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Article

Research on the Application of Mathematical Optimization Algorithms in Civil Engineering Courses and Strategies for Improving Teaching Effectiveness

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Abstract: Accurate recommendation of teaching resources broadens the feasible path for realizing students' personalized development. This paper constructs a civil engineering course resource recommendation system based on multi-dimensional data view to improve the level of intelligent recommendation of resources. Quantitative data weights are used to convert the multi-objective optimization problem into the optimal solution of objective function value, which reduces the difficulty of solving. The multi-objective particle swarm optimization algorithm (NEMOPSO) is introduced to enhance the global optimization capability and improve the accuracy of resource recommendation. Research shows that NEMOPSO can maintain population diversity and solution comprehensiveness in the process of optimization solving. The recommendation accuracy of single resource or multiple resource tasks ≧90%, memory occupation space ≦66MB, and running time ≦24 s. After the experiment, the mean values of the experimental class in the four engineering thinking dimensions were improved by 1.3486, 1.2787, 1.1631, and 1.2769, respectively, which were significantly different from the pre-experiment at the 0.01 level.

Keywords: multidimensional data view; civil engineering resource recommendation; multi-objective optimization; NEMOPSO

1. Introduction

As China's economic development continues to advance, there is an increasing demand for professionals in civil engineering-related fields [1-2]. In this new context, to better achieve the educational objectives of civil engineering programs at higher education institutions and successfully implement curriculum reforms, it is essential to strengthen students' professional competencies while enhancing their practical skills. This should be accompanied by the optimization of teaching content and innovative course development to address shortcomings in previous educational approaches [3-6]. Additionally, it is necessary to establish a new teaching philosophy, develop a learning plan tailored to the capabilities and needs of students in this field, and implement teaching in a step-by-step manner to promote students' all-round development, thereby cultivating high-quality, capable, and innovative talent for society [7-10]. Based on this, civil engineering education should align more closely with the basic requirements of social enterprises for the capabilities and competencies of relevant talent, fostering the development of professionals with strong engineering practice skills [11-13].

The continuous development of society and the advancement of science and technology have driven the development of modern education in China [14]. In the practice of teaching civil engineering-related courses, some scholars have proposed an optimized method for intelligent course teaching that integrates modern educational technology. With advantages such as visibility, dynamism, and interdisciplinary collaboration, these methods can visually and comprehensively demonstrate complex engineering projects, enabling engineering students to better understand theoretical concepts and enhance their ability to solve engineering problems through the integration of learning and application [15-18]. Literature [19] points out that in the new era, civil engineering teaching practices require new thinking patterns and technical expertise. Therefore, Building Information Modeling (BIM) has been introduced into course teaching to enhance students' efficiency in acquiring knowledge and improve their competitiveness in future employment. Literature [20] integrates Team-Based Learning (TBL) pedagogy with BIM information systems into civil engineering teaching processes, aiming to enhance students' architectural knowledge and information management capabilities in coursework, while cultivating individual and team performance in BIM project execution to achieve higher teaching outcomes. Literature [21] indicates that new information technologies are crucial for contemporary construction management (CM) education. Integrating BIM technology into CM courses not only improves teaching efficiency but also lays the foundation for students' future careers in terms of knowledge and skills. Literature [22] explores online tools used in civil engineering education to enhance teaching effectiveness. These tools support students' self-directed learning and teachers' educational guidance by conducting basic data analysis and course optimization, playing a significant role in online teaching processes. Literature [23] evaluates the application of virtual reality (VR) technology in civil engineering course instruction. VR technology provides students with more realistic learning and experimental experiences by simulating real-life scenarios, effectively enhancing their concentration in civil engineering courses and ultimately improving teaching effectiveness. Literature [24] compares the practicality of digital technologies such as virtual reality, augmented reality, and digital twins in architectural course instruction, fully demonstrating the positive role of digital teaching methods in enhancing students' professional capabilities. However, due to the reliance of information and communication technology on the powerful data functions of information software, most universities currently have limited application of this technology in professional course teaching, with a narrow scope of application. Therefore, further promoting the application of mathematical optimization algorithms in course teaching can enhance the intelligence level of civil engineering courses, thereby improving students' professional competence and the quality of engineering talent cultivation [25-26].

Aiming at the multidimensional comprehensive consideration problem of civil engineering course resource recommendation, this paper chooses mathematical optimization algorithm to improve the level of resource recommendation. Construct the multidimensional data model for storing course detail information and realize the visual query of data information. Formally define the multi-dimensional information attributes and weight calculation methods, convert the multi-objective optimal solution problem into the extreme value solution under the constraints, and establish the Pareto optimal solution set. The multi-objective particle swarm optimization algorithm is used to achieve resource weight vector calculation and ranking, dynamically update the optimal recommended solution set, and optimize the global solution performance and convergence ability of the algorithm.

2. Application Analysis of Mathematical Optimization Algorithms

2.1. Problem Definition

In this paper, the system uses the data warehouse of multi-dimensional data view to build a multi-dimensional data model for course recommendation, and stores the multi-dimensional space quantity values of teacher information, course information, student evaluation, course dimension, course relevance coefficient, etc. In order to combine smaller dimension tables to improve query performance, the system adopts the snowflake model of course selection teaching information warehouse. Figure 1 shows the structure of the Snowflake Fact Warehouse model. Where, Course ID represents the course number and course set $course = \{c_1, c_2, \cdots, c_n\}$, Student ID represents the student number and student set $student = \{s_1, s_2, \cdots, s_n\}$, and Teacher ID represents the teacher number and teacher set $teacher = \{t_1, t_2, \cdots, t_n\}$. In the multi-objective teaching system, the selected parameters are "courses that students are taking", "courses that students have completed", and "courses that have been published in the system", and for Course ID, set flags for "courses that students are taking" to flag1 and "courses that students have completed" to flag2. Therefore, these two description parameters of the student constitute a student demand vector, and the course set is traversed with this demand vector, and the operation removes the record that the student has completed the course, that is, the more courses that the student is taking and the more courses he completes electively, the more detailed the course recommendation is, and the course recommended to the student is more in line with his previous learning plan, which is a more efficient and feasible recommendation mechanism to solve the problem of the next learning course recommendation plan when the student completes or is learning a course.

