Postprint of the SBO Algorithm Incorporating Educational Psychology

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Abstract

To address the deficiencies of the School-Based Optimization (SBO) algorithm, including poor search performance and susceptibility to local optima, this paper proposes an SBO algorithm integrated with educational psychology (SBO based on Educational Psychology, SBO-EP). During the teaching phase, the Zone of Proximal Development theory is introduced to implement grouped dynamic teaching for students, thereby enhancing the algorithm' s exploration capability. The achievement motivation theory is incorporated into the self-study phase, where dynamic self-study approaches are designed according to each student group' s achievement motivation to improve the algorithm' s exploitation capability. Following each learning cycle, a class reorganization operation is performed based on the peer effect to increase solution diversity. Numerical experiments are conducted using 40 CEC2021 test functions and 20 additional test functions of other types, and the SBO-EP algorithm is compared against Ant Colony Optimization, Spherical Vector-based Particle Swarm Optimization, Archimedes Optimization Algorithm, Grey Wolf Optimizer, Teaching-Learning-Based Optimization, TLBO incorporating cognitive psychology, and Student Psychology-Based Optimization. The results indicate that the SBO-EP algorithm demonstrates significant advantages in convergence speed, optimization accuracy, and stability. Finally, comparative experiments on combinations of the three strategies verify the effectiveness of the proposed improvements.

Full Text

Preamble

SBO Algorithm Integrated with Educational Psychology

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Abstract: To address the shortcomings of the School Based Optimization (SBO) algorithm, such as poor search performance and tendency to fall into local optima, this paper proposes an SBO algorithm based on Educational Psychology (SBO-EP). In the teaching phase, the "Zone of Proximal Development" theory is introduced to implement dynamic group teaching for students, enhancing the algorithm' s exploration capability. The "Achievement Motivation" theory is incorporated into the self-study phase, where dynamic self-study methods are designed based on each student group' s achievement motivation to improve the algorithm' s exploitation capability. After each learning round, a class reorganization operation is performed based on the "Peer Effect" theory to increase solution diversity. Numerical experiments are conducted using 40 CEC2021 test functions and 20 other types of test functions. The SBO-EP algorithm is compared with Ant Colony Optimization, spherical vector-based Particle Swarm Optimization, Archimedes Optimization Algorithm, Gray Wolf Optimization Algorithm, Teaching-Learning-Based Optimization, Cognitive Psychology Teaching-Learning-Based Optimization, and Student Psychology-Based Optimization. Results demonstrate that SBO-EP offers significant advantages in convergence speed, optimization accuracy, and stability. Finally, comparative experiments on combinations of the three strategies verify the effectiveness of the proposed improvements.

Keywords: SBO algorithm; Zone of Proximal Development theory; Achievement Motivation theory; Peer Effect

0 Introduction

The School Based Optimization (SBO) algorithm, proposed by Farshchin et al. in 2018, represents a novel metaheuristic optimization approach. Existing metaheuristic algorithms are primarily inspired by biological swarm sociality or natural phenomena, such as Genetic Algorithms (GA) and Simulated Annealing (SA). However, human groups possess the conscious ability to modify their behavior, making them more intelligent than ordinary biological systems. Consequently, metaheuristic algorithms simulating human group intelligence have become a research focus, including Teaching-Learning-Based Optimization (TLBO) and Brain Storm Optimization (BSO).

The SBO algorithm is a metaheuristic developed based on human group intelligence, inspired by multi-class teaching modes in schools. It extends the single-classroom model of TLBO by proposing a collaborative multi-class teaching optimization framework. In this collaborative mode, teachers from various classes can be assigned to teach in other classes, enabling knowledge sharing and dissemination throughout the entire school.

As a relatively recent development, research on the SBO algorithm remains limited, primarily focusing on solving practical optimization problems. Farshchin et al. applied SBO to steel frame design optimization, demonstrating its robustness and efficiency through several benchmark problems. Degertekin et al. utilized SBO for seismic optimization design of steel frames, while Abdelghany et al. employed it for solar cell parameter estimation. Current domestic and international research on SBO mainly concentrates on application problems, with further investigation needed to address algorithmic deficiencies and improve optimization performance.

This paper targets the SBO algorithm' s weaknesses in search capability and susceptibility to local optima by integrating theories from educational psychology. We design teaching strategies, self-study strategies, and class reorganization strategies to propose the SBO-EP algorithm, which significantly enhances exploration and exploitation capabilities while improving solution accuracy and convergence speed.

