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PAPER

Quality Optimizing Teaching Decisions in Flipped Classrooms through Data-Driven Strategies

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ABSTRACT

In the context of digitalized educational research, the rapid advancement of internet technologies and big data has catalyzed the transformation of traditional teaching models. The flipped classroom, recognized for its flexibility and efficiency, has garnered significant attention. However, the challenge of scientifically optimizing teaching decisions in flipped classrooms to maximize educational outcomes remains critical. Previous studies have achieved some progress in optimizing teaching decisions within flipped classrooms, yet they often suffer from a lack of methodological diversity, inadequate consideration of multi-level constraints, and struggle to adapt to dynamic teaching environments. Addressing these deficiencies, this research introduces a hybrid evolutionary algorithm combining differential evolution and greedy backtracking. Defined and classified constraints within flipped classroom teaching decisions, the construction of constraint networks, and the creation of multi-level decision spaces are transformed and solved through this hybrid algorithm, offering a systematic optimization strategy. Case analysis confirms the effectiveness and practicality of the proposed method, aiming to bolster decision-making in flipped classrooms and advance the development of digitalized teaching.

KEYWORDS

digitalized education, flipped classroom, teaching decision optimization, differential evolution, greedy backtracking, constraint satisfaction problem (CSP)

1 INTRODUCTION

In the context of digitalized educational research, with the rapid development of internet technology and the arrival of the big data era, traditional teaching models are undergoing profound transformations [1–4]. As a new teaching model, the flipped classroom leverages the advantages of information technology to combine knowledge impartation with classroom interaction, offering students a more flexible and efficient learning experience [5–8]. However, how to

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scientifically make teaching decisions and devise optimized teaching plans to maximize educational outcomes remains an urgent issue in the implementation of flipped classrooms.

The research on optimizing teaching decisions in flipped classrooms holds significant practical importance. On one hand, optimizing teaching decisions can enhance teaching quality and improve students' learning effects and proactivity; on the other hand, decision optimization based on data analysis can provide more scientific and rational teaching plans, promote rational allocation and efficient utilization of teaching resources, and advance the development and popularization of educational digitalization [9–11]. Furthermore, in-depth research into the optimization strategies of teaching decisions in flipped classrooms can also provide practical guidance for educational administrators and frontline teachers, helping them to implement and improve the flipped classroom teaching model.

Although existing research has achieved certain results in optimizing teaching decisions in flipped classrooms, there are still some deficiencies. Current methods often focus on single-dimensional optimization, lacking a systematic consideration of multi-level, multi-dimensional constraints [12–15]. Additionally, traditional optimization methods often rely on static data, struggling to adapt to dynamically changing teaching environments, leading to suboptimal results [16–19]. Therefore, there is an urgent need for an optimization method that can comprehensively consider multi-level constraints and dynamically adapt to teaching environments to better guide teaching decisions in flipped classrooms.

This research primarily includes the following aspects: Firstly, classify and define the various constraints in flipped classroom teaching decision schemes, clarifying the connotation and role of each type of constraint. Secondly, constructing a constraint network for flipped classroom teaching decision schemes will provide a structured model foundation for optimization decisions. Thirdly, based on the construction and transformation of a multi-level constraint-based flipped classroom teaching decision space, ensuring the rationality and comprehensiveness of the decision space. Fourthly, propose a CSP-solving strategy based on differential evolution and greedy backtracking, combining global search and local optimization to enhance solution efficiency and optimization results. Lastly, through case analysis, verify the effectiveness and practicality of the proposed strategy. This research aims to provide a scientific and systematic optimization method for teaching decisions in flipped classrooms, promoting the in-depth development and application of digitalized teaching.

2 CLASSIFICATION AND DEFINITION OF CONSTRAINTS IN FLIPPED CLASSROOM TEACHING DECISION SCHEMES

In the flipped classroom model, teaching plans need to meet the diverse learning needs and paces of different students. Traditional teaching plans cannot effectively adapt to individual differences among students, making optimization decisions complex. At the same time, with the development of educational technology, a large amount of student learning behavior and feedback data is available for analysis. Utilizing these data, key issues and optimization spaces in teaching can be more accurately identified. For this purpose, this paper employs a CSP approach to conduct effective searches and optimizations within the vast space of teaching plan design, aiming to enhance teaching effectiveness and student satisfaction. Specifically, from the lifecycle perspective of flipped classrooms, this paper standardizes and describes different types of teaching design constraints, forming a constraint network. These constraints reflect the relationships between various stages and elements in the teaching process. Further, through the systematic integration of nodes in the constraint network with nodes in the teaching design space, a multi-level teaching design space based on constraints is constructed. The optimization process of flipped classroom teaching plans is transformed into a teaching design CSP, and key information in the multi-level design space is extracted to form a CSP model. Finally, a hybrid evolutionary algorithm based on differential evolution and greedy backtracking search algorithms is proposed, with the optimization goals of maximizing student learning outcomes and teaching resource utilization, to make optimization decisions. Through the optimized search of the algorithm, the best flipped classroom teaching plan that meets the constraints is obtained.

