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Improved Nuclear Reaction Heuristic Intelligence Algorithm for Online Learning in Self-Monitoring Strategy Convergence

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Abstract

INTRODCTION: By analyzing the problem of self-monitoring in English online learning and constructing a strategy-integrated evaluation method, we can not only enrich the theoretical research results of self-monitoring in online learning, but also improve the independent learning ability and self-monitoring ability of students in English online learning.
OBJECTIVES: To address the problem of poor optimization performance of current fusion optimization methods.METHODS:This paper proposes an online learning self-monitoring strategy fusion method based on improved nuclear reaction heuristic intelligent algorithm. First, the problems and enhancement strategies of online learning self-monitoring are analyzed; then, the online learning self-monitoring strategy fusion model is constructed by improving the nuclear reaction heuristic intelligent algorithm; finally, the proposed method is verified to be effective and feasible through the analysis of simulation experiments.
RESLUTS: The results show that the fusion method of learning self-monitoring strategies on the line at the 20th iteration number starts to converge to optimization with less than 0.1s optimization time, and the error of the statistical score value before and after weight optimization is controlled within 0.05.
CONCLUSION:Addressing the Optimization of Convergence of Self-Monitoring Strategies for English Online Learning.

Keywords: fusion approach to English online learning; self-monitoring strategy; nuclear reaction heuristic intelligence algorithm; Cat chaotic mapping strategy

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1. Introduction

In the Internet era, informationization not only promotes economic development and cultural transmission, but also greatly promotes the development and change of education [1]. Under the promotion of "Internet +" in the education sector, English online learning has become a common way, as a necessary supplement to offline learning, an effective aid, a useful expansion, to promote learning efficiency, and to promote the development of education and change [2]. During the new crown, English online learning saved education, but at the same time, it also exposed the problems of English online learning [3]. English online learning makes some students independent learning lack of teacher's help and supervision, and by external interference and temptation, the learning process efficiency has decreased, and even lack of self-adjustment and self-monitoring [4]. By analyzing the problem of self-monitoring in English online learning, thinking about independent learning and self-monitoring strategies, and constructing a strategy integration evaluation method, we can not only enrich the theoretical research results of self-monitoring in English online learning, but also improve the independent learning ability and self-monitoring ability of students in English online learning [5]. Therefore, it is an extremely urgent task to study the evaluation method for the integration of self-monitoring strategies in English online learning [6].

Effective and objective self-monitoring strategy fusion evaluation method for English online learning should not only construct multi-dimensional and multi-subject English online learning self-monitoring strategy, but also adopt convenient, fast, objective and effective intelligent algorithms to solve the strategy fusion evaluation model to assess the feasibility of the strategy [7]. English online learning refers to online instruction and learning through Internet technology, and English online learning self-monitoring refers to the learner's initiative to monitor, control and adjust learning activities in the Internet learning process [8]. English online learning self-monitoring strategy integration analysis method mainly carries out research from three aspects, namely, learning psychology analysis, self-monitoring strategy, and English online learning process analysis [9]. In terms of students' learning psychology analysis, literature [10] found that students have certain self-control ability but poor self-control strategy through self-made students' self-control power scale and questionnaire students' self-control ability, and the experimental results found that students have certain self-control ability, but the self-control strategy is poor; literature [11] used questionnaires and interviews, and analyzed that students' self-control ability is weak, poor initiative, and they need the supervision of others; and literature [12] found that junior high school students' self-regulation of learning through the survey process needs the promotion of external forces. In terms of learning process self-monitoring strategies, literature [13] defined learner self-monitoring and gave a specific continuous process of self-monitoring, including self-observation, self-judgment, and self-response; literature [14] used factor analysis to classify self-monitoring as planning, preparation, awareness, method, execution, feedback, remediation, and summarization; literature [15] analyzed network self-monitoring by self-developed questionnaire table, analyzing online self-monitoring consists of four dimensions: cognitive self-monitoring, volitional self-monitoring, strategic self-monitoring, and emotional self-monitoring, and using random forest to construct self-monitoring strategy assessment model; Literature [16], for the problem of self-monitoring of writing learning, classifies self-control into formulating a writing plan before writing, and monitoring the attention and comprehension during the writing process. In terms of online learning process analysis, literature [17] proposed a machine learning-based analysis model for the effect of online use of speaking platforms for online teaching problems; literature [18] studied the process of English online learning as well as the defects during the epidemic, and proposed a method for analyzing the process of English online learning based on the Support Vector Machines; and literature [19] put forward a student-oriented strategy for English online learning, and used a neural network to construct English online learning evaluation model. In response to the above literature analysis, the existing online learning self-monitoring strategy integration methods have the following defects [20]:

1) There is less research on online learning self-monitoring strategy integration methods and a lack of quantitative research;

2) English online learning strategy evaluation methods using data-driven models lack generalizability;

3) The analysis of online learning self-monitoring strategies is not comprehensive enough to form a systematic evaluation system.

Population intelligence algorithms are a class of optimization algorithms that accomplish a given task by simulating the behavior of a population of organisms (or a natural/artificial population) by a group of simple individuals following a specific interaction mechanism [21]. For the online learning self-monitoring strategy fusion problem, intelligent optimization algorithms are required to construct the analysis method. Intelligent optimization algorithms make strategy fusion more effective, and their application to the online learning self-monitoring strategy fusion problem has become a hot research topic for experts and scholars in the field.