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1 SBO Algorithm

Common metaheuristic algorithms generate an initial population of potential solutions and gradually improve overall fitness through a systematic optimization process, allowing only intra-population collaboration. More sophisticated approaches employ multiple independent parallel populations to enhance exploration capability and overall efficiency. This multi-population collaborative method comprises two phases: first, independent metaheuristics explore different population regions of the search space; second, the most promising subregions are exploited. The SBO algorithm is precisely such a two-phase optimization algorithm based on multi-population collaboration. The first phase explores each independent class through teacher guidance, while the second phase focuses on identifying the most promising students. Conventional two-phase multi-population algorithms typically face challenges in selecting termination criteria for the first phase, requiring parameter tuning that introduces dependency and increases complexity. The SBO algorithm addresses this issue by introducing a multi-class collaborative framework, offering advantages of fewer parameters and stronger search capability.

The interaction mechanism in SBO involves: selecting teachers for each class to form an excellent teacher group, allocating teachers to classes using roulette wheel selection, conducting interactive learning between teachers and students within each class, and finally enabling peer learning among students within each class. In SBO, each candidate solution represents a student individual in a class, solution components represent subjects, and one iteration represents a complete teaching-learning process. The search process comprises three stages: teacher allocation, teaching phase, and learning phase, which work jointly to gradually improve class performance.

1.1 Teacher Allocation

Teacher allocation serves as the crucial link connecting different classes throughout the SBO teaching process. First, student fitness values within each class are compared to select the top performer, forming an excellent teacher team. Then, roulette wheel selection is employed to randomly choose one teacher from this team for each class to perform teaching tasks. This allocation method ensures that excellent teachers have a higher probability of entering classes for instruction while maintaining randomness. Through knowledge dissemination by excellent teachers across multiple classes, student learning efficiency improves and solution diversity increases.

1.2 Teaching Phase

After each class is assigned a teacher, the teacher independently conducts knowledge delivery within their assigned classes. Student groups learn from the teacher to improve their performance. In each independent class containing N students, individual student Xi updates their knowledge by combining their existing knowledge with the teacher' s instruction, attempting to approach the teacher' s level. The update equation is given by (1):

where and represent student i' s level in subject D before and after teaching, respectively, and represents the knowledge absorbed by student i through classroom instruction, expressed as the difference between the teacher and the class mean M, as shown in (2):

The Teaching Factor (TF) describes the degree of knowledge acquisition from classroom instruction, taking values of 1 or 2: $\mathrm{TF} = \mathrm{round}[1 + \mathrm{rand}(0, 1)]$, where r is a random number in (0,1). Student fitness values Fi are used to represent the class average level M, which demonstrates superior search efficiency compared to traditional weighted average calculations, as shown in (3):

1.3 Learning Phase

Following the teaching phase, students enter the learning phase, which involves knowledge exchange and sharing among individuals to improve performance through peer learning. In this phase, student i randomly selects another student j from the same class for learning and communication, integrating this with their own knowledge for updating. The update equation is given by (4):

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2 SBO-EP Algorithm

The SBO algorithm exhibits deficiencies in exploitation and exploration capabilities for complex function optimization problems and tends to fall into local optima. Its adaptive exploration and global search capabilities require improvement. Addressing these defects becomes crucial for enhancing algorithmic performance.

In educational psychology, Ausubel' s theory of meaningful reception learning distinguishes between "reception learning" and "discovery learning." To address SBO' s weak exploration, we introduce the "Zone of Proximal Development" theory into the teaching phase corresponding to reception learning, proposing a group teaching method. For weak exploitation, corresponding to discovery learning, we incorporate the "Achievement Motivation" theory to propose a group self-study phase. Dynamic learning factors based on habituation are introduced in both phases to adaptively enhance search capability. Finally, to address local optima susceptibility, we adopt class reorganization based on the "Peer Effect" theory to increase solution diversity and improve global search capability.

2.1 Teaching Phase Based on "Zone of Proximal Development" Theory

Vygotsky' s "Zone of Proximal Development" (ZPD) theory posits that student development comprises current and potential levels, with the difference between them constituting the ZPD. Teaching should target this zone, gradually eliminating the gap through teacher guidance to elevate student performance. Chinese scholar Wang Wenjing proposed establishing a new "teaching according to aptitude" perspective based on ZPD, where educators should thoroughly understand students' actual and potential developmental levels, guiding them toward their highest potential by identifying their ZPD. This theory aims to unlock student potential by creating improvement intervals that gradually stimulate performance through teaching-learning interactions.