Flipped classroom models need to meet the diverse learning needs and individual differences of students. By identifying and defining various constraints in teaching, it is possible to better adapt to the different learning paces and needs of students. Modern teaching processes have accumulated a large amount of student learning data, and through data analysis, key issues and optimization opportunities in the teaching process can be identified. The method based on CSP can translate these data into specific teaching decision constraints, guiding optimization strategies. Clarifying various constraints in the teaching process (such as time, resources, learning outcomes, etc.) and optimizing them can significantly enhance teaching effectiveness and student satisfaction.

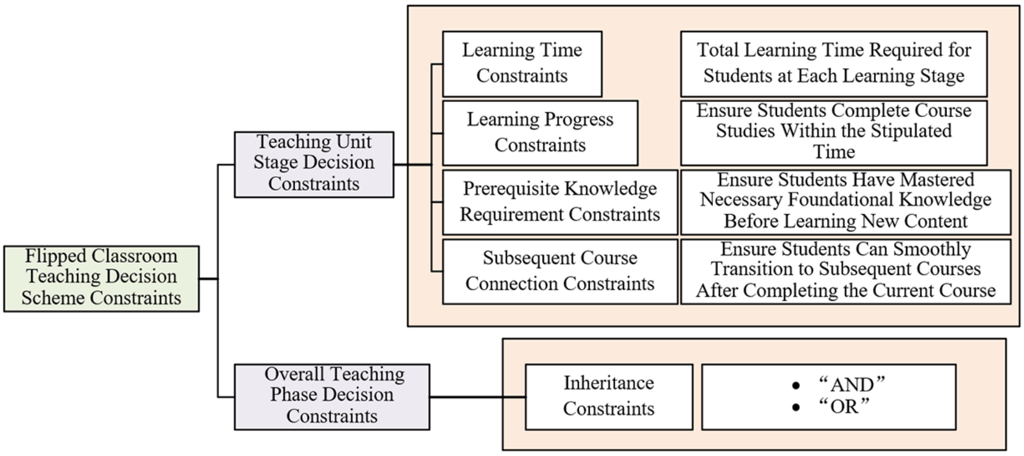


Fig. 1. Classification of teaching decision constraints in flipped classrooms

In the flipped classroom model, teaching design constraints can be divided into unit constraints and overall constraints. Unit constraints refer to teaching objectives, time schedules, resource configurations, etc., within specific courses or modules; overall constraints cover the entire semester or academic year's teaching plans, student learning progress, and outcome assessments. Specifically, teaching constraints can be identified and defined in the following aspects: Learning time constraints refer to the allocation of learning time for each unit, including pre-class preparation, in-class activities, and post-class review; learning progress constraints refer to the progress and outcomes of students at different time points, ensuring all students can complete learning tasks as planned; Associative constraints refer to the connectivity between different teaching modules, including prerequisite knowledge requirements and subsequent course connections, see Figure 1 for details.

Definition 1: Learning time constraint

Learning time constraint (Lt) represents the total amount of time required by students at each learning stage in a flipped classroom setting, which can be allocated based on specific teaching principles and the results of data analysis. In other words, the learning time constraints for each learning unit or module are determined by the overall learning time constraint O_{CO} and the time distribution coefficient z_u. Generally, the size of O_{CO} is determined by the teaching objectives and the course plan. This paper proposes a combined method of hierarchical analysis and data-driven analysis to obtain the time distribution coefficient z_u by analyzing student learning behaviors and time investments at different learning stages.

1. Obtaining subjective weights through the analytic hierarchy process (AHP)

   First, an AHP model is constructed, breaking down the time distribution issue of flipped classroom teaching into multiple levels. Specifically, courses can be divided into several learning units or modules, and the importance of each learning unit is evaluated based on teaching objectives and the significance of the learning content. Teaching experts or experienced teachers are invited to score these learning units. By constructing a judgment matrix and performing a consistency test, the importance weights of each learning unit are calculated. These weights represent the impact of subjective factors on the distribution of learning time. Specifically, a judgment matrix Z_{MA1} is constructed, setting the number of evaluation indicators to l and the number of configuration schemes for z_u to v.

$$Z_{MA1} = (x_{uk})_{l \times l} \; u, k = 1, 2, \dots, l; \tag{1}$$

   Z_{MA1} is normalized column-wise, and the weight of each indicator, β_u, is further calculated using the following formula:

$$\beta_u = \sum_{u=1}^{l} \frac{x_{uk}}{\sum_{k=1}^{l} \left(x_{uk} \right)} \tag{2}$$

   The maximum eigenvalue is calculated based on the following formula:

$$\eta_{MAX} = \sum_{u=1}^{l} \frac{[Z_{MA1} \beta u]_u}{l \beta u} \tag{3}$$

   Further, the consistency of the matrix is verified through the consistency index CR:

$$CR = \frac{CI}{RI}, CI = \frac{(\lambda_{\max} - l)}{(l-1)} \tag{4}$$

2. Obtaining objective weights through the entropy method

Next, collect data on student learning in different units, including time spent on pre-class preparation, in-class participation, and post-class review. Using this data, the time distribution weights for each learning unit are calculated through the entropy method. First, the collected learning time data is standardized to eliminate dimensional effects. Further, a standardized decision matrix, $Z_{MA2} = (y_{uk})_{vl}$ is obtained:

For teaching input indicators:

$$y'_{uk} = \frac{y_{uk} - MINy_{uk}}{MAXy_{uk} - MINy_{uk}} \tag{5}$$

For teaching effectiveness indicators:

$$y'_{uk} = \frac{MAXy_{uk} - y_{uk}}{MAXy_{uk} - MINy_{uk}} \tag{6}$$

Then, calculate the information entropy of the time distribution data for each learning unit to measure its uncertainty. The entropy value for the k-th indicator can be calculated using the following formula:

$$r_k = -j\sum_{u=1}^{v} y'_{uk} U_v(y'_{uk}) \tag{7}$$

Based on the magnitude of the information entropy, calculate the objective weights for each learning unit. The greater the entropy, the smaller the weight, and vice versa. The weight for each indicator, α_u, can be obtained through the following calculation:

$$\alpha_u = \frac{1 - r_k}{\sum_{u=1}^{v}\left(1 - r_k\right)} \tag{8}$$

3. By integrating weights obtained from the AHP and the entropy method, the learning time distribution coefficient z_u is generated:

Ultimately, subjective and objective weights are integrated to produce a combined weight. Based on this, the learning time constraint corresponding to the learning phase can be expressed as $Mz_u = O_{CO} z_u$.

$$z_u = \frac{\beta_u \cdot \alpha_u}{\sum_{u=1}^{v}\left(\beta_u \cdot \alpha_u\right)} \tag{9}$$

Definition 2: Learning progress constraints (Tz)

Learning progress constraints are meant to ensure that students complete their course studies within the stipulated time, which is typically represented by inequalities. For example, to ensure that students complete the course on time, the completion time for each learning unit is restricted. Learning progress constraints can be determined by analyzing student learning data and teaching objectives, identifying the content and learning objectives that must be completed within a specific time frame for each learning unit.

$$Tz = \left\{ S\left(\sum_{k=1} ST_{u,k} \right) \leq S_{MAX} \right\} \tag{10}$$

where $ST_{u,k}$ is the k-th learning progress information in the u-th learning stage, and S_{MAX} is the maximum threshold value of $ST_{u,k}$ information.

Definition 3: Prerequisite knowledge requirements constraint (*Ro*) and subsequent course connection constraint (*Rz*)

The prerequisite knowledge requirements constraint ensures that students have mastered the necessary foundational knowledge before learning new content, arranging the learning content sequentially. For instance, before studying an advanced programming course, one must complete the basic programming course. The subsequent course connection constraint ensures that students can smoothly transition to subsequent courses after completing the current course, arranging the learning content accordingly. For example, to smoothly advance to advanced courses, one must achieve a certain grade in the basic course. Prerequisite knowledge requirements and subsequent course connection constraints are represented by a directed graph, defined as follows:

$$Ro = \{Vu, Vk, 1OR0\} \tag{11}$$

$$Rz = \{Vu, Vk, -1OR0\} \tag{12}$$

Where the arrangement order of knowledge node *Vu* preceding knowledge node *Vk* is represented by 1, –1 indicates there is no preceding or subsequent associative constraint between *Vu* and *Vk*, and 0 indicates no constraints on the knowledge node.

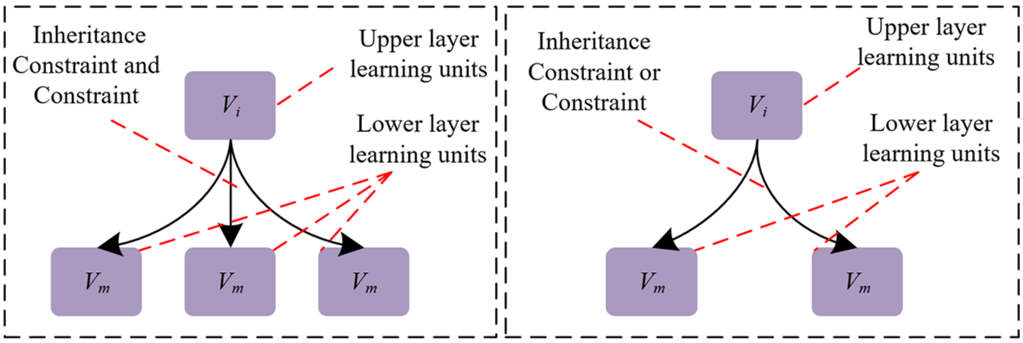


Fig. 2. Expression of inheritance constraint relationships

Definition 4: Inheritance constraints (*Rt*)

Inheritance constraints (*Rt*) represent the association and dependency relationships between different learning units in a flipped classroom model, mainly including "AND" constraints and "OR" constraints, as shown in Figure 2. For example, a complex learning objective can be decomposed into multiple sub-objectives; the complex learning objective is achieved only when all sub-objectives are met; alternatively, the complex learning objective can be partially achieved when any one of the sub-objectives is met. Assume the upper learning unit is represented by *Vi*; the lower learning unit is represented by *Vm*; and the "AND" and "OR" inheritance constraints are represented by *Rt-AND* and *Rt-OR*, respectively.