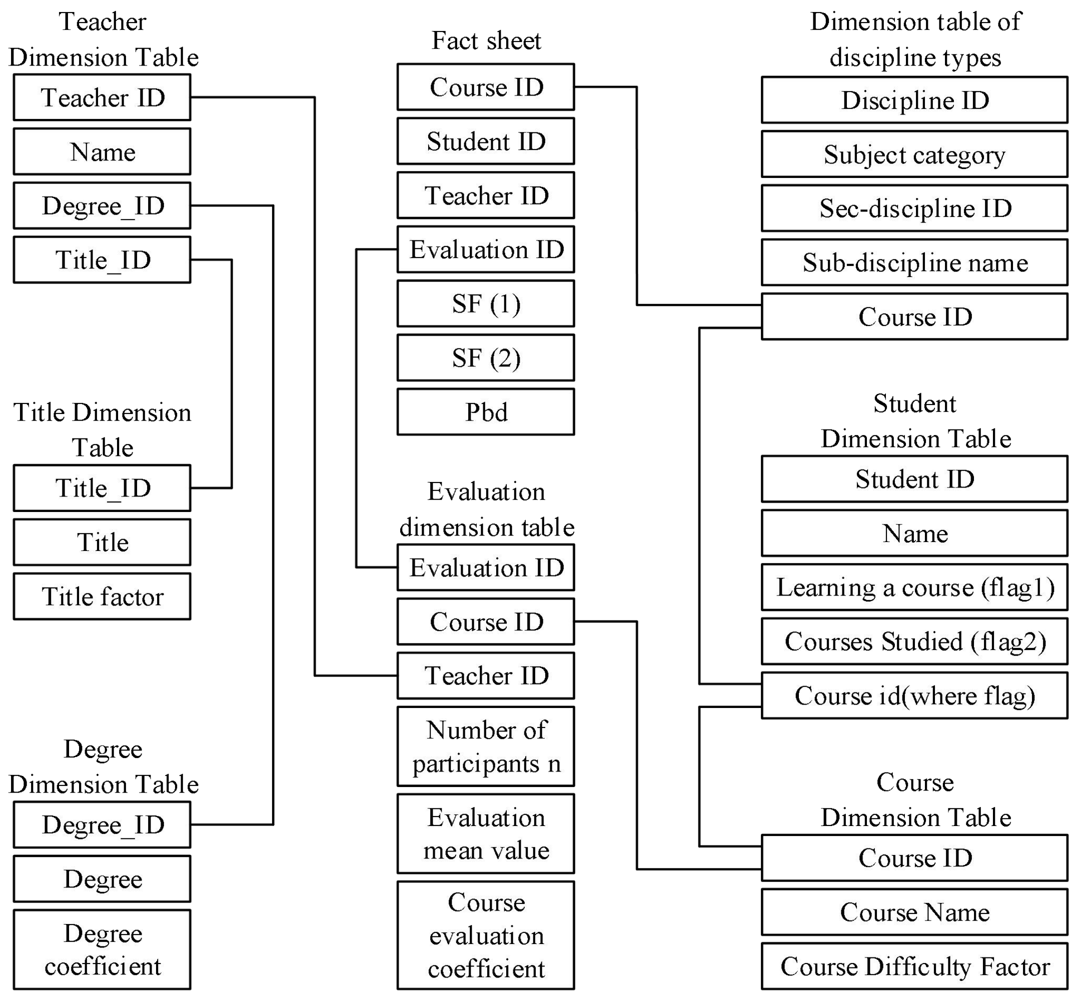


Figure 1. Snowflake fact warehouse model structure.

Formal definitions as well as statute processing are performed for relevant attributes in the data warehouse such as course, student, teacher, course difficulty, course recommendation index, etc:

Definition 1: Teaching Factor (Tf). It is used to statute the title of the course teaching faculty, academician and above $Tf = 0.55$, professor $Tf = 0.45$, associate professor $Tf = 0.35$, lecturer $Tf = 0.25$, assistant professor and others $Tf = 0.15$.

Definition 2: Degree Factor (Df). It is used to statute the degree of the course instructor, Ph.D. $Df = 0.55$, M.A. $Df = 0.45$, B.A. $Df = 0.35$, and others $Df = 0.25$.

Definition 3: Course instructor professionalism (Tr). Used to statute the professionalism of the course instructor, with larger values indicating greater professional recognition of the instructor.

$$Tr = nRt_i / \left(2\sum_{p=1}^{n} Rt_p \right) + Tf \times Df \tag{1}$$

where: n denotes the number of degrees earned by the instructor; Rt_i denotes the relevance of the instructor's i th major to the courses taught. The range of values of Rt_i is defined as follows:

$$Rt_i = \begin{cases} 1.0, & \text{Consistent} \\ r, & \text{Related} \end{cases} \tag{2}$$

where: $r(0.0 < r < 1.0)$ denotes the correlation coefficient.

Definition 4: Professional Relevance (Pr), $0.10 < Pr \leq 1.00$. It is used to statute the professional relevance of a course. Define a given course as C, a sub-discipline ensemble as H, and a first-level discipline ensemble as U. There exists, $C \in H_i \in U_q \mid C \in H_j \in U_q \mid C \in U_p$ and thus $Rd_i(i = 1, 2, \cdots, l)$ denotes the relevance of the course with respect to the first-level disciplines, $Rs_i(i = 1, 2, \cdots, k)$ denotes the relevance of the course to the sub-discipline. Larger values of Pr indicate greater course relevance.

$$Pr = Rd_i \times (1 + Rs_i) \times w_i / 2 \text{ and } \sum_{i=1}^{n} (Rd_i \times Rs_i) = 1.0 \tag{3}$$

where: n denotes the total number of courses; H_i, H_j is any sub-discipline contained in any first-level discipline; U_q, U_p is any first-level discipline. w_i is the value of course major weights, defined as follows:

$$w_i = \begin{cases} 1.00, & \text{Core compulsory courses} \\ 0.80, & \text{Main elective courses} \\ 0.60, & \text{Elective course} \\ [0, 0.60), & \text{Other} \end{cases} \tag{4}$$