Inspired by this theory, we define the difference between teacher level and student current level as the ZPD—the potential interval for improvement through receiving teacher knowledge. We implement "teaching according to aptitude" to facilitate different students approaching teacher level through their respective learning styles. Drawing from the Group Teaching Optimization Algorithm (GTOA), we transform the single teaching mode into a group teaching mode. Using class average performance as the standard and following the principle of "heterogeneous between groups, homogeneous within groups," students are divided into excellent and ordinary groups. Dynamic differential teaching schemes are designed for each group' s ZPD to unlock their potential and improve overall class performance. Excellent students have higher overall levels, faster knowledge absorption, and relatively smaller ZPD, allowing teachers to balance guidance for both individual improvement and class average elevation. For minimization problems, the excellent group dynamic teaching update equation is given by (5):

Ordinary students have higher potential development levels and relatively larger ZPD spaces, so teachers focus primarily on guiding this group toward potential achievement. The ordinary group dynamic teaching update equation is given by (6):

During the gradual elimination of ZPD through teacher guidance, the "habituation principle" must be considered. Accepting new knowledge is a progressive process. In early teaching stages, students require an adaptation period where learning state depends mainly on original level. As teaching progresses and students adapt to new learning rhythms, dependence on original level decreases while new knowledge acceptance increases. Therefore, a dynamic learning factor w is introduced to simulate habituation, defined by (7):

where t represents current iteration number and Iter_max represents maximum iteration number. The improved group teaching phase based on ZPD theory simulates how students of different levels in real classrooms approach teacher level by eliminating ZPD differences, reaching their potential maximum level. Algorithmically, this means excellent and poor solutions within each population undergo group optimization, gradually approaching the population' s optimal solution. Compared to SBO' s single overall update strategy, the ZPD-based teaching phase effectively expands solution search range and improves exploration capability.

2.2 Self-Study Phase Based on "Achievement Motivation" Theory

Ausubel's "discovery learning" emphasizes that learners should actively establish connections between old and new knowledge for assimilation. Based on this, a self-study phase is added after teaching and learning phases to consolidate and strengthen knowledge absorption.

Atkinson' s "Achievement Motivation" theory distinguishes between success-oriented motivation and failure-avoidance motivation. Success-oriented individuals seek achievement, typically choosing higher goals for satisfaction. For these students, assigning difficult tasks can stimulate learning enthusiasm. Failure-avoidance individuals prefer stable progress, choosing easily achievable goals to maintain steady development. For these students, low-competition goals help maintain learning state. Drawing from achievement motivation theory and using the same grouping method and habituation-based dynamic learning factor w from the teaching phase, we propose a student self-study phase. The Student Psychology-Based Optimization Algorithm and Cognitive Psychology Teaching-Learning-Based Optimization Algorithm similarly group students based on psychological expectations or locus of control, designing appropriate learning goals and methods for each group.

Excellent students, analogous to success-oriented individuals, aim for achievement by targeting the best performer, measuring their gap and continuously learning to reach top performance. The update equation is given by (8):

Ordinary students, analogous to failure-avoidance individuals, prefer steady, progressive learning, targeting class average level to build foundation and identify gaps before seeking higher goals. The update equation is given by (9):

2.3 Class Reorganization Strategy Based on "Peer Effect"

Coleman' s "Peer Effect" concept suggests that individuals within a group are influenced by peers'characteristics and performance. Research shows that mixed-class grouping strategies can effectively improve overall class performance under positive peer effects.

In SBO' s learning phase, students primarily reference classmates within the same class, limiting reference samples and risking local optima. To diversify learning and expand positive peer influence, a mixed-class grouping strategy is applied to all classes. After each iteration, class reorganization is performed before entering the next learning round.

To verify the impact of class reorganization on solution diversity, Griewangk and Salomon functions are used as examples, comparing distribution diagrams of 50 two-dimensional students in one class before and after iteration. As shown in Figure 1, before the first iteration' s class reorganization, solutions are densely distributed with limited range. After reorganization, solutions become more dispersed with wider distribution and significantly improved diversity, while still finding optimal solutions without reducing search efficiency. This demonstrates that class reorganization substantially increases solution diversity and improves global exploration capability.

2.4 SBO-EP Algorithm Steps

In summary, the framework of the proposed SBO-EP algorithm is shown in Figure 2. The specific steps are:

Step 1: In NC classes, randomly generate initial student populations of dimension NP×D within search space [LB, UB].