Aiming at the problems of the current online learning self-monitoring strategy fusion method, this paper proposes an online learning self-monitoring strategy fusion method based on the improved nuclear reaction heuristic intelligence algorithm. The main contributions of this paper are: (1) analyzing the problems of online self-monitoring learning and proposing self-monitoring strategies by means of questionnaires and online data review; (2) constructing a model for the fusion of online learning self-monitoring strategies by using the improved nuclear reaction optimization algorithm with Cat's chaotic mapping strategy and Levy's flight strategy; (4) verifying the validity of this paper's proposed method by simulation, and at the same time improving the convergence speed of the optimization algorithm. convergence speed of the optimization algorithm.

2. Self-monitoring strategies for online learning

2.1. Problems with online self-monitored learning

Through online materials and questionnaires, this section explores the problems of online learning [22]:

Lack of study time planning

The lack of planning for study time is mainly manifested in the following ways: firstly, neglecting study plan making; secondly, time management students cannot balance study and recreation time well.

Single method of learning

According to the interview data, English online learning methods are relatively homogenous and cannot be used to learn to understand knowledge and skills through strategies such as note-taking.

Difficulty concentrating

Difficulty in concentration and poor learning results, mainly manifested in: first, interference from irrelevant networks, deviating from the learning objectives; second, insufficient concentration, difficult to maintain concentration on the lecture.

Lack of reflective action

It is clear from the interview data that the majority of the learners kept their reflection on their own motivation indeed and the flaws of the online teaching methods, and did not reflect on their own learning status so as to adjust their learning status.

Lack of initiative in learning

From the interviews, it can be seen that very few people are able to actively regulate their own learning state, and most people are more accustomed to classroom learning passively following the teacher's arrangement.

Poor interactivity

The current English online learning process, the teacher is mainly lecture method, the lack of teacher-student interaction, and the lack of timely test and feedback on the learning results, the lack of questions and other interactive ways to test the mastery of learners.

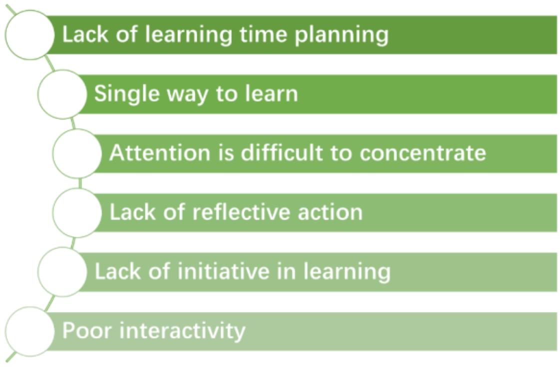

Figure 1. Problems with online learning

2.2. Analysis of online learning self-monitoring strategies

By analyzing the current situation of online learning self-monitoring, problems, and reasons, this section proposes some self-monitoring strategies by combining metacognitive theory and self-monitoring learning theory [23].

Self-efficacy enhancement strategies

Enhancing self-efficacy strategy S1 mainly includes enhancing students' self-confidence and role model experience sharing. In the process of enhancing students' self-confidence, teachers online should analyze students' needs and create to make students participate in teaching; the strategy of role model experience sharing refers to improving one's own confidence and stimulating action adjustment by observing the behavior of role model characters and learning from the experience of role models.

Maintaining Good Motivation Strategies

Maintaining Good Motivation Strategy S2 mainly refers to the online teacher's use of his or her own charisma and the fun of teaching activities to stimulate learning interest.

Enhancement of learning and guidance strategies

Strengthening the learning method guidance strategy S3 includes teachers developing students' ability to make plans, developing students' ability to reflect and evaluate, and motivating feedback to prompt students to form learning habits.

Enhancing Teaching Interaction Strategies

Strengthening the interactive teaching strategy S4 includes online assessment and feedback, peer support learning, and knowledge and skills development. Online learning feedback refers to the teacher to test the learning effect of learners anytime and anywhere, through the feedback results to master the student learning situation; peer support learning refers to the problems encountered and including students and other peers to communicate and interact with each other; knowledge and skill concurrently refers to the on-line course, should be done to achieve the integration of knowledge learning and skills training.

Promoting Two-Way Co-Education Strategies

Promoting two-way co-education strategy S5 means that the online learning process gives, in addition to the teacher, other relevant people should English online learning supervision, complete with others to monitor the learning process.

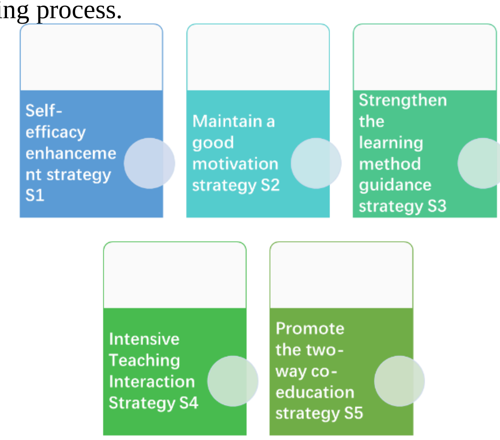

Figure 2. Online Learning Self-Monitoring Strategy

3. Nuclear Reaction Optimization Algorithm

In order to evaluate the effect of self-monitoring strategy fusion for English online learning, this paper quantifies the fusion of self-monitoring strategies for English online learning by combining the nuclear reaction heuristic optimization algorithm and proposes a strategy fusion method based on an intelligent optimization algorithm. The nuclear reaction optimization algorithm is a physically inspired group-based intelligent optimization algorithm proposed in 2019 [24]. The algorithm mainly solves the classical single-objective function, CEC 2018 test set, and engineering constraints, and was recognized as an excellent paper at the IEEE CEC 2019 Conference on Evolutionary Computation [25].

