Hierarchical Collaborative Optimization Model for Landscape Engineering Curriculum Oriented to Cultivating Competency in Complex Systems

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ABSTRACT Addressing the contradiction between heterogeneous student backgrounds and the industry demand for interdisciplinary talents, as well as fragmented knowledge modules in current curriculum reform, this paper constructs a hierarchical collaborative optimization model for landscape engineering curriculum oriented to complex-system competency cultivation. The model consists of four interconnected modules: knowledge analysis, collaborative optimization, front-end feedback, and backend optimization. The knowledge parsing module uses a knowledge-element semantic network and the Louvain algorithm to deconstruct the course into three logical levels: basic construction, system integration, and complex decision-making. The collaborative optimization module employs PageRank and Jaccard coefficients with dynamic weight allocation to generate a horizontal collaborative matrix and bind highly correlated knowledge elements. The front-end feedback module runs K-means clustering each teaching week, while the back-end feedback module runs a multi-constraint genetic algorithm after each course module. The experimental group achieves an average score of 88.58, and cross-knowledge collaborative calls increase by 174.8% compared with the control group. The model offers a transferable engineering-education optimization framework for complex-system courses, including electromagnetic and communication-engineering curricula.

INDEX TERMS hierarchical collaborative optimization, knowledge semantic network, complex systems education, engineering curriculum, dynamic feedback

I. INTRODUCTION

As a core compulsory course for landscape architecture majors, the landscape engineering course bears the key mission of cultivating students' comprehensive application of knowledge from multiple disciplines such as earthwork, water supply and drainage, electrical engineering, and paving to solve real-world site problems [1–2]. With the advancement of national strategies such as national spatial planning, sponge cities, and ecological restoration, engineering projects are increasingly showing complex system characteristics of multi-element coupling, multi-objective conflicts, and multi-party collaboration. For example, a typical landscaping project not only involves the cross operation of traditional occupations such as earthwork balance, water supply and drainage network, electrical lighting, and hard paving, but also needs to coordinate dynamic constraints such as ecological sensitivity, construction timing, cost control, and later operation and maintenance. This change has shifted the core competency requirements for practitioners from proficient operation in a single job to integrated design across systems and on-site decision-making in complex environments [3–4].

This article proposes a hierarchical collaborative optimization model for landscape engineering courses aimed at cultivating complex system capabilities:

(1) a course hierarchical deconstruction method based on knowledge element semantic network is proposed, which automatically clusters course content into three ability levels: "basic construction technology - system integration design - complex environment decision-making" through Louvain community division, providing a structured knowledge base for collaborative optimization;

(2) This article designs a dynamic weight allocation algorithm and a horizontal collaborative matrix to quantify the semantic correlation strength between knowledge elements based on improved PageRank and Jaccard coefficients, achieving mandatory bundling teaching of highly coupled knowledge elements;

(3) This article constructs a bidirectional closed-loop mechanism of "front-end clustering feedback+back-end genetic optimization". The front-end runs K-means clustering to dynamically adjust resource allocation density every teaching week, and the back-end runs multi-constraint genetic algorithm for each module to optimize the average score of comprehensive ability test based on difficulty coefficient and practical depth coefficient as decision variables. The four modules achieve temporal scheduling and linkage correction through unified configuration files and intermediate data tables.

The article structure is as follows: This article summarizes relevant work, elaborates on the hierarchical collaborative optimization framework, knowledge meta semantic network deconstruction, horizontal collaborative matrix construction, and bidirectional closed-loop feedback mechanism. It verifies the effectiveness of the model through experimental design, comparison of three levels of knowledge dimension capabilities, measurement of knowledge module coupling, and analysis of teaching resource allocation efficiency, and summarizes research conclusions.

II. RELATED WORK

The increasing heterogeneity of student backgrounds, the increasing demand for composite talents in the industry, and the deep integration of information technology and teaching, together constitute the macro background of the urgent need for landscape engineering courses to move from "fragmented reform" to "layered collaborative optimization models". Guo et al. [5] constructed and implemented a "five in one" teaching model, which integrates the five aspects of "theoretical teaching+virtual simulation+course training+on-site internship+competition driven". Liu et al. [6] designed and implemented a blended teaching model of "Learning Pass+BOPPPS" in the landscape engineering course. Based on the standards and projects of provincial and national landscape design and construction skills competitions, Jiao [7] carried out a systematic reform of the landscape engineering curriculum. From the perspective of ideological and political education in courses, Chen and Wu [8] embed ideological and political materials in theoretical lectures, case analysis, and practical training. Huo et al. [9] proposed and implemented differentiated teaching strategies for undergraduate students at different levels, respecting individual differences among students and achieving individualized teaching. This has reference significance for the teaching of landscape engineering courses in the context of multiple student sources.