Step 2: Calculate and compare fitness values of students in each class, selecting top performers to form the teacher team.

Step 3: Use roulette wheel selection to choose NC teachers from the teacher team, assigning one to each class for teaching activities.

Step 4: Teaching phase: Update student population using equations (5) and (6).

Step 5: Learning phase: Update student population using equation (4).

Step 6: Self-study phase: Update student population using equations (8) and (9).

Step 7: Class reorganization: Mix all students from NC classes and reorganize into NC new classes.

Step 8: Update iteration count $t = t + 1$. If termination condition $t = Iter\_max$ is satisfied, the algorithm terminates and outputs the global optimal solution; otherwise, return to Step 3.

3 Experiments and Results

3.1 Experimental Environment and Parameter Settings

To verify SBO-EP' s optimization performance, comparative experiments are conducted against Ant Colony Optimization (ACO), spherical vector-based Particle Swarm Optimization (SPSO), Archimedes Optimization Algorithm (AOA), Gray Wolf Optimization (GWO), Student Psychology-Based Optimization (SPBO), Teaching-Learning-Based Optimization (TLBO), Cognitive Psychology Teaching-Learning-Based Optimization (CPTLBO), and the original SBO algorithm. The CEC2021 suite of 40 functions and 20 other test functions are used to validate the improved algorithm' s superiority. Parameter settings for all compared algorithms are listed in Table 1.

The experimental environment is 64-bit Windows 10, Intel(R) Core(TM) i5-7200U CPU at 2.7GHz, 8GB RAM. Algorithms are implemented in MATLAB R2020b.

3.2 CEC2021 Function Tests

The 2021 IEEE Congress on Evolutionary Computation (CEC) single-objective parameter optimization competition proposed 10 scalable complex test functions in 10 and 20 dimensions. This paper extends these 10 benchmark functions with bias and rotation operations. If both operations are applied, it is denoted as type "11"; if neither is applied, type "00"; resulting in four extension combinations and 40 total test functions. Detailed information for the 10 CEC2021 benchmark functions is provided in Table 2.

Since theoretical optima vary across CEC2021 functions, differences between algorithm results and theoretical optima are calculated, with difference value 0 serving as the optimum for comparison. Maximum evaluation counts are set to 30,000 for fairness. SBO and SBO-EP use 10 classes × 30 students, while other algorithms use 30 individuals. Each algorithm runs independently 30 times in 10 dimensions. Mean values measure optimization capability, while standard deviations reflect stability. Results are shown in Table 3.

Table 3 results indicate that AOA achieves mean and standard deviation of 0 for functions f1 and f9 of types 10 and 11, showing relatively good accuracy and stability. GWO stably converges to optima for f8 of type 00 and f1 of types 10 and 11. CPTLBO achieves zero mean and standard deviation for f1 and f9 of types 10 and 11, and for f4 and f8 across all four types, demonstrating excellent accuracy and stability. SBO consistently finds optimal solutions for f1 of type 10 and f8 across all types. SPSO, SPBO, and TLBO fail to optimize any functions to optimality, showing poor performance.

The proposed SBO-EP algorithm achieves optimization mean values reaching the order of -300 for f9 and f10 of types 00 and 01 among the complex CEC2021 functions, significantly outperforming the other eight algorithms. Except for these six functions, all other unimodal, basic, hybrid, and composite functions achieve zero mean and standard deviation across 30 independent runs, consistently converging to optimal solutions. This verifies SBO-EP' s superior optimization capability and stability.

To comprehensively validate SBO-EP' s reliability and superiority, statistical testing is performed using Wilcoxon rank-sum tests at a 5% significance level against other algorithms on all 40 CEC2021 functions. Using SBO-EP versus SBO as an example, calculated p-values are shown in Table 4 (NaN indicates both algorithms converge to optima). All other p-values are below 0.05, statistically confirming SBO-EP' s superiority. Similar significant results are obtained for other algorithms (detailed results omitted due to space constraints).

For intuitive performance comparison, convergence curves for functions f3, f4, f6, and f7 of type 00 are plotted in Figure 3. The curves show SBO-EP converges rapidly, achieving high precision within 100 iterations, clearly outperforming other algorithms in both convergence speed and accuracy.

3.3 High-Dimensional Function Tests

Beyond the 40 CEC2021 functions, 20 additional test functions are selected to verify performance on high-dimensional problems. Function details are provided in Table 5.