$$Rt = \{Vi, Vm, Rt - AND, Rt - OR\} \tag{13}$$

3 SCP SOLVING STRATEGY BASED ON DIFFERENTIAL EVOLUTION AND GREEDY BACKTRACKING

To find the optimal teaching plan within the multi-level teaching design space, this paper employs a hybrid evolutionary algorithm combining differential evolution and greedy backtracking search algorithms. Differential evolution, as a type of stochastic direct search and global optimization algorithm, features robustness and the capability of global optimization. This algorithm, by conducting a global search across the design space, effectively explores multiple potential solutions, avoiding local optima. Especially in the context of complex teaching design issues, differential evolution can rapidly identify teaching plans that satisfy all constraints through random mutation and selection operations. This global optimization capability is particularly important for addressing teaching design issues involving numerous constraints and multi-level variables. Meanwhile, the greedy backtracking search algorithm, as a major method of informed search, utilizes heuristic information to conduct systematic and leaping searches of the design space. During the design of teaching plans, the greedy backtracking search algorithm can employ a depth-first strategy to search each teaching node according to priority. If a choice fails to meet the constraints or achieve the objectives, the algorithm activates a backtracking mechanism to revert to the previous step, or even several steps back, to select alternative paths. This effectively prevents repeated failures and enhances solving efficiency. Additionally, the greedy backtracking search algorithm can quickly find compliant teaching plans in large-scale design spaces, adapting to the dynamic adjustment needs of teaching plans.

The hybrid evolutionary algorithm primarily consists of two parts: (1) employing differential evolution to iterate populations for solving large-scale optimization problems; and (2) utilizing greedy backtracking search to check whether individuals in the population meet teaching design constraints. Initially, the differential evolution algorithm generates a new population through mutation, crossover, and selection operations, where each individual represents a teaching plan. This algorithm, through random mutation and selection, can effectively explore multiple potential solutions, avoiding local optima and ensuring the identification of the optimal solution in complex teaching design spaces. The global search capability of differential evolution enables it to handle teaching design issues containing numerous constraints and multi-level variables. Secondly, during the optimization process, the greedy backtracking search algorithm is used to check whether individuals in the population meet teaching design constraints. Variable ordering is considered an important preprocessing technique, with the order of variable instantiation being crucial for the solving process. This paper employs a greedy algorithm based on minimum remaining value ordering, prioritizing teaching variables with numerous constraints. This ordering method effectively reduces the complexity of solving enhances search efficiency. The specific process involves selecting teaching variables with the most constraints from all levels of the teaching plan, unfolding constraint checks, and, if a teaching variable is assigned, applying forward checking to handle all variables and constraints, determining whether the teaching plan meets the constraints. Through this method, teaching plans that fail to meet constraints can be detected and removed early, effectively enhancing the search efficiency of the plan. Moreover, to supplement the population needed for the next iteration, a random population generator is established. This generator ensures that there are sufficient individuals for the differential evolution algorithm to operate on in each iteration, maintaining the diversity and stability of the algorithm.