Definition 5: Course Difficulty Coefficient (Cd), $0.10 \leq Cd \leq 1.00$. Indicator used to statute the difficulty of the course, the larger the indicator indicates that the course is more difficult to learn. The value of the difficulty coefficient of the course is taken from the questionnaire of the system expert teachers, students who have completed the course online voting. The questionnaire contains ratings of other prerequisite courses, which ultimately give individual difficulty ratings. Given the interval $[C_{\min}, C_{\max}]$ for the difficulty coefficient of each course, the more students who participated in the study, the more just the combined individual reality of the voting results for the course. Cd takes the value interval [0.10, 1.00], and the difficulty coefficient Cd is:

$$Cd = \frac{Q - Q_{\min}}{Q_{\max} - Q_{\min}} (C_{\max} - C_{\min}) + C_{\min} \tag{5}$$

where: Q denotes the difficulty value of the course, and the weight ratio of the system expert teacher and the students to the difficulty value given by the course is $w : (1 - w)$; p is the amount of questionnaires of the system expert teacher; q is the amount of questionnaires of the students who have completed the course; and Ad_i is the difficulty value given by the questionnaire.

$$Q = \frac{\mathrm{w}}{P} \sum_{i=1}^{p} Ad_i + \frac{1 - w}{q} \sum_{i=1}^{p} Ad_i \tag{6}$$

Definition 6: Comprehensive Course Evaluation (Ce) $(0.10 \leq Ce \leq 1.00)$: indicates the comprehensive rating of a course, with higher scores indicating that the course is more useful and accepted by students. Ce takes the value interval [0.10, 1.00], $C'_{\max}$ is the maximum value of the comprehensive evaluation of the course, and $C'_{\min}$ is the minimum value. The formula for the comprehensive course evaluation Ce is:

$$Ce = \frac{Pe - Pe_{\min}}{Pe_{\max} - Pe_{\min}}(C'_{\max} - C'_{\min}) + C'_{\min} \tag{7}$$

The curriculum is constantly revised as it evolves over time, thus let Pe be the average annual score of curriculum participation in the evaluation. Ty_n denotes the number of expert teachers participating in the evaluation in year $n(1 \le n \le N)$, and $Te_n(0.0 \le Te_n \le 100.0)$ denotes the value of the evaluation given by this course in year n. Sy_n denotes the number of expert teachers participating in the evaluation in year n, $Se_n(0.0 \le Se_n \le 100.0)$ denotes the value of the evaluation given by this course in year n, and the ratio of the weight of systematic expert teachers and students to the comprehensive evaluation of the course is $v:(1-v)$. The course Pe in year N is denoted as:

$$Pe = \frac{v\sum_{n=1}^{N} Ty_n \times Te_n}{\sum_{n=1}^{N} Ty_n} + \frac{(1-v)\sum_{n=1}^{N} Sy_n \times Se_n}{\sum_{n=1}^{N} Sy_n} \tag{8}$$

2.2. Mathematical Description of Multi-Objective Optimization Problem

A multi-objective optimization problem is simply the simultaneous optimization of multiple objectives to obtain an optimal solution set under certain constraints. In the optimization process, the problem is usually transformed into a problem of finding the maximum or minimum value of all optimization objectives. Assuming that a certain MOP has M optimization objective functions, the objective functions constrain each other, and it is necessary to make the values of these M objective functions as small as possible while satisfying the constraints, the mathematical model can be expressed as Equation (9).

$$\begin{cases} \min_x F(x) = (f_1(x), f_2(x), \cdots, f_M(x)) \\ s.t. \quad g_i(x) \le 0, \quad i = 1, 2, \cdots, p \\ s.t. \quad h_j(x) = 0, \quad j = 1, 2, \cdots, q \\ x \in X \subset R^n, x = (x_1, x_2, \cdots, x_n) \end{cases} \tag{9}$$

where M denotes the number of objective functions, $x = (x_1, x_2, \cdots, x_n) \in X$ is an n-dimensional decision vector, and X is an n-dimensional decision space; $F(x)$ is an M-dimensional objective vector function, which denotes a set of M vector functions mapped from the decision space to the objective space; $g_i(x)$ and $h_j(x)$ denote the corresponding inequality constraints and equational constraints of the problem, p is the number of inequality constraints and q is the number of equational constraints, respectively.

Definition 1 (Feasible Solution): x is called a feasible solution if there exists x that is a solution satisfying the constraints and the decision space in equation (9).

Definition 2 (Pareto dominance relation): for a minimization multi-objective optimization problem, given any two feasible solutions x and x^*, the concept of dominance is introduced in order to determine which one is better, and if both Eqs.(10) and Eqs.(11) are satisfied, then x^* is said to dominate x, denoted as $x^* < x$.

$$\forall i \in \{1, 2, \cdots, M\}, f_i(x^*) \le f_i(x) \tag{10}$$

$$\exists j \in \{1,2,\cdots,M\}, f_j(x^*) < f_j(x) \tag{11}$$

Definition 3 (Pareto optimal solution): if a feasible solution x is not dominated by any other feasible solution in the decision space, the feasible solution x is called a Pareto optimal or non-dominated solution and is denoted as Equation (12).

$$\neg x^* \in R^n, x^* \prec x \tag{12}$$

Definition 4 (Pareto optimal solution set): the set constituted by all Pareto optimal solutions that satisfy the constraints in a multi-objective optimization problem is called the Pareto optimal solution set, denoted as Equation (13).

$$P = \{x \in R^n \mid \neg x^* \in R^n, x^* \prec x\}\} \tag{13}$$

Definition 5 (Pareto front): the range corresponding to the objective function $F(x)$ on the set of Pareto optimal solutions is called the Pareto front.

2.3. NEMOPSO

2.3.1. MOPSO Framework

The velocity update formulation and position update formulation of the multi-objective particle swarm optimization algorithm are as follows:

$$c_2 r_2 (gBest_k(t) - x_i(t)) \tag{14}$$

where $x_i(t)$ is the velocity vector of the i th particle, c_1 is the self-learning factor coefficients, c_2 is the social learning factor coefficients, r_1, r_2 take the values in the range of [0.0, 1.0], and $gBest_k$ is the population to find the of the globally optimal solution.

Particle i learns from the population optimum and uses it for its own position update.

2.3.2. NEMOPSO Parameter Initialization

Initialize the number of particle populations and the number of weight vectors, specify the number of particle neighbors, in this paper, we set the number of particle neighbors to 5, and initialize the external maximum capacity $AR = 55$.

