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Retraction

Retracted: Classroom Resource Optimization of the English Four-Step Model Based on Deep Learning

Security and Communication Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Zhao and L. Wang, "Classroom Resource Optimization of the English Four-Step Model Based on Deep Learning," *Security and Communication Networks*, vol. 2021, Article ID 7741425, 10 pages, 2021.

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Research Article

Classroom Resource Optimization of the English Four-Step Model Based on Deep Learning

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The existing LBL (lecture-based learning) and CBL (case-based learning) teaching modes of English majors in colleges and universities do not contribute to cultivating students' inquisitive thinking and independent learning ability, whereas the problem-centered PBL (problem-based learning) teaching mode can precisely make up for these shortcomings. This study firstly constructed a PBL "four-step" teaching mode and then realized the innovative application of PBL teaching model in the teaching of English majors in new universities. Then, we designed a method of English classroom resource optimization based on IMOCS-BP neural network, and then, the classroom resource optimization reconstructs the teaching process with unique connotation essence. The experiments show that the BL "four-step" teaching model is designed to achieve the four key elements of "flexible English learning environment, transformed learning the culture, customized content and professional educators"; the designed neural network has optimized the English classroom resources.

1. Introduction

The rapid development of modern information technology has pushed the wave of foreign language education reform, and the opportunity to optimize grammar teaching by transforming new technologies into teaching techniques and seeking teaching mechanisms that fit each discipline. "Optimization of classroom resources" has emerged in the wave of education informatization and has become a hot topic in education reform at home and abroad [1, 2]. The smart classroom, which integrates the advantages of multimedia, informatization, personalization, diversification, and cooperation, can inject vitality into English grammar teaching and provide new teaching ideas, thus improving the teaching effect.

The teaching model refers to a more stable structural framework and active procedure of teaching activities established under the guidance of certain teaching ideology and teaching theory [3]. Research on teaching models has probably gone through three stages: introduction and practical precipitation in the 1980s, theoretical research and disciplinary construction in the 1990s, and practical construction and regional promotion in the 21st century. Although after decades of active exploration and practice, teaching models have been effectively developed and progressed [4], each teaching mode has its own advantages and shortcomings, and no teaching mode is perfect. Therefore, a single teaching mode cannot meet the needs of complex teaching, and in specific teaching practice, we should move from a single mode construction to the comprehensive application of various modes, absorb the essence of various teaching modes, learn from the strengths of all, optimize the combination of modes, and pursue the optimization of teaching effect. The traditional LBL teaching mode and CBL teaching mode [5] are not conducive to the cultivation of students' inquiry thinking, independent learning, and teamwork. In order to meet the requirements of undergraduate teaching and the needs of social development, English majors in new universities need to actively introduce advanced teaching concepts, innovate teaching modes, and optimize the combination of modes, so as to improve teaching quality and enhance teaching level.

LBL is a traditional teaching mode in which the teacher is the main subject in the classroom, and the students are passive learners, which is a typical indoctrination teaching mode [6]. CBL is an abbreviation of case-based learning, which is a group discussion teaching model based on case studies [7, 8].

In the education industry, AI is used not only to save teachers' manpower and improve teaching efficiency but also to drive changes in teaching methods. Taken AI-driven personalized education as an example, data on student assignments, classroom behavior, and exams to personalize the diagnosis of different students' learning situations are collected [9].

According to the different degrees of combination of existing teaching modes and PBL teaching mode, this study firstly constructs a "four-step" teaching mode of PBL to realize the innovative application of PBL teaching mode in the teaching of English majors in new universities in a step-by-step manner. Then, we designed a method of English classroom resource optimization based on IMOCS-BP neural network, and then, the classroom resource optimization reconstructs the teaching process with unique connotation essence. The introduction of neural network's English classroom resource optimization method in English grammar teaching has positive significance for optimizing English grammar teaching.

2. Related Work

As a new concept of teaching and learning that has received much attention in the information age, scholars at home and abroad have different definitions of classroom resource optimization [10–12]; they believed that classroom resource optimization refers to the reversal of in class and out-of-class activities and shifting teaching and learning activities originally conducted in the traditional classroom to off-class and vice versa. Also, the use of learning technologies, especially multimedia, provides new learning opportunities for students.