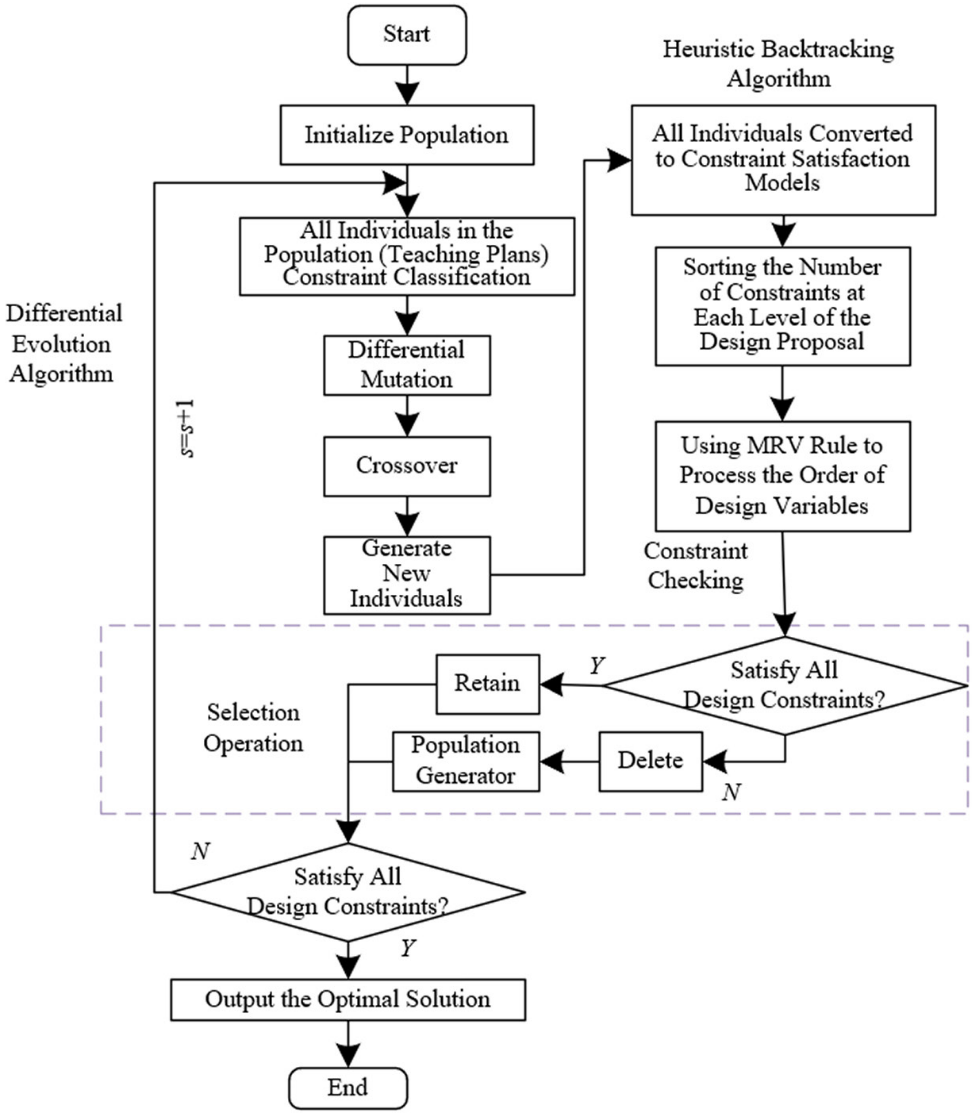


Fig. 3. Flowchart of the hybrid evolutionary algorithm

Figure 3 provides a flowchart for the hybrid evolutionary algorithm. The following are the detailed solution steps:

Step 1: Initialize the population. Set the initial iteration stage to $s = 1$, extracting a subset of teaching plans that satisfy constraints from the multi-level constraint-based teaching design space to form the initial population O_0. Each teaching plan is represented by a multi-level model. Mutation and crossover operators' ratio factors are set as D and ze respectively.

Step 2: Fitness function calculation. Use data analysis methods to estimate the effectiveness of each teaching plan, aiming for optimization of student learning outcomes in subsequent iterative optimization processes.

Step 3: Differential mutation and crossover. Implement individual mutation using a differential mutation strategy and perform crossover operations with the population and its mutant intermediates to form a new population. This step aims to increase the diversity of teaching plans through mutation and crossover operations, exploring more potential optimization options.

Step 4: Check the teaching constraints. Convert each individual in the obtained population into a CSP model and implement a greedy backtracking search algorithm based on minimum remaining values ordering to check if the design nodes in each teaching plan of the population satisfy the teaching constraints. Constraints include teaching time, resource allocation, student needs, etc.

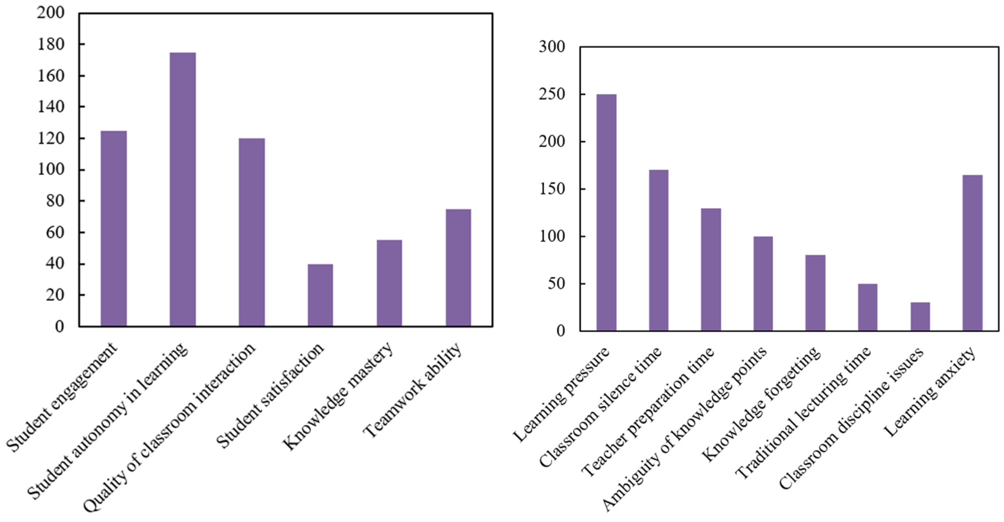
Step 5: Selection operation. Eliminate teaching plans that do not meet constraints through selection operations; only individuals that satisfy the constraint conditions are retained for the next generation. Additionally, generate new individuals through a random population generator to supplement the number of individuals for the next iteration, ensuring the diversity and stability of the population.

Step 6: Stop the condition. Repeat the evolutionary operations from Steps 2 to 5 for each selected individual in every iteration until all termination conditions are satisfied. These termination conditions can be either reaching a predetermined number of iterations or achieving the expected standard of optimization effects in the teaching plans.