2.3.3. Chebyshev Decomposition Methods

The Chebyshev decomposition method is used to decompose the multi-objective optimization problem of online learning resources into numerous single-objective subproblems, which are assigned unique weight vectors corresponding to them.

1) Calculate the weight vector of online learning resources. To solve the online learning resource recommendation model based on multi-objective optimization strategy, first decompose the online learning resource problem so that each online learning resource subproblem corresponds to a λ vector, and compute the weight vectors of the online learning resource subproblems:

$$\lambda_i^j = \left(\frac{rand(N,1)}{norm(rand(N,1))} \right)' \tag{15}$$

2) Online learning resources subproblem vector sorting. Because the neighborhood strategy in the evolutionary algorithm is to optimize the current vector using similar vectors, the distance between each weight vector needs to be calculated and sorted according to the distance to find the neighborhood of the current particle. The neighborhood of the current particle is found by utilizing the

$$D_{ij} = pdist2(\lambda_i, \lambda_j) \tag{16}$$

Find the distance between the weight vectors in the online learning resource, i.e., the distance between the subproblems, and sort them using $S = sort(D)$.

3) Determine the current learning resource neighborhood. Based on the above S value and $Neighbors = S(1:T)$ obtain the particle neighborhood, i.e., a number of learning resources that are similar to the current learning resource. T is the number of learning resources randomly selected among the number of several learning resources, and $T = 3.0$ is set.

4) Solve for the learning resource neighbor fitness mean. If the three learning resources randomly selected from the neighborhood are $x_{p1}(t), x_{p2}(t)$ then the neighborhood mean value is

$$c_2 r_2 \frac{1}{3}(x_{p1}(t) + x_{p2}(t)) \tag{17}$$

5) Empower particles to explore new regions. Algorithms are prone to fall into local optimization at the late stage of optimization search and it is difficult to find the global optimal solution, therefore, the algorithms used in the online learning resources recommendation method are given the ability to explore new regions E , which aims to increase the ability of the algorithms to explore other regions within the solution space and to improve the algorithm's convergence performance. Explore New Regions Capability

$$E = \omega c_3 \cdot r \cdot (r - x_i(t)) \tag{18}$$

$c_3 = 0.0010$ of them.

2.3.4. Optimization Update Formula

According to the diversity-enhanced multi-objective particle swarm optimization algorithm, it is known that the social learning factor has the ability to deal with both diversity and convergence in satisfying the condition

$$\frac{1}{3}(c_1 + c_2) > 3(1 + \omega) \tag{19}$$

When the population never converges, the MOPSO update process is therefore optimized by omitting the self-learning factor, $c_1 = 0$, which results in the particle velocity update equation

$$v_i(t+1) = \omega v_i(t) + c_2 r_2 (\frac{1}{3}(x_{p1}(t) + x_{p2}(t)) - x_i(t)) \tag{20}$$

The way of updating the new position of the particle is affected by Eq. (17) and Eq. (18), and the updating equation is

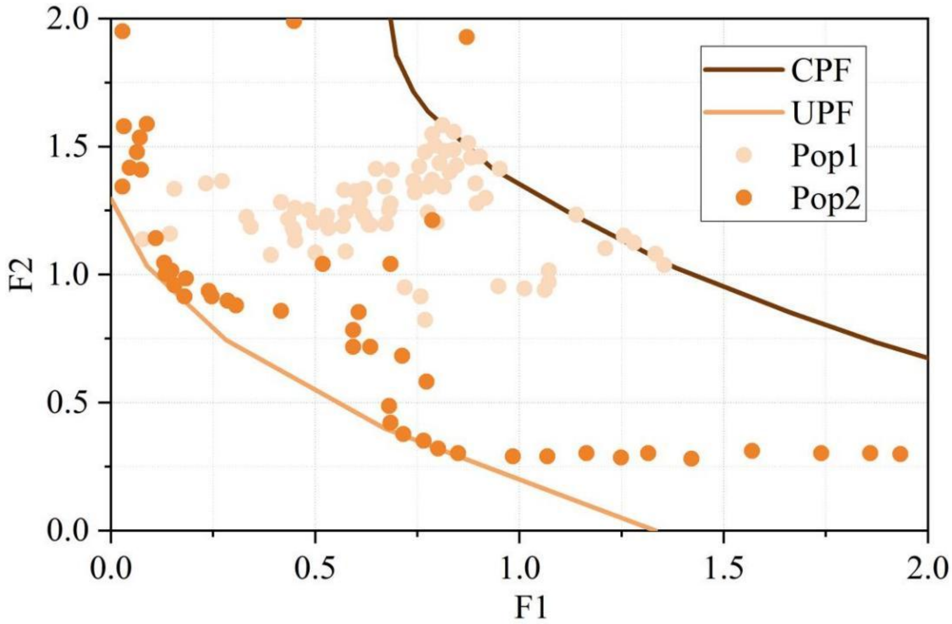
$$x_i(t+1) = x_i(t) + \sum_{k=1}^{N} c_2 r_2 (\frac{1}{3}(x_{p1}(t) + x_{p2}(t)) - x_i(t)) + E + v_i(t+1) \tag{21}$$