The founders of classroom resource optimization saw classroom resource optimization as a means and a mode of instruction that blended direct instruction with constructivist conceptions of learning models, increasing interaction and personalized contact time between teachers and students [13]; it also allowed content to be preserved and students to review it as they saw fit, so that students who were absent from class were not left behind. Classroom resource optimization reverses the order of knowledge transfer and knowledge internalization, so that knowledge transfer, which was originally done by teachers in class, is done after class with the aid of information technology, and knowledge internalization, which was originally done by students through after class homework and practice, is done in class with the help of teachers and peers [14].

The most important value of classroom resource optimization is the preclassroom videos, teacher-student communication, and effective face-to-face interactive teaching activities [15]. The study also points out that classroom resource optimization is not only about creating videos according to the instructional schedule but also about individualizing students' need, exploring their misconceptions about the content, and personalizing their education. It is emphasized that classroom resource optimization should include both interactive group learning activities in the classroom and individual computer-based learning instruction outside the classroom [16]. Although there is no definitive definition of classroom resource optimization, the essence of flipped teaching is very different from the traditional classroom.

3. Construction of the "Four-Step" Teaching Model

Based on the current situation and problems of the teaching mode of English majors in colleges and universities, and the advantages and shortcomings of PBL teaching mode in the process of application, the innovative research of PBL teaching mode in the teaching of English majors in colleges and universities is carried out by combining PBL teaching mode and traditional teaching mode, and constructing the PBL "four-step" teaching mode (see Table 1) [17]. The four-step teaching mode (see Table 1) is used to realize the effective application of PBL teaching mode in a step-by-step manner.

3.1. PBL "First-Order" Teaching Model. The first stage of PBL teaching mode is based on the traditional teaching mode, and the introduction stage is the initial stage of the four-stage PBL teaching mode. The teaching characteristics of this stage are mainly the traditional LBL teaching mode and CBL teaching mode, and the introduction of PBL teaching mode is mainly for freshmen, aiming to let students have a preliminary contact and understanding of PBL teaching mode. The teaching mode at this stage is suitable for theoretical basic courses, such as management, economics, and the like, because these courses require students' memory more and require students' practicality and applicability less, so the traditional "LBL + CBL" teaching mode is more suitable. However, in order to better promote the application of PBL teaching mode in English majors, the PBL teaching mode can be introduced at this stage, and one or two chapters can be selected for the application of PBL teaching mode in a targeted way, so that students can have preliminary contact with and understand the PBL teaching mode and lay the foundation for the promotion of PBL teaching mode in the next stage [18].

3.2. PBL "Second-Stage" Teaching Model. The second stage of PBL teaching mode is a stage in which the traditional teaching model is mainly supplemented by the PBL teaching mode. The teaching characteristics of this stage are still mainly traditional LBL teaching mode, supplemented by PBL teaching mode and CBL teaching mode, and the proportion of the application of PBL teaching mode should be significantly increased compared with the first stage. The

Table 1: "Four-step" teaching model.

Project hierarchy	Combination form	Application characteristics	Covered courses	Achieve goals
First order	Based on traditional teaching mode, PBL teaching mode is introduced	Based on LBL teaching mode, introducing CBL teaching mode into PBL teaching mode	Basic courses with strong theoretical nature, such as management and economics	Preliminary understanding of PBL teaching mode
Second order	Traditional teaching mode is the main teaching mode, supplemented by PBL teaching mode	LBL teaching mode is mainly used, PBL teaching mode is supplemented, and CBL teaching mode is also used	Theoretical and practical basic courses, such as economic law and investment	Preliminarily mastering of PBL teaching mode
Third order	Balanced distribution of traditional teaching mode and PBL teaching mode	Balanced distribution of LBL teaching mode, PBL teaching mode, and CBL teaching mode	Professional core courses with strong theoretical and practical nature, such as marketing and financial analysis	Better use of PBL teaching mode
Fourth order	PR teaching mode is the main teaching mode, supplemented by traditional teaching mode	PBL teaching mode is mainly supplemented by LBL teaching mode and CBL teaching mode	Comprehensive practical courses with strong practicality, such as ERP simulation training and financial accounting simulation training	Skillful use of PR teaching mode

teaching mode at this stage is suitable for theoretical and practical basic courses, such as economic law and investment science. These courses require a high level of memorization, as well as practicality and application. Therefore, on the basis of the traditional LBL and CBL teaching modes, the PBL teaching mode, which focuses on the practical and application training of students, is more conducive to the cultivation of students' comprehensive quality and ability.