3.1. Inspiration mechanisms

The NRO algorithm is inspired by the physical nuclear reaction phenomenon. Nuclear reactions include nuclear fission and nuclear fusion, in which nuclear fission refers to the heavy nucleus under the bombardment of thermal neutrons split into two nuclei, the split nuclei include odd and even nuclei, in which the odd nuclei are divided into primary and secondary splitting products; nuclear fusion is the nucleus through the absorption of energy into the ionic state, either to overcome the Coulomb repulsion force by the nuclear force is only bound together, or only receive the Coulomb force to slow down the approach to the or repel each other.

3.2. Optimization process of NRO algorithm

Based on the above inspired ideas, a nuclear reaction-based optimization algorithm (NRO) is proposed in this section. Based on the above nuclear reaction theory, the NRO optimization process is divided into Nuclear Fission (NFi) and Nuclear Fusion (NFu) stages. Assuming that nuclear fission and nuclear fusion occur in a confined space, NFi occurs before and NFu occurs after, the energy generated after fission and neutrons after fusion are used to circulate NFi and NFu continuously until the nuclei in the whole space are stable, i.e., the optimal solution is found. Each optimal solution represents an atomic nucleus, and the stable state of the nucleus (optimal solution) is achieved by evaluating the binding energy per unit mass of the nucleus (objective function).The NRO algorithm is described as follows:

Initialization of nucleus populations

The NRO is initialized using a uniformly distributed initialization strategy:

$$\boldsymbol{X}_{i,d} = \boldsymbol{lb}_d + rand \cdot \left(\boldsymbol{ub}_d - \boldsymbol{lb}_d\right) \tag{1}$$

where $\boldsymbol{X}_{i,d}$ is the *dth* dimension state of the *ith* nucleus (optimized solution) in the confined space, and $\boldsymbol{ub}_d$ and $\boldsymbol{lb}_d$ denote the upper and lower bounds of the *dth* dimension of the search space.

Nuclear Fission Phase (NFi)

In the NFi stage, the nuclear fission reaction is simulated by using Gaussian wandering to produce new nuclei. According to the theory of nuclear fission, heated neutrons are utilized to bombard the heavy nuclei to obtain new atomic nuclei. Since nuclear fission is assumed to occur in a cycle with nuclear fusion, the production of thermal neutrons is given by the following equation:

$$\boldsymbol{Ne}_i = \frac{\left(\boldsymbol{X}_i + \boldsymbol{X}_j\right)}{2} \tag{2}$$

where $\boldsymbol{Ne}_i$ is the *i-th* thermal neutron, $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ denote the *i-th* and *j-th* nuclei, and $i \neq j$.

Odd-even nuclei split by absorbing free neutrons followed by splitting, producing secondary splitting products, which are mainly used for simulation development, and primary splitting products, which are mainly used for exploring optimal solutions. The even nuclei are more stable and cannot be excited by thermal neutrons. Considering the state of the nucleus after bombardment by thermal neutrons, introducing the splitting probability P_{Fi} , if the random number $rand \le P_{Fi}$, the nucleus is an odd nucleus; otherwise, the nucleus is an even-even nucleus, and the specific three states after absorbing thermal neutrons are shown in Fig. 3.

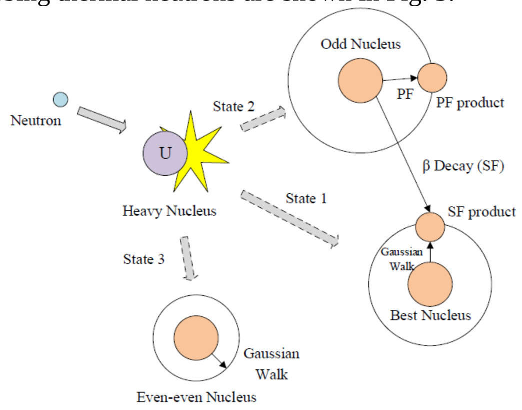

Figure 3 **Three fission states**

State 1: In order to distinguish the two products after the fission of the odd nucleus, the β-decay probability P_β is introduced. After the secondary fission product absorbs thermal neutrons, Gaussian wandering is used to simulate *β-decay* and find a stable state, while the difference between the current optimal solution and thermal neutrons is used to find the optimal solution. When the random number $rand \le P_\beta$, the state of the secondary fission product can be expressed as:

$$\boldsymbol{X}_i^{Fi} = Gaussian\left(\boldsymbol{X}_{best}, \sigma_1\right) + \left(randn \cdot \boldsymbol{X}_{best} - P_{ne} \cdot \boldsymbol{Ne}_i\right) g \tag{3}$$

$$\sigma_1 = \left(\frac{\log\left(iter\right)}{iter}\right) \cdot \left|\boldsymbol{X}_i - \boldsymbol{X}_{best}\right| \tag{4}$$

$$P_{ne} = round\left(rand + 1\right) \tag{5}$$

where $\boldsymbol{X}_i^{Fi}$ denotes the *ith* fission nucleus, $randn$ is a normally distributed random number, and $\boldsymbol{X}_{best}$ denotes the optimal nucleus. For Gaussian wandering, $\log\left(iter\right)/iter$ is used to balance the relationship between exploration and exploitation, where $iter$ is the number of iterations; the step size σ_1 is computed by $\boldsymbol{X}_i$ and $\boldsymbol{X}_{best}$; P_{ne} is a variance factor that jumps between the numbers 0 and 1, making the nuclei search range smaller.