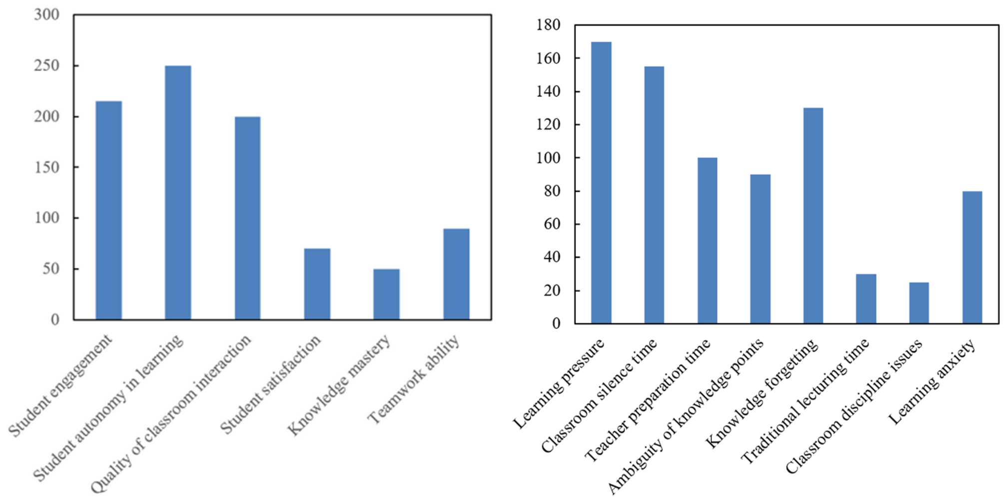
Step 7: Output the best results. Generate the best-optimized teaching plan within the teaching design space to be implemented as the optimal teaching plan under the flipped classroom model.

4 CASE ANALYSIS OF OPTIMIZED TEACHING PLAN DECISIONS FOR FLIPPED CLASSROOMS

This study conducts a detailed analysis of the changes in teaching effectiveness under the flipped classroom model by comparing the indicator data of the original and optimized teaching plans, thereby validating the effectiveness of data-driven teaching decision optimization. As shown in Figure 4, in the optimized plan, student engagement increased by 90, student autonomy in learning increased by 75, and the quality of classroom interaction increased by 80. This indicates that the optimized flipped classroom teaching plan significantly enhanced student participation and enthusiasm for autonomous learning, while also making classroom interactions more frequent and effective. Student satisfaction increased from 40 to 70, an increase of 30, indicating greater student approval and satisfaction with the new teaching plan. The level of knowledge mastery decreased from 55 to 50, a reduction of 5, which is due to students not yet fully adapting to the new teaching model during the transition phase. Teamwork ability increased from 75 to 90, an increase of 15, showing that the flipped classroom has a significant effect on promoting student teamwork. Learning pressure decreased by 80 and learning anxiety by 85, demonstrating that the optimized plan effectively reduced student learning pressure and anxiety, helping to create a more relaxed learning environment. Classroom silence time, teacher preparation time, ambiguity of knowledge points, traditional lecturing time, and classroom discipline issues all decreased. These reductions indicate that the optimized plan improved classroom efficiency, reduced ineffective time, and also lightened the teacher's workload, improving classroom discipline. The rate of knowledge forgetting increased from 80 to 130, an increase of 50, due to the need for further strengthening of knowledge review and consolidation under the flipped classroom model.



a) Original Teaching Plan Indicator Information



b) Optimized Teaching Plan Indicator Information

Fig. 4. Comparative analysis of indicator information between original and optimized teaching plans

Table 1. Combination configuration of time distribution coefficient z_u

No	Time Distribution Coefficient z_u				Teaching Effectiveness
	Pre-Class Preparation Phase	Class Activity Phase	Review and Consolidation Phase	Assessment and Improvement Phase	
1	0.3985	0.5687	0.0006	0.0301	1421.52
2	0.3654	0.6012	0.0006	0.0301	1503.23
3	0.4895	0.4751	0.0006	0.0301	1548.54
4	0.3985	0.6023	0.0002	0.0006	1687.24
5	0.3956	0.5784	0.0002	0.0305	1456.21
6	0.4215	0.5762	0.0002	0.0006	1628.35

This paper examines the impact of the combination configuration of time distribution coefficients on flipped classroom teaching effectiveness, verifying the effectiveness of the data-driven teaching decision optimization strategy. From Table 1, it can be seen that the pre-class preparation phase and the class activity phase occupy the majority of the time allocation. Among the various configuration schemes, the time distribution coefficients for the pre-class preparation phase range from 0.3654 to 0.4895 and for the class activity phase from 0.4751 to 0.6023. The time distribution coefficients for the review and consolidation phase and the assessment and improvement phase are lower, generally maintained between 0.0002 and 0.0305. Configuration scheme 4 (0.3985, 0.6023, 0.0002, 0.0006) achieved the highest teaching effectiveness at 1687.24. This indicates that the best teaching outcomes are achieved when more time is allocated to the pre-class preparation and class activity phases (pre-class preparation 0.3985, class activity 0.6023). Configuration scheme 6 (0.4215, 0.5762, 0.0002, 0.0006) also had a high teaching effectiveness of 1628.35. This scheme's time allocation for the pre-class preparation and class activity phases is close to that of scheme 4, with slight adjustments to the proportions, still achieving good results. Configuration schemes 1 (0.3985, 0.5687, 0.0006, 0.0301) and 5 (0.3956, 0.5784, 0.0002, 0.0305) had lower teaching effectiveness, at 1421.52 and 1456.21, respectively. Although these two schemes also had higher time allocations for the pre-class preparation and class activity phases, allocating more time to the review and consolidation phase and the assessment and improvement phase actually decreased the overall teaching effectiveness.