Park-Gaghan and Mokher [10] used propensity score matching and multiple regression analysis to compare the impact of different course structures and intensities on student success indicators. Based on content analysis, Fernando and Mohamed [11] pointed out that in most courses, OER accounts for a low proportion of teaching materials and is mainly composed of static text, with a lack of interactivity and multimedia resources. Cave [12] analyzed the evolution of the relationship between "abilities," "disciplinary knowledge," and "interdisciplinary themes" in Japan's curriculum reform. Mohammad [13] analyzed how to integrate moderate Islamic teachings and implementation strategies into curriculum reform. Kuang and Duan [14] used a multi-level linear model to analyze large-scale academic quality monitoring data and identify key factors that affect the effectiveness of curriculum implementation. Existing research has failed to deconstruct and collaboratively restructure course content based on the inherent correlation structure of knowledge itself. This paper constructs a hierarchical collaborative optimization model for complex system capability cultivation, which includes knowledge meta semantic network deconstruction, dynamic weight collaborative matrix, bidirectional closed-loop feedback, and genetic algorithm optimization, forming a computable, iterative, and transferable teaching optimization framework.

III. METHOD

A. HIERARCHICAL COLLABORATIVE OPTIMIZATION FRAMEWORK

The optimization framework consists of four modules in series: knowledge parsing, collaborative optimization, front-end feedback, and back-end optimization (Figure 1).

The knowledge analysis module receives the teaching syllabus and textbook chapter texts of the landscape engineering course, and outputs a hierarchical knowledge graph based on the knowledge meta semantic network. The collaborative optimization module reads the graph and uses a dynamic weight allocation algorithm to calculate the horizontal correlation strength between knowledge elements within the same level, generate a collaborative matrix, and adjust the initial teaching resource allocation weights of each knowledge element accordingly [15]. The front-end feedback module runs once every teaching week, using multi-source data on student behavior (video viewing completion rate, first correct exercise rate, exercise redo frequency, forum questioning frequency, homework late submission frequency, classroom check-in situation) to perform K-means clustering (K=3, maximum iteration 500 times), dividing students into three ability groups, and adjusting the exercise push density and micro video viewing task volume of each knowledge element in the next week in real time based on this. The backend feedback module is triggered after the completion of each course module (approximately 3–4 weeks), running a multi-constraint genetic algorithm (population size 100, crossover probability 0.8, mutation probability 0.05, with a termination criterion set to 200 iterations), with course difficulty coefficient (0.3–1.0) and practice depth coefficient (0.2–1.2) as decision variables, maximizing the average score of students' comprehensive ability test while meeting the constraints of the teaching syllabus's upper limit of class hours and important knowledge point coverage rate $\geq 90\%$. The four modules implement temporal scheduling through a unified configuration file (JSON format) and an intermediate data table (MySQL).