State 2: The primary fission product has no β-decay, then the fissioned nucleus mainly searches around $\boldsymbol{X}_i$, while the search range is more random, and at the same time, the thermal neutron with a larger search range is used to find the nucleus stable state with the difference of the current optimal solution. When the random number $rand > P_\beta$, the state of the primary fission product is expressed as:

$$\boldsymbol{X}_i^{Fi} = Gaussian\left(\boldsymbol{X}_{best}, \sigma_1\right) + \left(randn \cdot \boldsymbol{X}_{best} - P_{ne} \cdot \boldsymbol{Ne}_i\right) g \tag{6}$$

$$\sigma_1 = \left(\frac{\log\left(iter\right)}{iter}\right) \cdot \left|\boldsymbol{X}_i - \boldsymbol{X}_{best}\right| \tag{7}$$

$$P_{ne} = round\left(rand + 2\right) \tag{8}$$

where the parameter σ_2 is computed from the difference between a randomized kernel $\boldsymbol{X}_r$ different from $\boldsymbol{X}_i$ and the current optimal solution, and P_{ne} jumps between 1 and 2, making the kernel search range larger.

State 3: The even-even nucleus cannot be activated by thermal neutrons, and after being bombarded by thermal neutrons, it does Gaussian wandering motion, so the state is expressed as:

$$\boldsymbol{X}_i^{Fi} = Gaussian\left(\boldsymbol{X}_i, \sigma_2\right) \tag{9}$$

Nuclear Fusion Phase (NFu)

1) Ionization process

In the light fusion process, energy is first used to heat the light nuclei to a plasma state, and then the ions overcome the Coulomb force and combine together to become heavy nuclei through nuclear forces. During the ionization of nuclei, all nuclei are ranked by calculating the fitness value:

$$Pa_i = \frac{rank\left(fit\boldsymbol{X}_i^{Fi}\right)}{N} \tag{10}$$

Among them, Pa can decide whether the nucleus is ionized or not, the larger the value is, the larger the possibility of ionization is; $fit\boldsymbol{X}_i^{Fi}$ denotes the fitness value of $\boldsymbol{X}_i^{Fi}$, $rank\left(fit\boldsymbol{X}_i^{Fi}\right)$ denotes the ranking order of the ith nucleus, and N is the number of nucleus populations. If $Pa_i < rand$, the dth dimension ionization process of $\boldsymbol{X}_i^{Fi}$ is as follows:

$$\boldsymbol{X}_{i,d}^{Ion} = \boldsymbol{X}_{r1,d}^{Fi} + rand \cdot \left(\boldsymbol{X}_{r2,d}^{Fi} - \boldsymbol{X}_{i,d}^{Fi}\right),\ rand \le 0.5 \tag{11}$$

$$\boldsymbol{X}_{i,d}^{Ion} = \boldsymbol{X}_{r1,d}^{Fi} - rand \cdot \left(\boldsymbol{X}_{r2,d}^{Fi} - \boldsymbol{X}_{i,d}^{Fi}\right),\ rand > 0.5 \tag{12}$$

where $\boldsymbol{X}_{i,d}^{Ion}$ denotes the dth dimension of the ith nucleus after ionization, $\boldsymbol{X}_{i,d}^{Fi}$, $\boldsymbol{X}_{r1,d}^{Fi}$ and $\boldsymbol{X}_{r2,d}^{Fi}$ denote the fission nuclei, and $i \ne r1 \ne r2$. If $Pa_i \ge rand$, the fission nucleus is relatively stable and not ionized, its state is expressed as follows:

$$\boldsymbol{X}_{i,d}^{Ion} = \boldsymbol{X}_{i,d}^{Fi} + round\left(rand\right) \cdot rand \cdot \left(\boldsymbol{X}_{worst,d}^{Fi} - \boldsymbol{X}_{best,d}^{Fi}\right) \tag{13}$$

where $\boldsymbol{X}_{worst,d}^{Fi}$ is the dth dimension of the worst fission product. During the ionization process, the stable fission products are retained and the unstable fission products are ionized. According to the elite strategy, the stable ionized product is selected as the preferred solution.

2) Fusion processes

The fusion probability is calculated in the same way as the ranking of the adaptation values for the ionization process:

$$Pc_i = \frac{rank\left(fit\boldsymbol{X}_i^{Ion}\right)}{N} \tag{14}$$

where Pc_i is the fission probability of the ith ionized nucleus $\boldsymbol{X}_i^{Ion}$ and $rank\left(fit\boldsymbol{X}_i^{Ion}\right)$ denotes the ranking of $\boldsymbol{X}_i^{Ion}$ based on the fitness value. Similar to the ionization process, if $Pc_i < rand$, fusion occurs; otherwise, $\boldsymbol{X}_i^{Ion}$ uses the Coulomb force to update the current state, which is shown in Fig. 4.20.

State 1: Two ionized light nuclei overcome the Coulomb force and collide and combine together due to nuclear forces. This state utilizes a differential strategy to model the collision and aggregation with the following expression:

$$\boldsymbol{X}_i^{Fu} = \boldsymbol{X}_i^{Ion} + rand \cdot \left(\boldsymbol{X}_{r1}^{Ion} - \boldsymbol{X}_{best}^{Ion}\right) + rand \cdot \left(\boldsymbol{X}_{r2}^{Ion} - \boldsymbol{X}_{best}^{Ion}\right) - e^{-norm\left(\boldsymbol{X}_{r1}^{Ion} - \boldsymbol{X}_{r2}^{Ion}\right)} \cdot \left(\boldsymbol{X}_{r1}^{Ion} - \boldsymbol{X}_{r2}^{Ion}\right) \tag{15}$$

where $\boldsymbol{X}_i^{Fu}$ denotes the ith fusion product, $\boldsymbol{X}_{r1}^{Ion}$, $\boldsymbol{X}_i^{Ion}$ and $\boldsymbol{X}_{r2}^{Ion}$ are the ionized nuclei, and $i \ne r1 \ne r2$ is the ionized nucleus. The first term of Eq. (4.54) represents the current state of the nucleus, the second term represents the difference between $\boldsymbol{X}_{r1}^{Ion}$ and $\boldsymbol{X}_{best}^{Ion}$, and the third term represents the overcoming of the Coulomb force by $\boldsymbol{X}_i^{Ion}$ and $\boldsymbol{X}_{r2}^{Ion}$. The third coefficient has the ability to balance exploitation and exploration.