This paper analyzes the teaching effectiveness of flipped classrooms under different constraint configurations to validate the effectiveness of the data-driven teaching decision optimization strategy. As seen in Figure 5, the pre-class preparation phase and the classroom activity phase occupy the majority of the time allocation. In each configuration scheme, the time allocation for the pre-class preparation phase ranges from 400 to 750 minutes and for the classroom activity phase from 700 to 1000 minutes. The time allocated for the review and consolidation phase is 0 minutes, and for the assessment and improvement phase, it ranges from 50 to 100 minutes. Configuration scheme 4 (650 minutes of pre-class preparation, 1000 minutes of classroom activity, and 50 minutes of assessment and improvement) achieved the highest teaching effectiveness of 1687.24. This indicates that the best teaching results are obtained when more time is allocated to the pre-class preparation and classroom activity phases (650 minutes for pre-class preparation, 1000 minutes for classroom activity). Configuration scheme 6 (700 minutes of pre-class preparation, 700 minutes of classroom activity, 50 minutes of assessment and improvement) also had high teaching effectiveness, with a score of 1628.35. This scheme allocated more time to the pre-class preparation phase, with slightly less for classroom activity, but still achieved good results. Configuration schemes 1 (600 minutes of pre-class preparation, 700 minutes of classroom activity, 50 minutes of assessment and improvement) and 5 (600 minutes of pre-class preparation, 700 minutes of classroom activity, 100 minutes of assessment and improvement) had lower teaching effectiveness, with scores of 1421.52 and 1456.21, respectively. Although these two schemes allocated considerable time to the pre-class preparation and classroom activity phases, the longer duration allocated to the assessment and improvement phase actually decreased the overall teaching effectiveness.

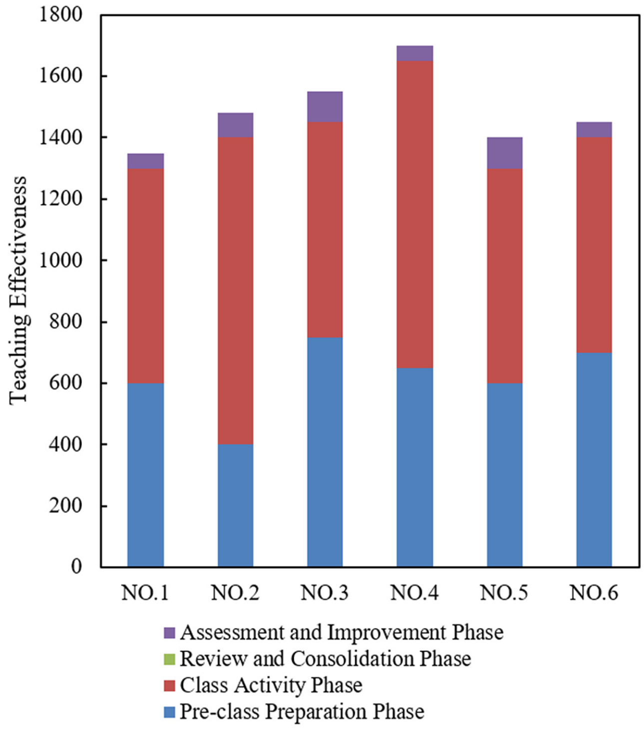


Fig. 5. Analysis of teaching effectiveness under different constraint configurations

This paper analyzes the teaching effectiveness of flipped classrooms under different constraint configurations to validate the effectiveness of the data-driven teaching decision optimization strategy. As shown in Figure 6, the pre-class preparation phase and classroom activity phase occupy the majority of the time allocation. In each configuration scheme, the time allocation for the pre-class preparation phase ranges from 380 to 780 minutes and for the classroom activity phase from 660 to 1060 minutes. The time allocated for the review and consolidation phase is 0 minutes, and for the assessment and improvement phase, it ranges from 60 to 130 minutes. Configuration scheme 4 (600 minutes of pre-class preparation, 1060 minutes of classroom activity, and 70 minutes of assessment and improvement) achieved the highest teaching effectiveness of 1687.24. This indicates that the best teaching results are obtained when more time is allocated to the pre-class preparation and classroom activity phases (600 minutes for pre-class preparation, 1060 minutes for classroom activity). Configuration scheme 6 (780 minutes of pre-class preparation, 840 minutes of classroom activity, and 60 minutes of assessment and improvement) also had high teaching effectiveness, with a score of 1628.35. This scheme allocated more time to the pre-class preparation phase, with slightly less for classroom activity, but still achieved good results. Configuration schemes 1 (560 minutes of pre-class preparation, 800 minutes of classroom activity, 80 minutes of assessment and improvement) and 5 (550 minutes of pre-class preparation, 840 minutes of classroom activity, 130 minutes of assessment and improvement) had lower teaching effectiveness, with scores of 1421.52 and 1456.21, respectively. Although these two schemes also allocated considerable time to the pre-class preparation and classroom activity phases, the longer duration allocated to the assessment and improvement phase actually decreased the overall teaching effectiveness.