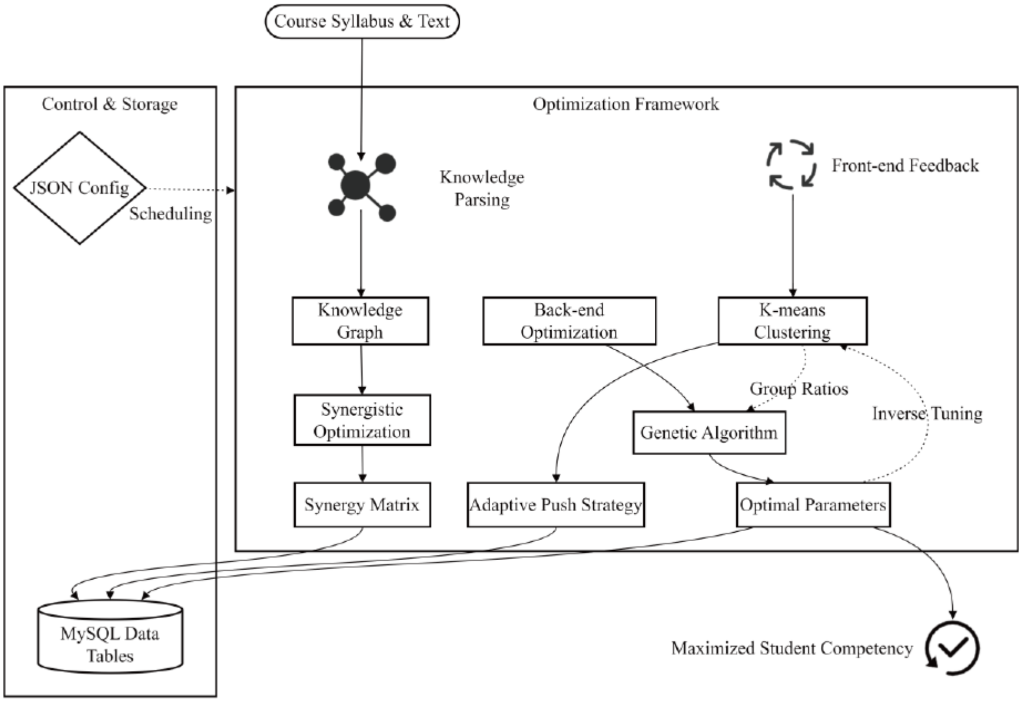

FIGURE 1. Optimization Framework

The grouping ratio output by the front-end clustering is used to correct the initial population distribution of the back-end genetic algorithm. To prevent predictive bias and overfitting during teaching transitions, the optimal difficulty coefficient output by the back-end is applied to reverse-adjust the front-end feature normalization parameters using an exponential smoothing weight ($\beta = 0.3$), ensuring that real-time behavioral data remains the primary driver while historical performance provides a stabilized baseline [16–17].

B. COURSE LAYERED DECONSTRUCTION BASED ON KNOWLEDGE META SEMANTIC NETWORK

The specific operation of knowledge element semantic network analysis is to first break down the entire teaching content of landscape engineering courses into indivisible minimum knowledge units, with each knowledge element defined by triplets (conceptual terms, operational actions, constraint conditions). For example, the concept term for the "elevation setting out" knowledge element is "construction elevation", the operation action is "annotation+review", and the constraint condition is "error $\leq$ 5mm". When extracting semantic relationships between knowledge elements, three types of relationships are pre-set: "pre-post", "similarity-substitution", and "whole-part" [18]. The strength of the relationship is calculated through two indicators: co-occurrence frequency (the number of times it appears in the same teaching video or chapter) and adjacent probability in the teaching sequence (the proportion of two knowledge elements appearing adjacent in the standard teaching sequence), and the weighted sum of the two is:

$$S_{ij} = w_c \cdot C_{ij} + w_p \cdot P_{ij} \tag{1}$$

S_{ij} is the semantic relationship strength between knowledge element i and knowledge element j, w_c is the weight coefficient of co-occurrence frequency (set to 0.5), C_{ij} is the number of times knowledge element i and j appear together in the same teaching video or chapter, w_p is the weight coefficient of adjacent probability (set to 0.5 based on experience), and P_{ij} is the proportion of adjacent occurrences of knowledge element i and j in the standard teaching sequence.

The threshold is set to 0.6, and edges above this value are retained as valid edges:

$$e_{ij} = \begin{cases} 1, & S_{ij} \geq 0.6 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

e_{ij} is the edge preserving indicator variable, where 1 indicates the establishment of a valid connection between knowledge elements i and j, and 0 indicates no connection is established.

After obtaining a directed weighted network, the Louvain algorithm (with a resolution parameter of 1.2) is used for community partitioning, automatically identifying the three highest modularity subgraphs. These three subgraphs correspond to three logical levels: the first level is the "basic construction technology level", which includes knowledge elements related to single job operations such as earthwork engineering, masonry engineering, and reinforced concrete engineering; The second level is the "system integration design layer", which covers knowledge elements of cross coordination among multiple systems such as water supply and drainage, electrical, and pavement; The third level is the "complex environmental decision-making layer", which includes knowledge elements that require on-site judgment such as high slope stability, soft foundation treatment, and ancient tree protection [19–20]. Table 1 summarizes the network structure indicators of three logical levels.

TABLE 1. Layered Deconstruction and Semantic Relationship Strength of Knowledge Elements in Landscape Engineering Courses

Level name	Number of KEs	Intra-level edges	Inter-level in-edges	Avg. semantic relation strength	Density coefficient
Basic construction technology level	24	68	0	0.52	0.123
System integration design level	31	112	42	0.67	0.155
Complex environment decision-making level	18	43	29	0.74	0.141
Total course network	73	223	71	0.61	0.084

Each knowledge element is uniquely labeled with its level, and within each layer, directed edges are established in the order of teaching. Only the vertical edges from the base layer to the integration layer and then to the decision layer are retained between layers, and the reverse edge weights are reset to zero. The output format is a GML graphic file.