State 2: If the ion cannot overcome the Coulomb force, the binding fails. To simulate this state, two unique differential evolution strategies are used, which are represented as follows:

$$\boldsymbol{X}_i^{Fu} = \boldsymbol{X}_i^{Ion} - 0.5 \cdot \left(\sin\left(2\pi \cdot freq \cdot iter + \pi\right) \cdot \frac{Max\_iter - iter}{Max\_iter} + 1 \right) \cdot \left(\boldsymbol{X}_{r1}^{Ion} - \boldsymbol{X}_{r2}^{Ion} \right). \tag{16}$$

$$rand > 0.5$$

$$\boldsymbol{X}_i^{Fu} = \boldsymbol{X}_i^{Ion} - 0.5 \cdot \left(\sin\left(2\pi \cdot freq \cdot iter + \pi\right) \cdot \frac{iter}{Max\_iter} + 1 \right) \cdot \left(\boldsymbol{X}_{r1}^{Ion} - \boldsymbol{X}_{r2}^{Ion} \right), \tag{17}$$

$$rand \le 0.5$$

Where $iter$ and Max_iter denote the current iteration number and the maximum iteration number, and $freq$ is the sinusoidal function frequency, the specific value is obtained by adjusting the parameter. Equation (16) simulates two ionized nuclei close to each other approaching a rate-decreasing state, which is mainly used for exploitation; Equation (17) simulates nuclei repelling each other and moving away, which is mainly used for exploration. The nuclei with better fitness values are retained through an elite strategy.

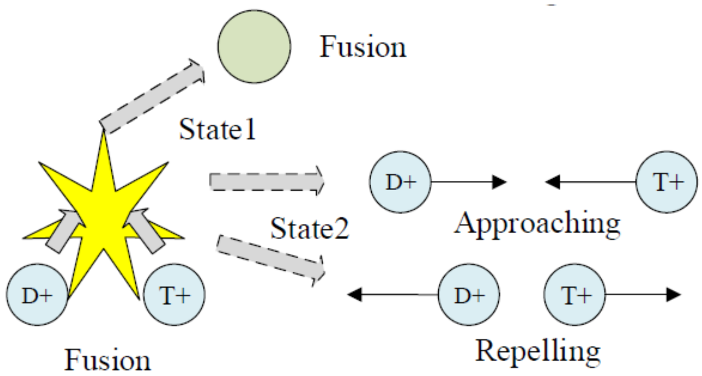

Figure 4. Fission state after ionization

The NRO algorithm employs a boundary control strategy, while the optimization can be stopped if the maximum number of iterations is reached or a certain accuracy is achieved.

4. Nuclear reaction optimization algorithm based on Cat strategy and Levy flight strategy

Although the optimization performance of NRO algorithm is better, the nuclear fission (NFi) and nuclear fusion (NFu) processes still have defects, which make the NRO algorithm poorly diversified and will fall into local optimum. In order to overcome the above defects, this section adopts the Cat chaotic mapping strategy and Levy flight strategy to improve the NRO algorithm.

4.1. Improvement strategies

Cat chaotic mapping strategy

In the standard NRO algorithm, the population random initialization method produces uneven distribution of individual positions and poor stability, which reduces the optimization accuracy of the algorithm.The Cat mapping strategy is a two-dimensional reversible chaotic mapping with a simple structure, which has better traversal and iterative speeds and can be computed to obtain uniform chaotic sequences [26]. In order to increase the initial population diversity, this paper adopts Cat chaotic strategy to improve the population initialization process of NRO algorithm.The kinetic equation of Cat chaotic strategy is calculated as follows:

$$\begin{bmatrix} x_{n+1} \\ y_{n+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_n \\ y_n \end{bmatrix} \text{mod} 1 \tag{18}$$

where the interval of the chaotic sequence generated by Cat is [0,1] and mod denotes the modulo operation.

Levy Flight Strategy

Levy flight has a small flight step in a long time, and occasionally produces a longer flight step to increase the diversity of the flight [27]. the NRO algorithm nuclear fission phase State2 is easy to produce a local optimum. In order to overcome this defect, the Levy flight strategy is used to improve the search efficiency of the nuclear fission phase of the NRO algorithm.The specific formula for the Levy flight model is as follows:

$$x_i^{t+1} = x_\alpha + randn \cdot Levy\left(x_i^t\right) + randn \cdot \left| x_{lbest,i} - x_i^t \right| \tag{19}$$

$$Levy\left(x_i^t\right) = \alpha \cdot s \cdot \left(x_\alpha - x_i^t\right) \tag{20}$$

Where x_i^{t+1} denotes the i th gray wolf individual in the $t+1$ th generation, $Levy(\cdot)$ denotes the Levy flight model, α denotes the scale factor, which takes the value of $[-1,1]$; s is the random wandering step, which is calculated as follows:

$$s=\frac{u}{|v|^{1/\beta}} \tag{21}$$

$$\sigma_u=\left[\frac{\Gamma(1+\beta)\cdot\sin(\pi\cdot\beta/2)}{\Gamma((1+\beta)/2)\cdot\beta\cdot 2^{(\beta-1)/2}}\right]^{1/\beta} \tag{22}$$

$$\sigma_v=1 \tag{23}$$

Where, u and v are parameters obeying normal distribution, i.e. $u \sim N(0,\sigma_u^2)$, $v \sim N(0,\sigma_v^2)$, $\Gamma(\cdot)$ are gamma functions.