3.3. PBL "Third-Order" Teaching Model. The "third stage" of PBL is the stage of balanced distribution of traditional teaching mode and PBL teaching mode. This stage is characterized by the balanced distribution of traditional LBL teaching mode and PBL teaching mode and CBL teaching mode, and the proportion of PBL teaching mode is further increased and equal to the traditional teaching model. The teaching mode at this stage is suitable for core course with a strong theoretical and practical orientation, such as marketing and financial analysis. These courses require a high level of memorization, practicality, and application. Therefore, under the condition that the traditional LBL teaching mode and PBL teaching mode have equal weight, it is more favorable to further enhance students' independent thinking and knowledge application ability.

3.4. PBL "Fourth-Order" Teaching Model. The "fourth stage" of PBL teaching mode is a stage in which PBL teaching mode is the main teaching mode and traditional teaching model is supplemented. The teaching characteristics of this stage are mainly PBL teaching mode, supplemented by LBL teaching mode and CBL teaching mode, which completely overturn the traditional teaching mode and greatly increase the proportion of PBL teaching mode, aiming to make students master PBL teaching mode, mainly for junior and senior students. The teaching mode at this stage is suitable for comprehensive practical classes with a strong practical orientation, such as ERP simulation training and accounting simulation training. These courses do not require a high level of memory, but they require a high level of practicality and applicability. Therefore, the "fourth-order" teaching mode, which is mainly based on PBL and supplemented by traditional teaching mode, is more conducive to the cultivation of students' comprehensive quality and abilities such as independent thinking, independent learning, and teamwork [9, 15, 19].

The "four-step" teaching model of PBL is built by combining the advantages and shortcomings of the existing LBL and CBL teaching models and the new PBL teaching model of English majors in new universities. This model organically combines the three teaching modes and complements their strengths and weaknesses so as to achieve complementary advantages. The application of the innovative PBL teaching mode in new universities aims to update the teaching concept and enrich the teaching mode, so as to gradually improve the teaching quality and teaching level of economics and management majors in new universities and cultivate talents that meet the requirements of undergraduate teaching and the needs of social development.

4. IMOCS-BP Neural Network Algorithm

4.1. Improved Multiobjective Cuckoo Search (IMOCS) Algorithm. The BP neural network achieves nonlinear mapping for differential transfer and adapts to the changing external environment by continuously self-learning through forward transmission signals and reverse transmission errors to adjust the weights and thresholds [12, 20]. The topology of the BP neural network with input, implicit, and output layers is shown in Figure 1. The weights and thresholds of the BP neural network are initialized by random assignment, which cannot achieve the desired prediction effect at a faster rate during training and are prone to fall into local optimal solutions. In this study, the initial weights and thresholds of the BP neural network are optimized by IMOCS.

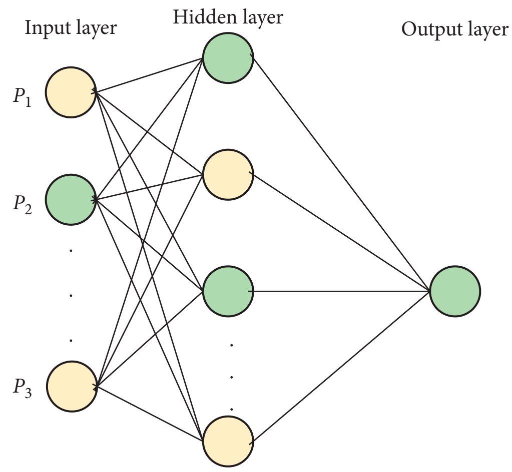

FIGURE 1: BP neural network.