C. CONSTRUCTION OF HORIZONTAL COLLABORATION MATRIX BASED ON DYNAMIC WEIGHT ALLOCATION

The rows and columns of the horizontal collaborative matrix are all knowledge elements within the same level, and the matrix elements represent the weights of two knowledge elements that should be simultaneously strengthened or co-taught during the teaching process. The input of the dynamic weight allocation algorithm is the hierarchical knowledge graph obtained in the previous step, and the output is the collaborative matrix of each level [21–22]. The algorithm execution is divided into three steps: the first step is to calculate the basic influence score of each knowledge element, using an improved PageRank algorithm:

$$PR(i) = \frac{1-d}{N} + d \sum_{j \in M(i)} \frac{PR(j)}{L(j)} \tag{3}$$

$PR(i)$ refers to the PageRank score of knowledge element i, which measures its fundamental influence in the knowledge graph. d is the damping coefficient, set to 0.85, N is the total number of knowledge elements, $M(i)$ is the set of all knowledge elements pointing to knowledge element i, and $L(j)$ is the degree of emergence of knowledge element j (i.e. the number of edges starting from j).

Iterate until the score change is less than 1e-6. The second step is to calculate the structural similarity between knowledge element pairs, using Jaccard coefficient to measure the proportion of their common neighbors to all neighbors:

$$J(i,j) = \frac{|\Gamma(i) \cap \Gamma(j)|}{|\Gamma(i) \cup \Gamma(j)|} \tag{4}$$

$J(i,j)$ is the Jaccard similarity between knowledge element i and j, and $\Gamma(i)$ refers to the set of all neighboring knowledge elements of knowledge element i (including predecessor and successor).

Simultaneously taking into account the reciprocal of the distance in the co-occurrence text - if two knowledge elements appear in the same teaching video and the interval does not exceed 5 sentences, the similarity can increase by an additional 0.1. Step three, dynamically integrate the above two indicators to generate the final weight:

$$W_{ij}(t) = \alpha(t) \cdot \frac{PR_i + PR_j}{2} + (1 - \alpha(t)) \cdot Sim_{ij} \tag{5}$$

$W_{ij}(t)$ represents the collaborative weight that should be simultaneously strengthened between knowledge elements i and j at time t of the course progress. $\alpha(t)$ is the dynamic fusion coefficient, whose value varies with the teaching progress t: 0.7 in the early stage (first 1/3 of class hours), 0.5 in the middle stage, and 0.3 in the later stage. Sim_{ij} is the structural similarity between knowledge elements i and j, including Jaccard coefficient and text distance correction term [23].

All weights undergo row normalization to ensure that the sum of each row element is 1, with four decimal places retained during normalization. The output collaborative matrix is stored as a CSV file, with both row and column indexes being unique identifiers of knowledge elements (in

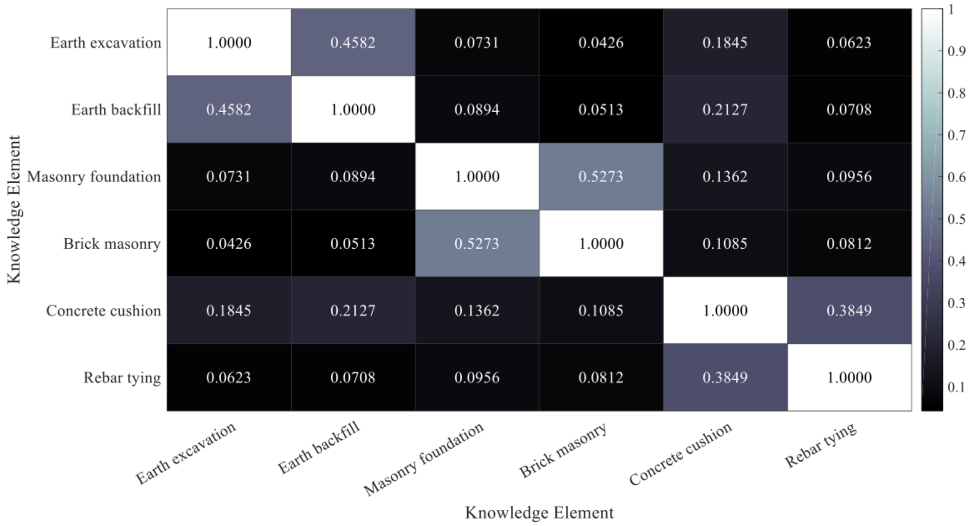

FIGURE 2. Collaborative Weight Measurement Matrix

the format of "hierarchically ordinal named"). The usage rules of collaborative matrix: Knowledge element pairs with weights higher than 0.2 are forcibly bound to the same teaching task package, while knowledge element pairs with weights lower than 0.05 must be arranged with at least one teaching unit interval, and the intermediate value is not a mandatory requirement.