3. Analysis of the Effectiveness of Mathematical Optimization Algorithms in Civil Engineering Courses

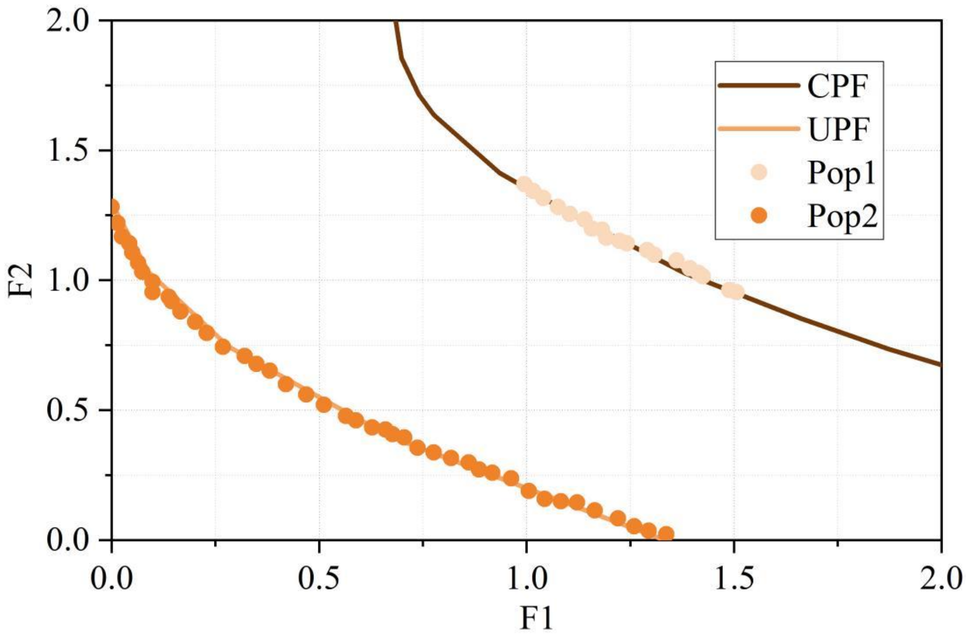
3.1. Analysis of the Effect of the NEMOPSO Algorithm

3.1.1. Population Diversity Analysis by NEMOPSO Algorithm

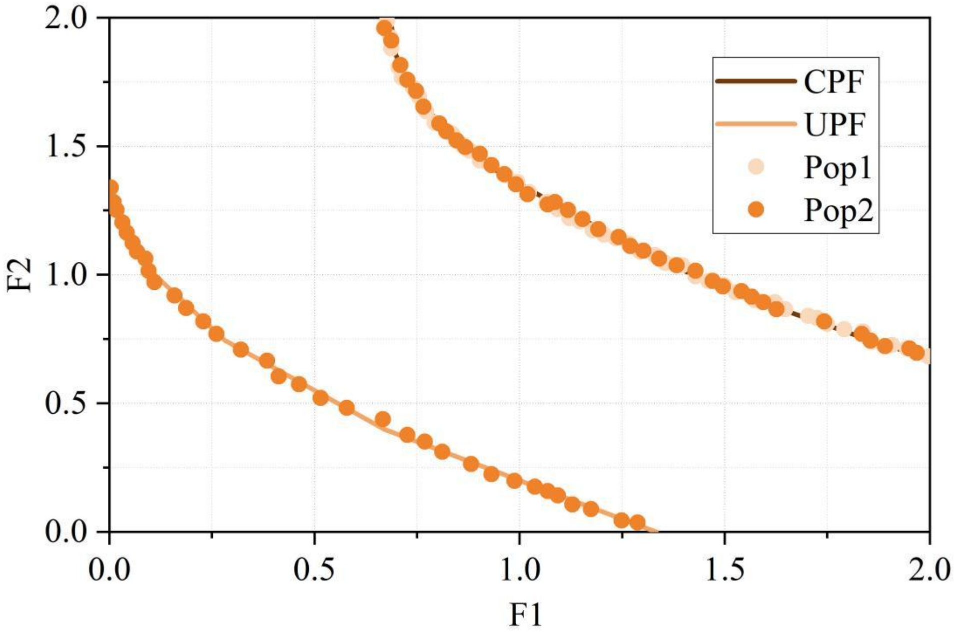
Compare the convergence process of the same type of multi-objective optimization algorithms to determine the effect of population diversity maintenance and optimal solution during the running process. Figure 2 shows the late distribution of populations of the three algorithms on the data set LIRCMOP2. Where Population1 (Pop1) is used to converge to CPF and Population2 (Pop2) is used to explore better diversity to assist Population1.Compared with other existing dual populations, the auxiliary population Pop2 in NEMOPSO does not completely ignore the constraints. In the later stages of the search, the auxiliary population Pop2 retains some solutions with better constraints but poorer convergence, which means that it will have retained information about both the common personality (CPF) and the unique personality (UPF). The light-orange and medium-orange dots denote the main and auxiliary populations Pop1 and Pop2 of several multi-population algorithms, respectively, while the dark-brown and dark-orange lines denote the CPF and UPF of LIRCMOP2, respectively, and the white regions are all infeasible regions. It can be seen that for class IV problems like LIRCMOP2, the auxiliary population Pop2 in NEMOPSO will still retain some high-quality individuals with poor convergence on the CPF but good feasibility and diversity, which will contribute their information when the two populations interact, and will help the main population Pop1 to maintain diversity. When facing this kind of problem with complex constraints, the auxiliary population Pop2 in the CTAEA algorithm does not provide effective information for the main population, and the algorithm's operation does not move in a good direction in the middle and late stages.The auxiliary population Pop2 in the CCMO converges to the UPF of the problem in the early stage, but it does not provide new information on the CPF for the main population Pop1 in the middle and late stages, and the algorithm only finds a small fraction of solutions on the CPF. In NEMOPSO, on the other hand, both the main population Pop1 and the auxiliary population Pop2 move toward the UPF in the early part of the search, and part of the auxiliary population Pop2 reaches the UPF in the middle part of the search, while the other part searches with the main population Pop1 near the CPF, and the main population Pop1 eventually finds the CPF and maintains good diversity with the help of the auxiliary population Pop2.