4.2. Improvement Algorithm Steps and Processes

According to the principle and mechanism analysis of CatLevyNRO algorithm, the flow of CatLevyNRO algorithm is shown in Fig. 5, and the specific steps are as follows:

Step 1: Initialize the CatLevyNRO population size with the number of iterations;

Step 2: Initialize CatLevyNRO population. Initialize the CatLevyNRO population using the Cat chaotic mapping strategy, calculate the fitness value, or obtain the current optimal value and optimal solution;

Step 3: In the NFi phase, a new nucleus is generated using the Levy flight strategy to simulate a nuclear fission reaction;

Step 4: In the NFu phase, the population location information is updated by combining the ionization process and the fusion process;

Step 5: Calculate the fitness value and select and retain the better solution using an elite selection strategy;

Step 6: Determine whether the number of iterations reaches the maximum number of iterations. If it reaches, output the optimal solution and optimal value; otherwise, return to step 3.

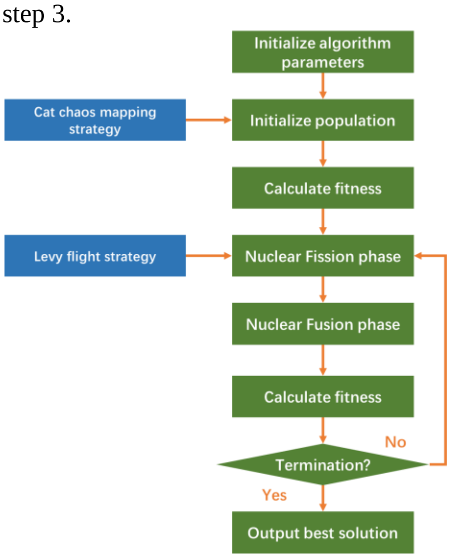

Figure 5. Flowchart of the CatLevyNRO algorithm

5. Ideas for applying the CatLevyNRO algorithm to the problem of converging self-monitoring strategies for on-line learning

In order to verify the effectiveness and superiority of the proposed method in this paper, this section applies the online learning self-monitoring strategy, uses a questionnaire to obtain data, and optimally solves the fusion weights through comparative analysis to verify the effectiveness of the proposed strategy.

5.1. Data acquisition

In order to verify the effectiveness of the algorithm, combined with the online learning self-monitoring strategy, this section adopts the questionnaire on the online learning self-monitoring ability of college students, by comparing the Likert-type scores of the five strategy elements in the online learning ability questionnaire of college students before and after the use of self-monitoring strategy [28], establishing the score difference objective function, and constructing the fusion optimization model, the The CatLevyNRO algorithm was utilized to solve the fusion weights of the students in the questionnaire.

5.2. Objective function

Corresponding to the five aspects of enhancing self-efficacy strategy, maintaining good motivation strategy, strengthening learning method guidance strategy, strengthening teaching interaction strategy, and promoting two-way co-education strategy, this paper proposes self-efficacy weighting $\boldsymbol{w}_1$, maintaining good motivation weighting $\boldsymbol{w}_2$, strengthening learning method guidance weighting $\boldsymbol{w}_3$, strengthening teaching interaction weighting $\boldsymbol{w}_4$, and promoting two-way co-education weighting $\boldsymbol{w}_5$.

In order to optimize the weights of online self-monitoring strategies of college students for each respondent, this section uses the difference between the scores of college students' questionnaires before and after applying self-monitoring strategies for English online learning as the weight optimization objective function:

$$S_{all} = \sum_{t=0}^{end} \left(w_1 \left(S_t^1 - S_{t,0}^1 \right) + w_2 \left(S_t^2 - S_{t,0}^2 \right) + w_3 \left(S_t^3 - S_{t,0}^3 \right) + w_4 \left(S_t^4 - S_{t,0}^4 \right) + w_5 \left(S_t^5 - S_{t,0}^5 \right) \right) \tag{24}$$

$$w_1 + w_2 + w_3 + w_4 + w_5 = 1 \tag{25}$$

Where S_{all} is the value of the weight optimization objective function, S_t^1, S_t^2, S_t^3, S_t^4 and S_t^5 are the questionnaire scores of the t th student after applying the self-monitoring strategy for English e-learning, and $S_{t,0}^1$, $S_{t,0}^2$, $S_{t,0}^3$, $S_{t,0}^4$ and $S_{t,0}^5$ are the questionnaire scores of the t th student before applying the self-monitoring strategy for English e-learning.

5.3. Optimization Process for Fusion of Online Learning Self-Monitoring Strategies Based on CatLevyNRO Algorithm

According to the optimization decision variables and objective function, the flow chart of the fusion optimization method of self-monitoring strategy for English online learning based on CatLevyNRO algorithm is shown in Figure 6, and the specific steps are as follows:

Step 1: Conduct a web-based questionnaire to obtain Likert-type scores on students' self-monitoring ability in English online learning before applying self-monitoring strategies in English online learning;

Step 2: The same batch of students were trained using the self-monitoring strategy for English online learning, and a questionnaire survey was conducted to obtain the Likert-type scores after applying the self-monitoring strategy for English online learning;

Step 3: Initialize the population as well as the number of iterations;

Step 4: Calculate the value of the fitness function;

Step 5: Update the population location information according to the nuclear fission phase and fusion phase mechanisms;

Step 6: Calculate the fitness value and select and retain the better solution using an elite selection strategy;

Step 7: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the optimal fusion weight value, and execute step 8, otherwise continue to execute step 4;

Step 8: Based on the fusion weight values, construct a fusion model of self-monitoring strategies for English online learning.