Figure 2 shows the normalized collaborative matrix of six representative knowledge elements (earthwork excavation, earthwork backfilling, masonry foundation, brick wall masonry, concrete cushion layer, steel reinforcement binding) in the basic construction technology layer. Actual test data shows that knowledge element pairs with close front back relationships or similar operational characteristics exhibit higher collaborative weights (such as "earthwork excavation-earth backfill" reaching 0.4582, "masonry foundation-brick masonry" reaching 0.5273), while knowledge element pairs without direct logical correlation have significantly lower weights (such as "earthwork excavation steel bar binding" only 0.0623).

D. BIDIRECTIONAL CLOSED-LOOP FEEDBACK MECHANISM AND MULTI-CONSTRAINT GENETIC OPTIMIZATION

The front-end feedback mechanism runs once every teaching week. Export six types of behavior data for each student in the past week from the course platform: video viewing completion rate, first correct exercise rate, exercise redo frequency, forum questioning frequency, homework late submission frequency, and classroom attendance [24–25]. Standardize these six dimensional data using Z-score:

$$z = \frac{x - \mu}{\sigma} \tag{6}$$

z is the standardized eigenvalue, x is the original behavior data value, μ is the mean of the behavior feature among all students, and σ is the standard deviation of the behavior feature among all students.

Use K-means++initialization strategy for clustering, with a fixed number of K=3 and Euclidean distance as the distance metric:

$$dist(x, y) = \sqrt{\sum_{k=1}^{6}(x_k - y_k)^2} \tag{7}$$

$dist(x, y)$ is the Euclidean distance between the student feature vectors x and y, x, y are the six dimensional behavioral feature vectors of two students, and x_k, y_k are the values on the k-th dimensional feature, respectively. The convergence condition is that the centroid offset is less than 0.01. The three types of clustering outputs are labeled as "high input group", "medium input group", and "low input group" according to their average completion rate within the group, from high to low. According to the proportion of people in each group, adjust the teaching resource allocation density for each knowledge element in the next week: the high input group can receive expanded cases and optional deep reading (resource coefficient multiplied by 1.0), the medium input group can receive standard exercises and explanatory videos (coefficient 0.8), and the low input group can receive basic concept repeated push notifications and prompt pop ups (coefficient 0.5). Resource adjustment is output as a JSON configuration file, with fields including knowledge element ID, resource type, and deployment coefficient [26].

The backend feedback mechanism is triggered after each teaching module (3–4 weeks) is completed. The encoding method of the multi-constraint genetic algorithm utilizes continuous parameter encoding (real-value representation) to better map the coefficients of difficulty and depth to the optimization space, and two decision variables - course difficulty coefficient D (value range 0.3–1.0) and practical depth coefficient P (value range 0.2–1.2) - are concatenated to form a chromosome. The fitness function is the average score of students' comprehensive ability test after the end of the module:

$$f(D,P) = \frac{1}{n}\sum_{i=1}^{n} score_i \tag{8}$$

$f(D,P)$ is the fitness function value, which is the average score of a student's comprehensive ability test given the difficulty coefficient D and the depth of practice coefficient P. $score_i$ is the score of the i-th student's comprehensive ability test.

Simultaneously impose three hard constraints: the absolute Pearson correlation coefficient between difficulty coefficient and pass rate should not exceed 0.2:

$$|\rho(D, \text{passrate})| \leq 0.2 \tag{9}$$

$\rho(D, \text{passrate})$ refers to the Pearson correlation coefficient between D and the passing rate of students. The coefficient of practical depth shall not exceed the reciprocal of the number of available sets of experimental equipment (resource constraint), and the coverage rate of important knowledge points specified in the teaching syllabus shall be $\geq 90\%$. Adopting tournament selection (scale 5), single point crossover (probability 0.8), and uniform variation (probability 0.05) [27–28]. The algorithm runs for 200 generations, with 2 elite individuals retained in each generation. Take the chromosome with the highest fitness in the final generation as the optimal parameter output, and write it into the teaching configuration file for the use of the next module. Front end linkage mechanism: The optimal difficulty coefficient output by the backend is used to recalculate the Z-score weights of the six behavioral features before the next round of front-end clustering, making the clustering closer to the current learning load.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL DESIGN AND EVALUATION INDICATORS