(a) CTAEA on LIRCMOP2



(b) CCMO on LIRCMOP2

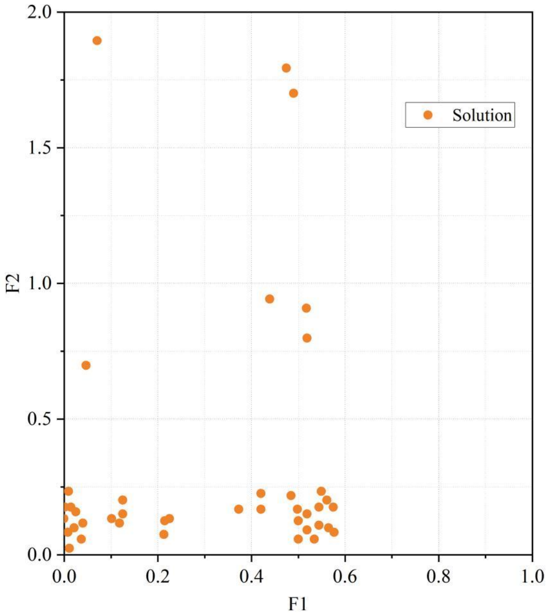


(c) NEMOPSO on LIRCMOP2

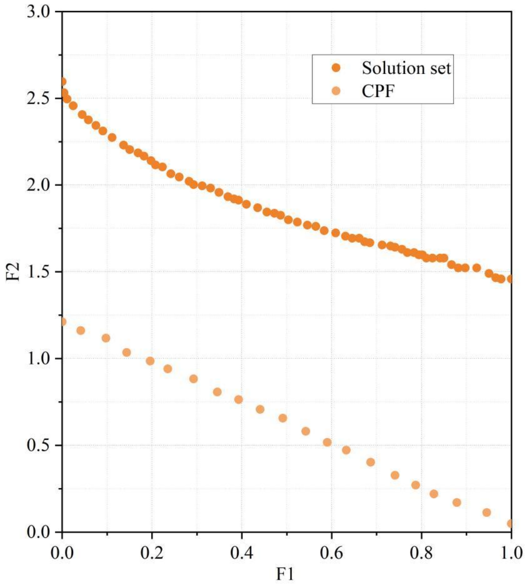
Figure 2. Late-stage population distribution of three algorithms on LIRCMOP2.

3.1.2. Solution Effectiveness Analysis of the NEMOPSO Algorithm

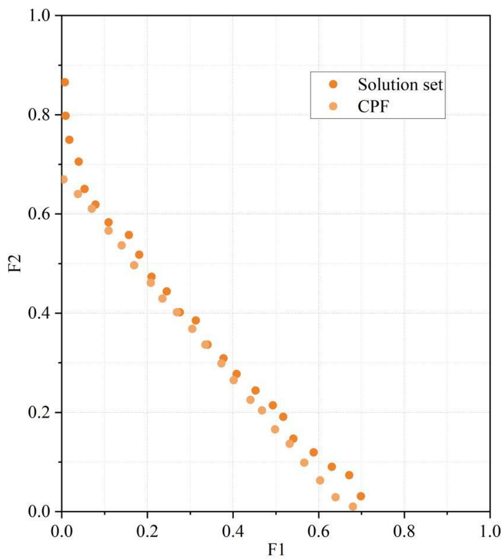
After testing the population diversity maintenance effect of the NEMOPSO algorithm, the same three algorithms are selected for solution effectiveness experiments on the multi-objective solution dataset DOC4. Figure 3 shows the average running results of the three algorithms on DOC4. The solution set of CTAEA is densely distributed in the range of 0.0-0.6 in F1 and 0.0-0.25 in F2; the solution set of CCMO is uniformly distributed in the position of 0.0-1.0 in F1 and 1.25-2.75 in F2, which is almost linearly parallel to the CPF of DOC4, but far away from each other. The NEMOPSO algorithm, on the other hand, is linearly parallel, and the solution sets are much closer to the CPF, which verifies the solution effectiveness of the NEMOPSO algorithm in dealing with complex constrained problems, and it can improve the effectiveness of resource recommendation for civil engineering courses.



(a) CTAEA on DOC4



(b) CCMO on DOC4



(c) NEMOPSO on DOC4

Figure 3. Average running results of the three algorithms on DOC4.

3.2. Test the Effect of Course Resource Recommendation Based on Multi-Objective Optimization

After the introduction of NEMOPSO algorithm in the resource recommendation system, the effect of civil engineering course resource recommendation is tested. The resource recommendation method based on knowledge organization is chosen as a comparison method, and together with the method of this paper, a single resource recommendation task and multiple resource recommendation tasks are completed respectively, and the corresponding evaluation index data are counted. Table 1 shows the statistical results of resource recommendation effect test data of civil engineering courses of the 2 methods. Figure 4 shows the comparison of the memory share and time consumption of resource recommendation of the 2 methods. The resource recommendation method based on multi-objective optimization consistently has fewer runs, higher correct resource recommendation rates, and smaller memory footprints and faster runtimes in 3 single-resource recommendation tasks and 3 multi-resource recommendation tasks. The method requires only 19 and 25 runs in the single- and multi-resource recommendation tasks, respectively, and the recommendation correctness is always greater than or equal to 90%. Among the six tasks, the highest memory footprint is 66MB and the highest time consumed is 24s, which is much lower than the comparison methods. That is, the method in this paper is more advantageous in terms of running performance and recommendation effect.

Table 1. Test data on the effect of course resource recommendations.

Experimental type and group		Knowledge organization			Multi-objective optimization		
		Output the number of runs of the recommended results	Quantity of all resources	Recommend the correct quantity of resources	Output the number of runs of the recommended results	Quantity of all resources	Recommend the correct quantity of resources
Single resource recommendation task	A1	45	30	17	19	30	27
	A2	43	35	19	19	35	31
	A3	42	20	10	19	20	18
Multiple resource recommendation tasks	B1	56	50	31	25	50	45
	B2	57	55	34	25	55	51
	B3	51	52	28	25	52	49

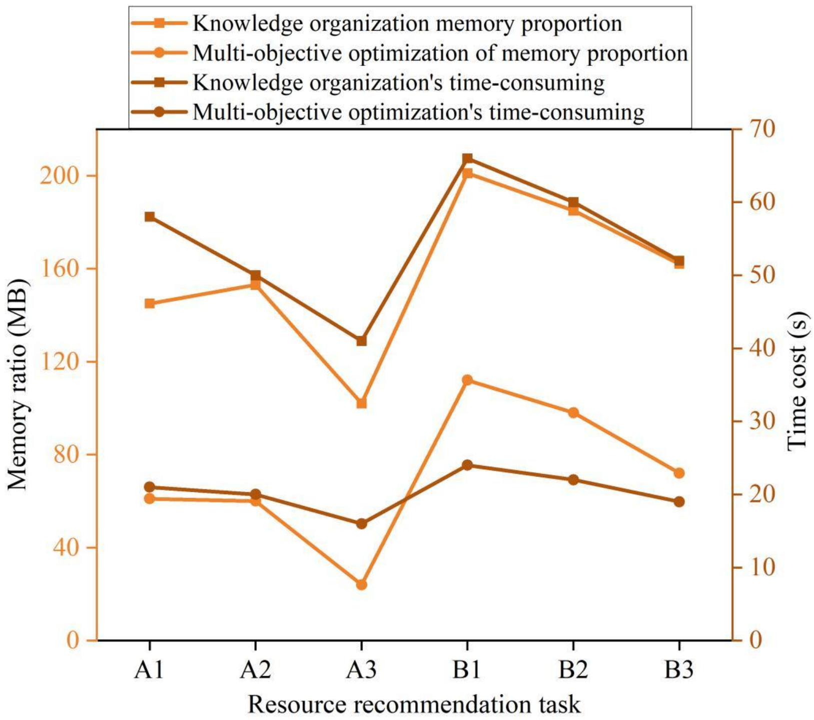


Figure 4. Comparison of memory usage and time consumption of 2 methods.

