptive genetic algorithm. Experimental validation shows that the method exhibits good performance in spatial optimization and allocation, and the social adaptability of the optimal solution in the set of Pareto-optimal solutions reaches 76.37 points, and the investment is controlled within a reasonable range of 5,290,000 yuan per set. The convergence test of the algorithm shows that when the number of iterations exceeds 12 generations, the k value of 4 presents stronger convergence characteristics, which proves the scientificity and effectiveness of the parameter settings. The results of the user satisfaction survey show that the rating for the European style target is 3.35 points, indicating that different design styles have different degrees of influence on the subjective judgment of users.

The study provides innovative technical paths and methodological support for the multifunctional space design of modern houses. The improved adaptive genetic algorithm effectively solves the limitations of traditional optimization methods in complex spatial layout problems, and realizes the efficient search of the global optimal solution by dynamically adjusting the algorithm parameters. The introduction of the multi-user interactive design concept makes the design process closer to the actual use requirements and improves the practicality and acceptability of the design solution. The application of spatial point cloud data provides accurate data support for 3D spatial modeling, ensuring the accuracy and implementability of the design results.

The research results are of great significance in promoting the innovative development of housing design concepts. By organically integrating the English learning function into the housing design, it not only improves the efficiency of space utilization, but also provides new ideas for the optimization of the home education environment. The method can be promoted and applied to other types of multifunctional space design, providing technical reference for the intelligent development of the architectural design field. In the future, the performance of the algorithm can be further improved and the application scenarios can be expanded to contribute to the technical power for building a more intelligent and humanized living environment.

Funding

This research was supported by the Research on The Path to Enhancing the Ideological and Political Ability of High School English Teachers in the Context of AI (project number: 2025-JSJYYB-051).

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