This paper selects two parallel classes of landscape architecture major in a university. The experimental group ($n = 42$) arranges weekly teaching tasks according to the hierarchical knowledge map and collaboration matrix output in Section 3, and adjusts the exercise push density and micro video viewing amount according to the front-end clustering results. After each module is completed, the difficulty coefficient and practice depth coefficient obtained from the back-end genetic algorithm optimization are used to update the assessment and training of the next module. The control group ($n = 40$) adopted a linear chapter order and a unified homework and examination plan. Table 2 summarizes the mean and standard deviation of various pre-test indicators between the experimental group and the control group. The data shows that the two groups maintain a high degree of consistency across multiple dimensions of knowledge.

TABLE 2. Overall Statistics of Pre-test Scores for the Experimental and Control Groups

Pre-test indicator	Experimental group mean	Experimental group SD	Control group mean	Control group SD
Overall pre-test score (full mark 100)	75.26	7.89	75.28	7.92
Pre-test basic knowledge score (full mark 40)	30.15	3.42	30.22	3.38
Pre-test knowledge application score (full mark 30)	21.96	2.85	22.10	2.79
Pre-test engineering drawing reading score (full mark 20)	14.38	2.11	14.42	2.08
Pre-test construction process sequencing score (full mark 10)	7.35	1.24	7.38	1.21

B. QUANTITATIVE ANALYSIS OF TEACHING EFFECTIVENESS

1) Comparison of Three Levels of Knowledge Dimension Abilities

After the course, a comprehensive ability assessment was conducted. The assessment paper consists of three parts: construction technology (30 points), integrated design (40 points), and environmental decision-making (30 points). The evaluation process adopts double-blind review, and the experimental group and control group students complete the online and offline comprehensive assessment within the same time. Figure 3 summarizes the scores of the

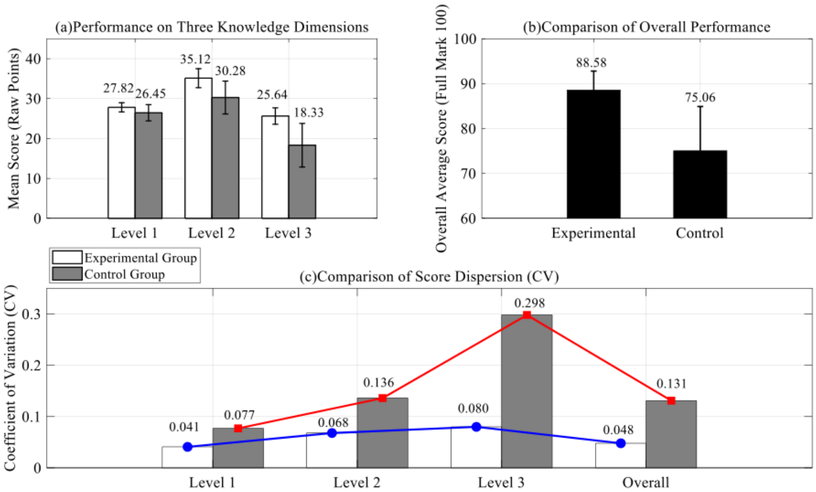

FIGURE 3. Statistics of scores for three levels of knowledge dimensions

experimental group and control group in three knowledge dimensions.

On the basis of highly equal pre-test scores (total mean 75.26 vs 75.28) between the experimental group and the control group, there was a significant differentiation in post test comprehensive abilities. The total average score of the experimental group reached 88.58, which was 13.52 points higher than the control group's 75.06, and the coefficient of variation (CV=0.048) was much lower than that of the control group (0.131), indicating that the hierarchical collaborative model not only improved the overall academic level, but also significantly narrowed the gap among students. From the three dimensions of knowledge, the experimental group of basic construction technology scored 27.82 slightly higher than the control group's 26.45, and the improvement was relatively gentle; The experimental group of system integration design layer had a significant improvement of 35.12 compared to the control group of 30.28; The experimental group of 25.64 in the complex environment decision-making layer is almost 1.4 times that of the control group 18.33, and the coefficient of variation of the control group in this dimension is as high as 0.298, showing severe polarization. This confirms that the proposed model has a much better effect on cultivating the ability of high-order complex systems than traditional linear teaching. Its core mechanism lies in the hierarchical knowledge graph and bidirectional feedback, which enables students to receive sufficient targeted training in decision-making scenarios.