3.3. Controlled Experiment on Resource Recommendation Assisted Learning Based on Multi-Objective Optimization

The trained resource recommendation system was applied to 2 freshman classes of civil engineering majors in T University to set up a control experiment to test the effectiveness of multi-objective optimization based resource recommendation system for assisted learning. In this case, the 2 classes were both 40 students, the control class was taught using traditional teaching methods, and the experimental class was taught using the resource recommendation system for assisted learning with no remaining variables. The experiment lasted for 2 semesters, and tests were set up before and after the experiment to investigate the changes in the students' level of engineering thinking.

3.3.1. Independent Samples t-test of the Results of the Pre-Test of Thinking Level in the Two Classes

Table 2 shows the results of the independent samples t-test for the pre-test of thinking level in both classes. The p-value of the four dimensions of engineering thinking level (engineering decision-making thinking: p=0.534, engineering design thinking: p=0.628, engineering implementation thinking: p=0.579, and engineering evaluation thinking: p=0.633) of the two classes is greater than 0.05, which indicates that there is no significant difference between the levels of the two classes in these four dimensions. Therefore both classes can be used for controlled experimental study.

Table 2. Independent sample t-test of the pretest results of 2 classes.

Dimension	Class	N	Mean value	Standard deviation	T	Df	Sig. (Double Tail)
Engineering decision-making thinking	Control class	40	3.4912	0.4692	-0.246	80	0.534
	Experimental Class	40	3.2496	0.5529			
Engineering design thinking	Control class	40	3.5006	0.4506	0.632	80	0.628
	Experimental Class	40	3.4533	0.5233			
Engineering implementation thinking	Control class	40	3.4729	0.4654	0.257	80	0.579
	Experimental Class	40	3.4721	0.5542			
Engineering evaluation thinking	Control class	40	3.4735	0.4723	-0.073	80	0.633
	Experimental Class	40	3.4912	0.5231			

3.3.2. Independent Samples t-test for Pre- and Post-Test Results of Thinking Level in Control Classes

Table 3 shows the results of independent samples t-test for the pre- and post-test results of the thinking level of the control class. The mean values of the control class in the four dimensions of engineering decision-making thinking, engineering design thinking, engineering implementation thinking, and engineering evaluation thinking increased by 0.2472, 0.3921, 0.4434, and 0.5080, respectively, indicating that the levels of these four dimensions have a certain magnitude of improvement to the general level. However, the p-value of all four dimensions is greater than 0.05, indicating that there is no significant difference in the measurement data of these four dimensions in the control class before and after the experiment, and the students' level of thinking is not significantly improved.

Table 3. Independent sample t-test for pre and post-test results of the control class.

Dimension	Class	N	Mean value	Standard deviation	T	Df	Sig. (Double Tail)
Engineering decision-making thinking	Control class pre-test	40	3.4912	0.4692	-6.038	40	0.072
	Control class post-test	40	3.7384	0.5317			
Engineering design thinking	Control class pre-test	40	3.5006	0.4506	-6.795	40	0.081
	Control class post-test	40	3.8927	0.5182			
Engineering implementation thinking	Control class pre-test	40	3.4729	0.4654	-6.253	40	0.075
	Control class post-test	40	3.9163	0.5923			
Engineering evaluation thinking	Control class pre-test	40	3.4735	0.4723	-6.734	40	0.086
	Control class post-test	40	3.9815	0.5026			

3.3.3. Independent Samples t-test for Pre- and Post-Test Results of Thinking Level in Experimental Classes

Table 4 shows the results of independent samples t-test for the pre- and post-test results of thinking level in the experimental class. The p-value of the 4 dimensions of engineering decision-making thinking, engineering design thinking, engineering implementation thinking, and engineering evaluation thinking of the students in the experimental class is equal to 0.001, which is less than 0.01, which shows that there is a significant difference between the pre- and post-experimentation measurements of these 4 dimensions at the 0.01 level. And the mean values of these 4 dimensions were increased by 1.3486, 1.2787, 1.1631 and 1.2769 respectively, which indicates that the levels of these 4 dimensions were substantially increased to a high level. The above data indicate that the use of resource recommendation system based on multi-objective optimization algorithm to assist students' learning has a greater enhancement effect on engineering thinking of college students.

Table 4. Independent sample t-test for pre-post test results of Experimental Class.

Dimension	Class	N	Mean value	Standard deviation	T	Df	Sig. (Double Tail)
Engineering decision-making thinking	Experimental class pre-test	40	3.2496	0.5529	-8.924	40	0.001
	Experimental class post-test	40	4.5982	0.6017			
Engineering design thinking	Experimental class pre-test	40	3.4533	0.5233	-8.273	40	0.001

	Experimental class post-test	40	4.7320	0.6632			
Engineering implementation thinking	Experimental class pre-test	40	3.4721	0.5542	-8.640	40	0.001
	Experimental class post-test	40	4.6352	0.7628			
Engineering evaluation thinking	Experimental class pre-test	40	3.4912	0.5231	-8.608	40	0.001
	Experimental class post-test	40	4.7681	0.5239			

4. Conclusion

This paper introduces the NEMOPSO algorithm to optimize the effect of resource recommendation in civil engineering courses, and experimentally tests its effect on improving students' engineering thinking level. In three single resource recommendation tasks, this paper's method only needs to run 19 times to complete the resource recommendation; in three multi-resource recommendation tasks, this paper's method only needs to run 25 times to complete the resource recommendation. And the accuracy of resource recommendation is always higher than 90%. In the process of resource recommendation, the highest memory occupation space is only 66MB, and the highest time consumption is only 24s, which is better than the comparison method. At the end of the control experiment, the experimental class's engineering decision-making thinking, engineering design thinking, engineering implementation thinking, and engineering evaluation thinking had $p < 0.01$, and the mean values were improved by 1.3486, 1.2787, 1.1631, and 1.2769 points, respectively. Compared to the control class with $p > 0.05$ and the mean improvement of 0.2472, 0.3921, 0.4434, and 0.5080, the level of engineering thinking in the experimental class has improved more. In the future, multimodal civil engineering class teaching resources can be introduced to improve the resource recommendation range of the system.