SBO-EP and six other algorithms solve these 20 functions in 1000 dimensions, running independently 30 times with maximum evaluation counts of 30,000. Performance metrics of best, mean, worst, and standard deviation are reported in Table 6.

Results show that ACO performs well on F15 and F20, stably converging to optima on F15. SPSO converges to optima on F13 and F15 with relatively stable results on F13. AOA finds optima on F1, F2, F5, F11, F14, and F17, with stable convergence on F1, F2, and F17. GWO shows poor optimization capability, failing to find optima on any function with large magnitude results. SPBO converges to optima on F1, F12, F13, F15, and F20, but with large standard deviations on F1 and F20, indicating instability. TLBO shows poor capability, only occasionally converging to optima on F12. CPTLBO stably converges to optima on F1, F2, F15, and F17, with occasional convergence on F11 but large standard deviation, showing overall good performance. SBO only stably finds optima on F2, placing it at a disadvantage.

SBO-EP demonstrates significantly superior performance across all metrics compared to the other eight algorithms. For F7, where AOA, SPBO, TLBO, and SBO all fail to escape local optima with large initial values, SBO-EP rapidly converges to optima, demonstrating fast convergence and strong exploration capability independent of initial solutions. Except for F12 and F18, all other functions achieve zero across all four evaluation metrics, showing remarkable solution accuracy and stability. Wilcoxon rank-sum tests at 5% significance level on all 20 functions yield p-values below 0.05 (N/A when both algorithms reach optima), statistically confirming SBO-EP' s superiority.

Representative convergence curves for functions F1, F4, F8, and F17 in 1000 dimensions are plotted in Figure 4. For F1 and F17, both AOA and SBO-EP converge to optima, but SBO-EP converges significantly faster with exponential convergence trends. For F4 and F8, only SBO-EP converges to optima with stable trends without local optima entrapment. This confirms SBO-EP' s clear advantages in convergence speed and stability.

3.4 Comparison of Improved Strategy Combinations

SBO-EP' s optimization performance results from the combined effects of three strategies: ZPD-based teaching phase, achievement motivation-based self-study phase, and peer effect-based class reorganization. To validate each strategy' s effectiveness, combination experiments are conducted. Algorithms using only strategy 1, 2, or 3 are denoted SBO-EP1, SBO-EP2, and SBO-EP3, respectively. Algorithms using strategy pairs (1+2, 1+3, 2+3) are denoted SBO-EP4, SBO-EP5, and SBO-EP6.

Four test functions are selected: f1 and f7 from CEC2021 type 00, and F10 and F18 from the 1000-dimensional suite. With 30,000 evaluation counts, each algorithm runs independently 30 times. Best, worst, mean, and standard deviation results are reported in Table 7, with iteration curves from the 15th run shown in Figure 5.

Results show that from a single-strategy perspective, SBO-EP1 and SBO-EP2 outperform SBO, indicating strategies 1 and 2 substantially improve exploitation and exploration, with strategy 1 contributing more significantly to solution accuracy. Strategy 3 alone shows no optimization for any function. When combining two strategies, solution accuracy further improves, with SBO-EP4 (strategies 1+2) showing the best performance. The combination of strategies 1 and 3 also demonstrates significant contribution, validating strategy 3' s effectiveness in assisting other strategies and helping escape local optima. When all three strategies are combined, optimization capability is effectively enhanced, achieving highest solution accuracy and fastest convergence. Optimal solutions are found for f1, f7, and F10, while high precision is achieved for F18, showing clear improvement over other combinations.

The eight-strategy combination experiments confirm that strategies 1 and 2 contribute significantly to exploration capability, while strategy 3 substantially enhances global optimization capability when combined with the others. These experiments validate the effectiveness of the three-strategy combination and SBO-EP' s superiority, with all p-values from Wilcoxon rank-sum tests against other combinations being below 0.05, further confirming statistical significance.

4 Conclusion

The SBO algorithm is a metaheuristic based on multi-class collaborative teaching. To address its low optimization accuracy and weak global search capability, this paper proposes SBO-EP, an SBO algorithm integrating educational psychology features with dynamic grouping. First, the ZPD theory with habituation principle is applied to group teaching updates, improving exploration capability. Second, the achievement motivation theory with habituation principle is used to propose a group self-study phase, enhancing exploitation capability. Finally, peer effect-based class reorganization after each learning round increases solution diversity and global search capability.