2) Measurement of Coupling Degree of Knowledge Modules

This article quantifies the collaborative effects between modules through the "Knowledge Element Call Log" of students' final assignments. It uses Python scripts to extract the frequency of cross level knowledge points (such as "water supply and drainage pipe network" and "micro terrain earthwork") in student design schemes. Test process setting: If two heterogeneous module knowledge elements are called in the same design partition, it is recorded as one effective collaboration, and the results are shown in Table 3.

TABLE 3. Analysis of Cross Knowledge Module Collaborative Call Frequency and Coupling Degree

Collaboration Type	Experimental Group Avg. Call Frequency	Control Group Avg. Call Frequency	Improvement Rate (%)	Module Coupling Coefficient
Technology-Design Layer Collaboration	15.42	8.24	87.1%	0.425
Design-Decision Layer Collaboration	12.18	4.15	193.5%	0.338
Technology-Decision Layer Collaboration	8.65	2.12	308%	0.241
Three-Layer Global Collaboration	6.54	1.08	505.6%	0.182
Comprehensive Collaboration Mean	10.69	3.89	174.8%	0.297

Through quantitative analysis of the frequency of cross knowledge element calls in the final assignment, it was found that the experimental group significantly outperformed the control group in various types of collaborative call indicators, with a comprehensive collaborative call mean of 10.69 times, nearly 2.7 times that of the control group's 3.89 times, and a comprehensive improvement rate of 174.8%. The cross layer collaboration between the technical and decision-making layers has significantly improved, with the experimental group calling 8.65 times while the control group only called 2.12 times, resulting in an improvement rate of up to 308%; The frequency of three-layer global collaborative calls in the experimental group was 6.54 times, while the control group only had 1.08 times, an increase of 505.6%. This dramatic percentage increase is primarily attributed to the "near-zero" baseline in the control group, where students rarely attempted to integrate complex decision-making with basic technology due to the "island" effect of traditional linear teaching. Qualitative analysis of assignments shows that the experimental group successfully bridged these gaps by utilizing the horizontal collaborative matrix, transforming isolated tasks into systemic engineering solutions. This cognitive shift from "fragmentation" to "systematization" is the core manifestation of the cultivation of complex system capabilities.

C. EFFICIENCY ANALYSIS OF TEACHING RESOURCE ALLOCATION

1) Dynamic evaluation of resource allocation

This article collected the weekly average resource allocation density data of the experimental group for six core knowledge elements (water supply network, drainage network, electrical wiring, pavement construction, micro terrain treatment, lighting design) of the "system integration design layer" in a complete course module (4 weeks, a total of 16 teaching units). The genetic algorithm takes the coefficient of course difficulty and the coefficient of practice depth as decision variables, and aims to maximize the average score of students' comprehensive ability test. It runs once after each module ends, and outputs the optimal resource allocation scheme for the next module. Figure 4 compares the resource allocation density of the above knowledge elements before the algorithm runs (based on initial experience allocation) and after it runs (starting to apply optimization results in the second module).

Data shows that after genetic algorithm optimization, resource allocation no longer presents an average or randomized distribution, but rather "peak shaving and valley filling" based on the core position of knowledge elements in collaborative networks and real-time feedback from students. For example, the resource density of exercises for "drainage network" and "micro terrain processing" increased by 35.6% and 105.7% respectively, indicating that the optimization model identified these two knowledge elements as key bottlenecks that constrain students' system integration ability, and thus carried out targeted reinforcement. On the contrary, the exercise resource density for "Electrical Wiring" and "Lighting Design" decreased by 15.8% and 13.3% respectively, freeing up redundant resources. This dynamic adjustment allows resources to flow from the "low efficiency zone" to the "high demand zone", verifying the non-linear optimization ability of genetic algorithms on resource allocation curves under multiple constraint conditions.

2) Improvement of Resource Utilization Efficiency

By adjusting the resource allocation strategy through a hierarchical collaborative optimization model, the aim is to improve the utilization rate of various resources and reduce their volatility. The resource utilization rate is defined as the ratio (%) of actual usage to actual available capacity. The mean utilization rate and within group standard deviation (SD) of the experimental group and control group on 5 key resources for 8 consecutive teaching weeks were collected, as shown in Table 4. The data acquisition steps are as follows:

1) Export the usage duration and number of people for each resource per week from the device reservation system;

2) Retrieve download and playback logs of digital resources from the course platform API;

3) Calculate the average utilization rate and within group standard deviation of various resources each week to measure the balance of resource utilization.