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References

1. Sun, S., Su, Z., & Cui, S. (2017, December). Study on the continuing education innovative talents training mode of civil engineering major. In IOP Conference Series: Earth and Environmental Science (Vol. 100, No. 1, p. 012197). IOP Publishing.
2. GUO, D. (2024). Innovation and Practice of Cultivating High-quality Technical and Skilled Personnel in Civil Engineering. Journal of Educational Theory and Practice, 1(1), 79-90.
3. Shirazi, A., & Behzadan, A. H. (2015). Design and assessment of a mobile augmented reality-based information delivery tool for construction and civil engineering curriculum. Journal of Professional Issues in Engineering Education and Practice, 141(3), 04014012.
4. Castellanos, A. B., Guzmán, M. S., & Ruiz, D. P. (2019). Reflection strategy for teaching construction projects in Civil Engineering. Alteridad, 14(1), 122-137.
5. Pan, S., Zuo, T., & Wang, Y. (2022, April). Application of the teaching mode of "PAD class" in the teaching of civil engineering specialty in higher vocational colleges. In 2022 International Conference on Social Sciences and Humanities and Arts (SSHA 2022) (pp. 754-758). Atlantis Press.
6. Bartels, N., & Stolz, K. (2024). Project-and Research-Based Teaching in Civil Engineering. International Journal of Engineering Pedagogy, 14(6).
7. Pejić, P., Stojiljković, S., & Dosković, M. (2019). Advanced teaching methods application and its benefits in descriptive geometry at the faculty of civil engineering and architecture in niš. Tehnički vjesnik, 26(6), 1814-1820.
8. Bhatia, A., & Chen, P. C. (2015, June). Active learning pedagogies promoting the art of structural and civil engineering. In 2015 ASEE Annual Conference & Exposition (pp. 26-151).
9. Fini, E. H., Awadallah, F., Parast, M. M., & Abu-Lebdeh, T. (2018). The impact of project-based learning on improving student learning outcomes of sustainability concepts in transportation engineering courses. European Journal of Engineering Education, 43(3), 473-488.
10. Sanal, I. (2018). A review on student-centred higher education in civil engineering: evaluation of student perceptions. International Journal of Continuing Engineering Education and Life Long Learning, 28(2), 205-217.
11. Bae, H., Polmear, M., & Simmons, D. R. (2022). Bridging the gap between industry expectations and academic preparation: Civil engineering students' employability. Journal of Civil Engineering Education, 148(3), 04022003.
12. Anastasiu, L., Anastasiu, A., Dumitran, M., Crizboi, C., Holmaghi, A., & Roman, M. N. (2017). How to align the university curricula with the market demands by developing employability skills in the civil engineering sector. Education Sciences, 7(3), 74.
13. Itani, M., & Srour, I. (2016). Engineering students' perceptions of soft skills, industry expectations, and career aspirations. Journal of professional issues in engineering education and practice, 142(1), 04015005.
14. Olowa, T., Witt, E., & Lill, I. (2020). Conceptualising building information modelling for construction education. Journal of Civil Engineering and Management, 26(6), 551-563.
15. Lassen, A. K., Hjelseth, E., & Tollnes, T. (2018). Enhancing learning outcomes by introducing BIM in civil engineering studies–experiences from a university college in Norway. Building Information Systems in the Construction Industry, 65.
16. Diao, P. H., & Shih, N. J. (2019). Trends and research issues of augmented reality studies in architectural and civil engineering education—A review of academic journal publications. Applied Sciences, 9(9), 1840.
17. Maksimova, S., Kutrunova, Z., Maksimov, L., & Voronov, A. (2017). Experience in the use of modern educational technologies in teaching professional disciplines of training direction "Civil Engineering". In MATEC web of Conferences (Vol. 106, p. 09020). EDP Sciences.
18. Dalloul, F., & Saoud, L. (2023). Proposing a framework for introducing the concept of engineering digitization to develop curricula: case study-Tishreen University, Faculty of Civil Engineering. International Journal of BIM and Engineering Science, 6(1), 34-51.
19. Sampaio, A. Z. (2015). The introduction of the BIM concept in civil engineering curriculum. International Journal of Engineering Education, 31(1), 302-315.
20. Zhang, J., Wu, W., & Li, H. (2018). Enhancing building information modeling competency among civil engineering and management students with team-based learning. Journal of Professional Issues in Engineering Education and Practice, 144(2), 05018001.
21. Abbas, A., Din, Z. U., & Farooqui, R. (2016). Integration of BIM in construction management education: an overview of Pakistani Engineering universities. Procedia Engineering, 145, 151-157.
22. Teegavarapu, R. S. V. (2018). Technology-enhanced learning for civil engineering education: Use of dynamic and virtual reality-based simulation, online data analysis and optimization tools. In Blended Learning in Engineering Education (pp. 305-320). CRC Press.
23. Arif, F. (2021). Application of virtual reality for infrastructure management education in civil engineering. Education and information technologies, 26(4), 3607-3627.
24. Sepasgozar, S. M. (2020). Digital twin and web-based virtual gaming technologies for online education: A case of construction management and engineering. Applied Sciences, 10(13), 4678.
25. García-Macías, E., Castro-Triguero, R., Saavedra Flores, E. I., Yanez, S. J., & Hinrechsen, K. (2019). An interactive computational strategy for teaching the analysis of silo structures in civil engineering. Computer Applications in Engineering Education, 27(4), 821-835.
26. Zhou, X. L., & Wang, J. H. (2016). Interactive computer for teaching biot poroelasticity modeling in civil engineering. Computer Applications in Engineering Education, 24(1), 5-15.