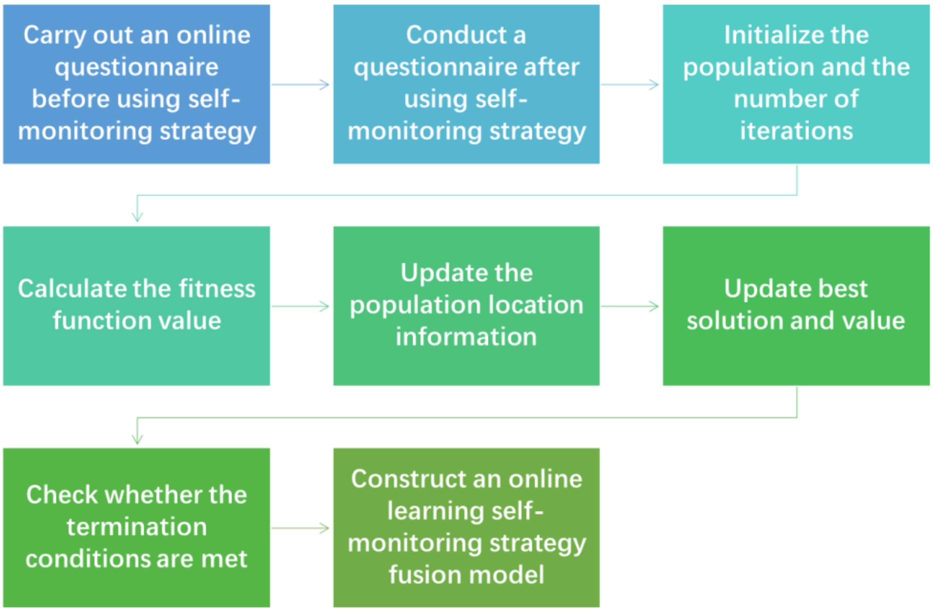

Figure 6. Flow chart of self-monitoring strategy optimization for English online learning

6. Experiments and analysis of results

6.1. Parameterization

In this paper, MATLAB 2021a is used for program writing, and the test environment is Windows 10 system with 16.0 GB of RAM. the experimental dataset is selected from the questionnaire data before and after the application of self-monitoring strategy for English online learning. The specific parameter settings of the fusion algorithm and the comparative fusion method proposed in this paper are shown in Table 1.

Table 1 Fusion method parameter settings

Arithmetic	parameterization
GWO	a=2-2×($iter/iter$)$_{max}$
SOS	Parameter-free optimization algorithm
TLBO	Parameter-free optimization algorithm
SFS	Maximum Diffusion Number (MDN) is set to 1.
ABC	n_0 =0.5×N, n_e =0.5×N, n_s =1, $Limit$=n_e ×D
NRO	p_{Fi} =0.75, p_β =0.1, freq=0.05
CatLevyNRO	p_{Fi} =0.75, p_β =0.1, freq=0.05

6.2 Analysis of experimental results

In order to verify the feasibility and effectiveness of the fusion weight optimization based on the CatLevyNRO algorithm, the survey scores before and after the self-monitoring strategy for English online learning were selected as the input data for the CatLevyNRO optimization weight analysis. The population number and maximum number of iterations of the algorithms are set to 50 and 500, respectively, and each algorithm optimizes each cultivation strategy weight independently for 20 runs.

Figure 7 gives the convergence process of English online learning self-monitoring strategy fusion weight optimization. From Figure 7, it can be seen that the fusion weight optimization of English online learning self-monitoring strategy based on CatLevyNRO algorithm converges the fastest, obtains the optimal objective function value in the 20th iteration, and solves for the optimal weight value. Figure 8 gives the number of weight optimization convergence iterations. From Fig. 8, it can be seen that GWO, SOS, TLBO, SFS, ABC, NRO, and CatLevyNRO algorithms converge at 110, 25, 76, 23, 95, 89, and 20 iterations, respectively. In conclusion, CatLevyNRO algorithm converges faster than other optimization algorithms and obtains the best weight optimization results.

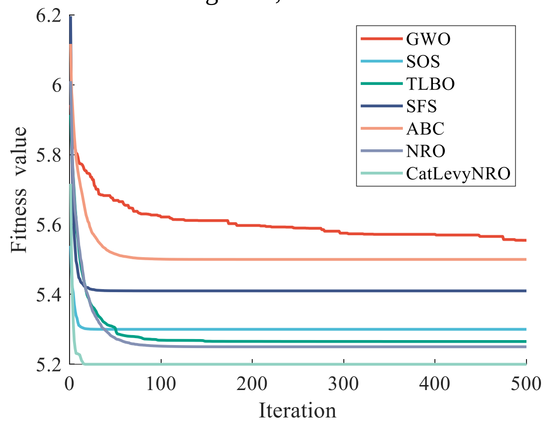

Figure 7. Convergence process of fusion weight optimization

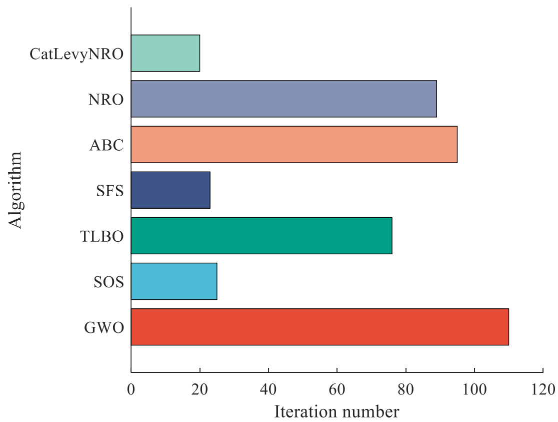

Figure 8. Number of convergence iterations for fusion weight optimization

Figure 9 gives the optimization results of self-monitoring strategy fusion weights for English online learning. As can be seen from Figure 9, the final results of the fusion weights of self-monitoring strategies for English online learning based on the CatLevyNRO algorithm: self-efficacy weights 0.31, maintaining good motivation weights 0.24, strengthening the learning method guidance weights 0.21, strengthening the teaching and learning interactions weights 0.17, and promoting the two-way co-education weights 0.07, and self-efficacy and good motivation strategies play the biggest role in self-monitoring. role is the largest.