Comprehensive testing on 40 CEC2021 functions and 20 other test functions, with comparisons against ACO, SPSO, AOA, GWO, SPBO, TLBO, CPTLBO, and SBO, demonstrates that SBO-EP achieves stronger search performance, faster convergence, and higher stability, validating its superiority. Strategy combination experiments further confirm the effectiveness of all three improvement strategies. SBO-EP shows strong competitiveness in optimization, with future work applying it to new energy vehicle power battery recycling network planning.

References

[1] Farshchin M, Maniat M, Camp C V, et al. School based optimization algorithm for design of steel frames [J]. Engineering Structures, 2018, 171: 326-335.

[2] Holland J H. Genetic algorithms [J]. Scientific American, 1992, 267(1): 66-73.

[3] Kirkpatrick S, Gelatt C D, Vecchi M P. Optimization by simulated annealing [J]. Science, 1983, 220(4598): 671-680.

[4] Rao R V, Savsani V J, Vakharia D P. Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems [J]. Computer-Aided Design, 2010, 43(3): 303-315.

[5] Shi Yuhui. Brain storm optimization algorithm [C]// Proc of the 2th International Conference in Swarm Intelligence. Berlin: Springer Press, 2011: 303-309.

[6] Degertekin S O, Tutar H, Lamberti L. School-based optimization for performance-based optimum seismic design of steel frames [J]. Engineering with Computers, 2021, 37(4): 3283-3297.

[7] Abdelghany R Y, Kamel S, Ramadan A, et al. Solar cell parameter estimation using school-based optimization algorithm [C]// Proc of the 24th IEEE International Conference on Automation. Chilean: IEEE Press, 2021: 1-6.

[8] Farshchin M, Camp C V, Maniat M. Optimal design of truss structures for size and shape with frequency constraints using a collaborative optimization

strategy [J]. Expert Systems with Applications, 2016, 66: 203-218.

[9] Camp C V, Farshchin M. Design of space trusses using modified teaching-learning based optimization [J]. Engineering Structures, 2014, 62: 87-97.

[10] Wang Huilai. Ausubel' s meaningful learning theory to the reform to instruction [J]. Journal of Tianjin Normal University: Social Science, 2011, 38(2): 67-70.

[11] Ma Yankun, Ye Haosheng. Contemporary development of Vygotsky' s "Zone of Proximal Development" Theory [J]. Psychological Development and Education, 2004, 20(2): 89-93.

[12] Wang Wenjing. The inspiration of Vygotsky' s "Zone of Proximal Development" Theory to instructional reform in China [J]. Psychological Exploration, 2000, 20(2): 17-20.

[13] Zhang Yiying, Jin Zhigang. Group teaching optimization algorithm: A novel meta heuristic method for solving global optimization problems [J]. Expert Systems with Applications, 2020, 148: 113246.

[14] Zhang Dingkun, Fang Liluo, Ling Wenquan. Theory and research status of self-efficacy [J]. Advances in Psychological Science, 1999, 17(1): 39-43, 11.

[15] Das B, Mukherjee V, Das D. Student psychology based optimization algorithm: A new population based optimization algorithm for solving optimization problems [J]. Advances in Engineering Software, 2020, 146: 102804.

[16] He Peiyuan, Liu Yong. New teaching-learning-based optimization algorithm with cognitive psychology theory and its application [J]. Application Research of Computers, 2022, 39(03): 785-789, 796.

[17] Zheng Lei. Neighborhood effects and peer effects in education: methods, evidences, and policy implications [J]. Journal of Educational Studies, 2015, 11(5): 99-110.

[18] Dorigo M, Birattari M, Stutzle T. Ant colony optimization [J]. IEEE Computational Intelligence Magazine, 2006, 1(4): 28-39.

[19] Phung M D, Ha Q P. Safety-enhanced UAV path planning with spherical vector-based particle swarm optimization [J]. Applied Soft Computing, 2021, 107: 107376.

[20] Hashim F A, Hussain K, Houssein E H, et al. Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems [J]. Applied Intelligence, 2021, 51(3): 1531-1557.

[21] Mirjalili S, Mirjalili S M, Lewis A. Grey wolf optimizer [J]. Advances in Engineering Software, 2014, 69(7): 46-61.

[22] Wang Yongliang, Wang Ting, Yao Chen. Adaptive weighted grey-wolf optimization algorithm based on Kent map [J]. Application Research of Computers, 2020, 37(S2): 37-40.