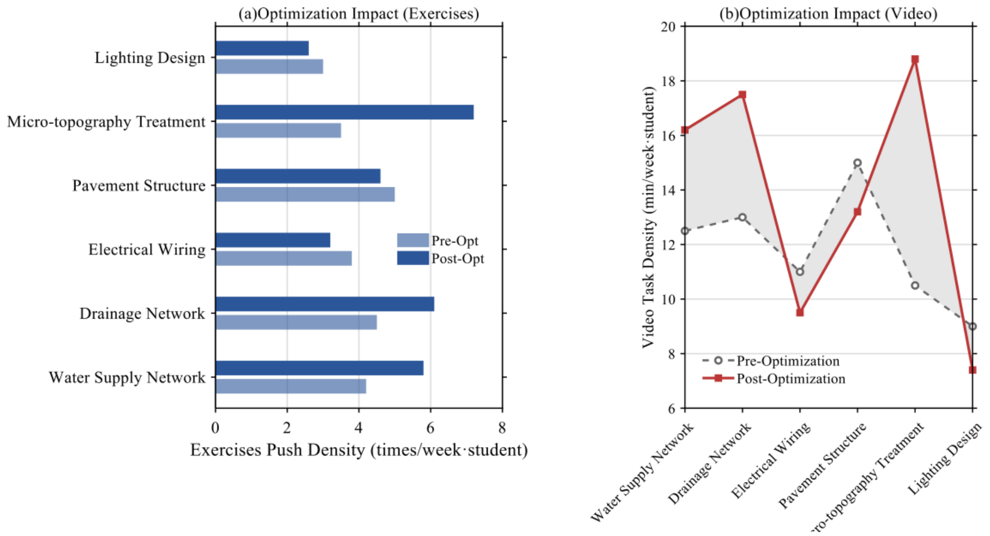

FIGURE 4. Comparison of resource allocation density of various knowledge elements before and after genetic algorithm optimization

TABLE 4. Comparison of Key Resource Utilization under Multiple Constraints (%)

Resource Type	Experimental Group (Mean Utilization)	Experimental Group (SD)	Control Group (Mean Utilization)	Control Group (SD)
Virtual Simulation Workstations	87.4	6.2	62.5	18.5
CAD Computer Lab	78.9	8.5	71.2	15.3
Construction Training Ground	82.1	7.1	54.8	22.6
Digital Resource Library	91.3	4.9	68.3	20.1
Instructor Consultation Slots	79.6	5.6	45.9	17.4

Comparing the two sets of data, it can be seen that the average utilization rate of the experimental group on all five types of resources is significantly higher than that of the control group, especially the virtual simulation workstation (87.4%), digital resource library (91.3%), and teacher coaching period (79.6%), indicating that the hierarchical collaborative model greatly activates the potential effectiveness of high-value resources through precise resource allocation. More importantly, the intra group standard deviation (SD) of various resource utilization rates in the experimental group was at a relatively low level. For example, the standard deviation of the utilization rate of the construction site was as high as 22.6% in the control group, showing an extreme imbalance of "congestion during busy hours and vacancy during idle hours"; The experimental group reduced the standard deviation to 7.1% through front-end and back-end feedback mechanisms, achieving "peak shaving and valley filling" in resource utilization. This proves that the model has successfully found the optimal strategy to achieve a high balance point in the utilization of various resources, while satisfying hard constraints such as the upper limit of class hours and knowledge point coverage of 90% or more, thereby improving the overall resource efficiency of the teaching system.

V. CONCLUSION

This article deconstructs the course into three logical levels: basic construction, system integration, and complex decision-making through a knowledge element semantic network. A dynamic weight allocation algorithm is used to generate a horizontal collaborative matrix that forcibly binds highly correlated knowledge elements. A bidirectional closed-loop feedback mechanism is formed using front-end K-means clustering and back-end genetic algorithm, significantly improving students' ability to integrate knowledge across levels and balance resource utilization. However, this study still has certain limitations: the current extraction of knowledge semantic relationships relies on manual annotation and preset thresholds, and has not yet been fully automated; The feedback mechanism is mainly based on behavioral data, with insufficient attention paid to deep features such as cognitive load and learning motivation. Future work can explore automated knowledge element extraction methods based on large language models, incorporating multimodal data such as eye tracking and physiological signals for cognitive state perception, and researching lightweight online optimization algorithms to improve model response speed and adaptive capabilities.

AUTHOR CONTRIBUTIONS

Conceptualization – Xiao Yang and Yunshan Cheng; methodology – Xiao Yang and Yunshan Cheng; investigation – Xiao Yang and Yunshan Cheng; writing-original draft preparation – Xiao Yang and Yunshan Cheng. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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