Algorithms	W1	W2	W3	W4	W5
GWO	0.29	0.37	0.12	0.09	0.13
SOS	0.14	0.15	0.19	0.32	0.20
TLBO	0.10	0.14	0.27	0.23	0.26
SFS	0.16	0.08	0.41	0.15	0.20
ABC	0.17	0.27	0.26	0.21	0.09
NRO	0.29	0.11	0.19	0.22	0.19
CatLevyNRO	0.31	0.24	0.21	0.17	0.07

Figuer 9. Comparison of fusion weight optimization results

Figure 10 gives the optimization time of English online learning self-monitoring strategy fusion weight optimization. From Figure 10, it can be seen that the optimization time of fusion weight optimization of self-monitoring strategy for English online learning based on CatLevyNRO algorithm is more than SFS algorithm and less than GWO, SOS, TLBO, ABC, and NRO algorithms.

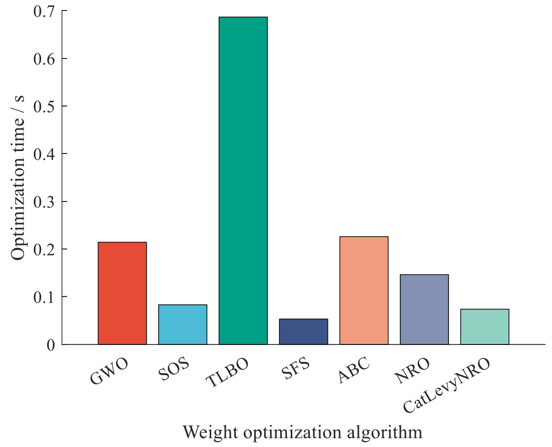

Figure 10. Comparison of fusion weight optimization time

In order to further verify the feasibility of optimizing the weights, this paper selects 60 college students as survey samples, statistically analyzes the questionnaire scores before and after applying the self-monitoring strategy for English online learning, and optimally solves the statistical data using the CatLevyNRO algorithm to obtain the results of the weight optimization, as shown in Figure 11 and Figure 12. As can be seen from Figure 11, the overall trend after weight optimization is similar to the overall trend before optimization. The average weight error notation over is shown in Figure 12. From Figure. 12, it can be seen that the error between the weight optimized value and the pre-optimization value is controlled within 0.05, indicating that the algorithm proposed in this paper is effective and feasible.

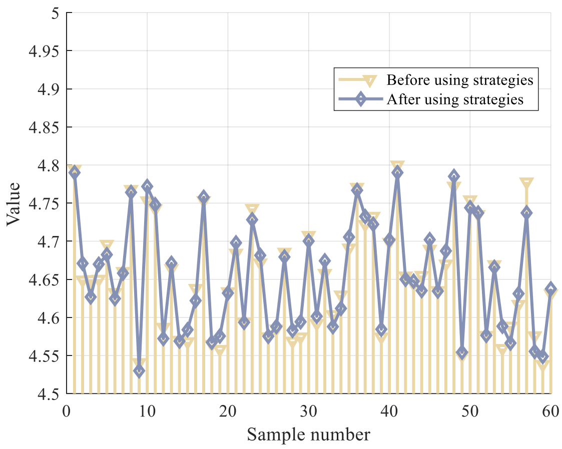

Figure 11. Comparison of scores before and after fusion weight optimization based on CatLevyNRO algorithm

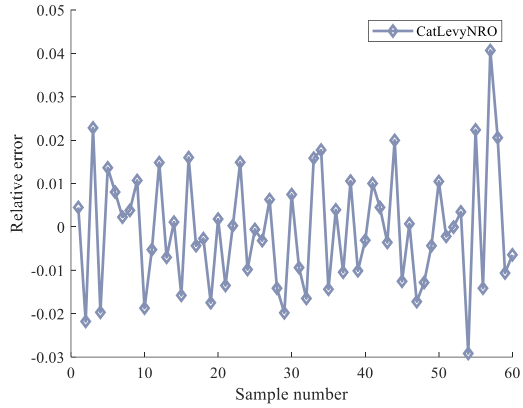

Figure 12. Score error before and after fusion weight optimization based on CatLevyNRO algorithm

7. Conclusion

In order to solve the problem of English online learning self-monitoring strategy fusion application analysis, this paper proposes an optimization method for English online learning self-monitoring strategy fusion based on CatLevyNRO algorithm. The method studies the problems of online learning self-monitoring, analyzes and proposes online learning self-monitoring strategies; improves the NRO algorithm by using Cat Chaos Mapping Strategy and Levy Flight Strategy, and proposes a fusion method of online learning self-monitoring strategies based on the improved NRO algorithm. Through experimental analysis, the online learning self-monitoring strategy fusion method in this paper is effective and feasible, and the convergence optimization starts in the 20th iteration, the optimization time is less than 0.1s, and the error of statistical score value before and after weight optimization is controlled within 0.05. The CatLevyNRO optimization algorithm is easy to fall into the optimization precocity, so the next step of the research focuses on further improving the optimization of online learning self-monitoring strategy fusion method based on the CatLevyNRO algorithm. the fusion optimization efficiency of online learning self-monitoring strategy.

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