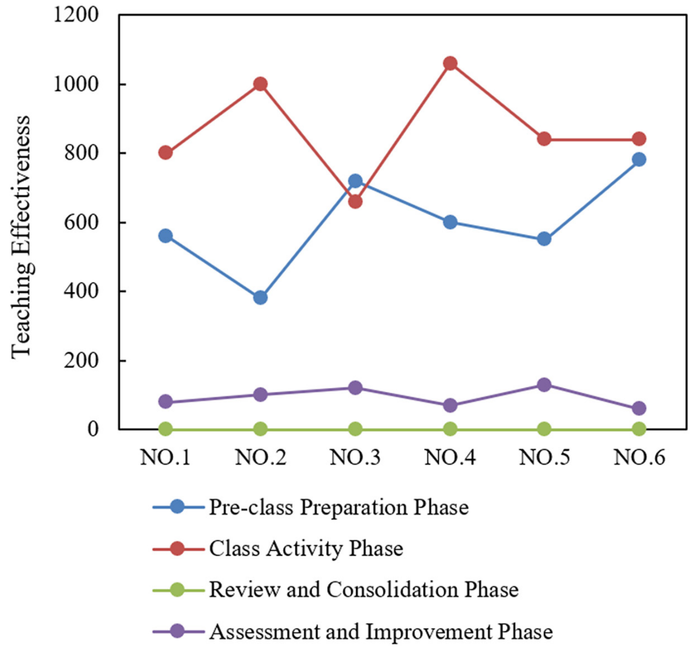


Fig. 6. Analysis of teaching effectiveness at different stages of flipped classroom teaching decision plans

By analyzing the teaching effectiveness under different time distribution coefficient combination configurations, this paper validates the effectiveness of the CSP-solving strategy based on differential evolution and greedy backtracking in optimizing flipped classroom teaching decisions. It can be concluded that rational allocation of time for pre-class preparation and classroom activities is key to enhancing the teaching effectiveness of flipped classrooms. The best configuration, scheme 4, shows that allocating 600 minutes for pre-class preparation and 1060 minutes for classroom activities is the optimal combination for improving teaching outcomes. Through data analysis, the optimized time distribution strategy significantly enhanced teaching effectiveness, reaching a peak of 1687.24, thus validating the effectiveness of the data-driven teaching decision optimization strategy proposed in this paper. It is evident that the constructed constraint network and multi-level decision space for flipped classroom teaching decision plans provide a structured model foundation for optimization decisions, ensuring the rationality and comprehensiveness of the decision space.

5 CONCLUSION

This paper primarily focuses on optimizing teaching decision schemes for flipped classrooms, covering four key areas. Firstly, it classifies and defines the various constraints involved in flipped classroom teaching decisions, providing a clear framework for subsequent optimization. Secondly, it constructs a constraint network for flipped classroom teaching decisions, offering a structured model foundation that enhances the intuitive and systematic handling of various constraints. Thirdly, it builds and transforms a multi-level flipped classroom teaching decision space, ensuring the rationality and comprehensiveness of the decision space, thus safeguarding the effectiveness and coverage of the decisions. Lastly, it introduces a problem-solving strategy based on differential evolution and greedy backtracking that combines global search with local optimization, improving the efficiency and effectiveness of solutions. This strategy has demonstrated high efficiency and effectiveness in handling complex teaching decision-making issues.

Experimental results indicate significant achievements in several areas. Firstly, by comparing original and optimized teaching plans, there is a noticeable improvement in teaching effectiveness, validating the effectiveness of the proposed optimization strategy. Secondly, by analyzing the teaching effectiveness under different time distribution coefficient combination configurations, the study identifies the best configuration schemes, providing strong data support for practical teaching scheduling. Additionally, by analyzing teaching effectiveness under different constraints, the study validates the applicability and effectiveness of the proposed decision model and optimization strategy across various conditions. Lastly, a detailed analysis of teaching effectiveness at different stages (pre-class preparation, classroom activities, assessment, and improvement) under various configurations provides a scientific basis for further optimizing time allocation and teaching activities at each stage.

In conclusion, the research outcomes of this paper hold significant academic and practical value. By optimizing flipped classroom teaching decision schemes, it presents an effective set of decision optimization strategies and methods, with experimental validation showing a significant enhancement in teaching effectiveness. This not only provides theoretical support for the implementation of flipped classrooms but also offers concrete guidance for teaching practice. However, the study has its limitations. Firstly, the experimental data are derived from a specific teaching environment, and the effects may differ in other settings; thus, future research needs to validate these findings in a broader range of educational contexts. Secondly, while the differential evolution and greedy backtracking strategy performed well in current experiments, combining them with other optimization algorithms might be necessary to enhance outcomes under more complex constraints.

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