The MOCS algorithm is an extension of the CS algorithm to multidimensional space, which inherits the advantages of the CS algorithm, such as strong global search ability, few parameters, and easy implementation [13], but still suffers from the influence of the CS algorithm resulting in a slow convergence rate. The basic idea of the CS algorithm is derived from the Levi non-Gaussian random flight behavior of birds and the breeding characteristics of cuckoos. In the individual flight, alternating short distance with small steps and long distance with large steps can prevent the algorithm from falling into local minima [14, 15]. The update process of all individual positions is shown in equation (1) as a Markov chain (MC) process.

$$x_{ij}^{m+1} = x_{ij}^{m} + \alpha \times L(\lambda), \tag{1}$$

where x_{ij}^{m} and x_{ij}^{m+1} denote the paths of the i-th test to $(i = 1, 2, \ldots, n)$ in the $j\,(j = 1, 2, \ldots, d)$th dimension of the mud and m 1st generation and the jump paths of the random search by Levy flight are denoted by $L(\lambda)$. Because the search step size is determined by the "Lévy flight," it is not guaranteed to have a large search step size in the first stage to speed up the convergence. In order to guarantee the convergence speed and accuracy of the algorithm, it is necessary to make the first search step large enough to find the optimal solution direction quickly, and as the number of iterations increases, the step size should be reduced to make the algorithm stable. Therefore, in this study, we proposed the IMOCS algorithm, which uses the cosine decrement method to define the decrement coefficients and introduces the function trend factor to realize the adaptive adjustment of the step size [16, 21].

$$\begin{aligned} \alpha_{\text{Iter}+1} &= a * \alpha_{\text{Iter}}, \\ a &= \cos\left(\frac{\pi}{2}\frac{\text{Iter}}{\text{Iter}_{\text{total}}}\right)\Delta f, \end{aligned} \tag{2}$$

where Iter and $\text{Iter}_{\text{total}}$ represent the number of current iterations and the total number of iterations, α_{Iter} is the current adaptive step factor, a is the influence factor, and $\Delta f = |f_{\text{Iter}+1} - f_{\text{Iter}}/f_{\text{Iter}}|$ is the trend of the value of the two iterations. The improved positions update process is

$$x_{ij}^{\text{Her}+1} = x_{ij}^{\text{ler}} + \alpha_{\text{teer}+1} \times L(\lambda). \tag{3}$$

In general, the cuckoo algorithm sets the probability of finding eggs to generate new solutions $p_a = 0.25$, but in the later stage, it may cause the loss of high-quality solutions and affect the convergence efficiency and accuracy of the algorithm. In order to avoid the impact on the algorithm caused by the loss of high-quality solutions, the probability p_a should be adjusted by the same reason as above, i.e., taking a larger value in the early stage and decreasing the value of p_a as high-quality individual solutions are generated to ensure the convergence speed of the algorithm.

$$p_a = p_{a\max} - \sin\left(\frac{\text{Iter}}{2\text{Iter}_{\text{total}}}\pi\right)(p_{a\max} - p_{a\min}), \tag{4}$$

where $p_{a\max}$ and $p_{a\min}$ are control parameters.

4.2. English Classroom State Estimation Based on IMOCS-BP Neural Network. Based on the IMOCS-BP neural network, we use IMOCS to globally search the space of each node of the BP neural network, optimize the initial value of each node on the basis of the global minimum value searched at the end of the iteration of IMOCS, and then perform the exact search by gradient descent method, estimating student classroom status based on IMOCS-BP neural network as shown in Figure 2.

The specific algorithm is as follows:

(1) Read the input output data input output.
(2) Set the number of bird nests (nodes), set the BP network structure, neptunium of input nodes, hiddenite of hidden layer nodes and outputted from output nodes, and construct the network net.
(3) Normalize the training set input_training output_training with the test set input_test output_test to obtain input and output.
(4) Set the control parameters for the update probability $p_{a\min}$, $p_{a\max}$.
(5) The number of bird nests n, the network structure parameters impugned, hiddenite, outputted, network net, and the normalized parameters input and output are taken as input parameters and optimized using IMOCS.
(6) Set the global search for lower limit nd, set the number of iterations iterative, and get the optimal initial weight and threshold bested after optimization by IMOCS.
(7) The optimal initial optimized weight and threshold bested is assigned to the BP neural network.
(8) Selection of transfer function: in general, the transfer function of the implicit layer in the BP neural network is a sigmoid function [22] with arbitrary input and output from 0 to 1. The traditional sigmoid will

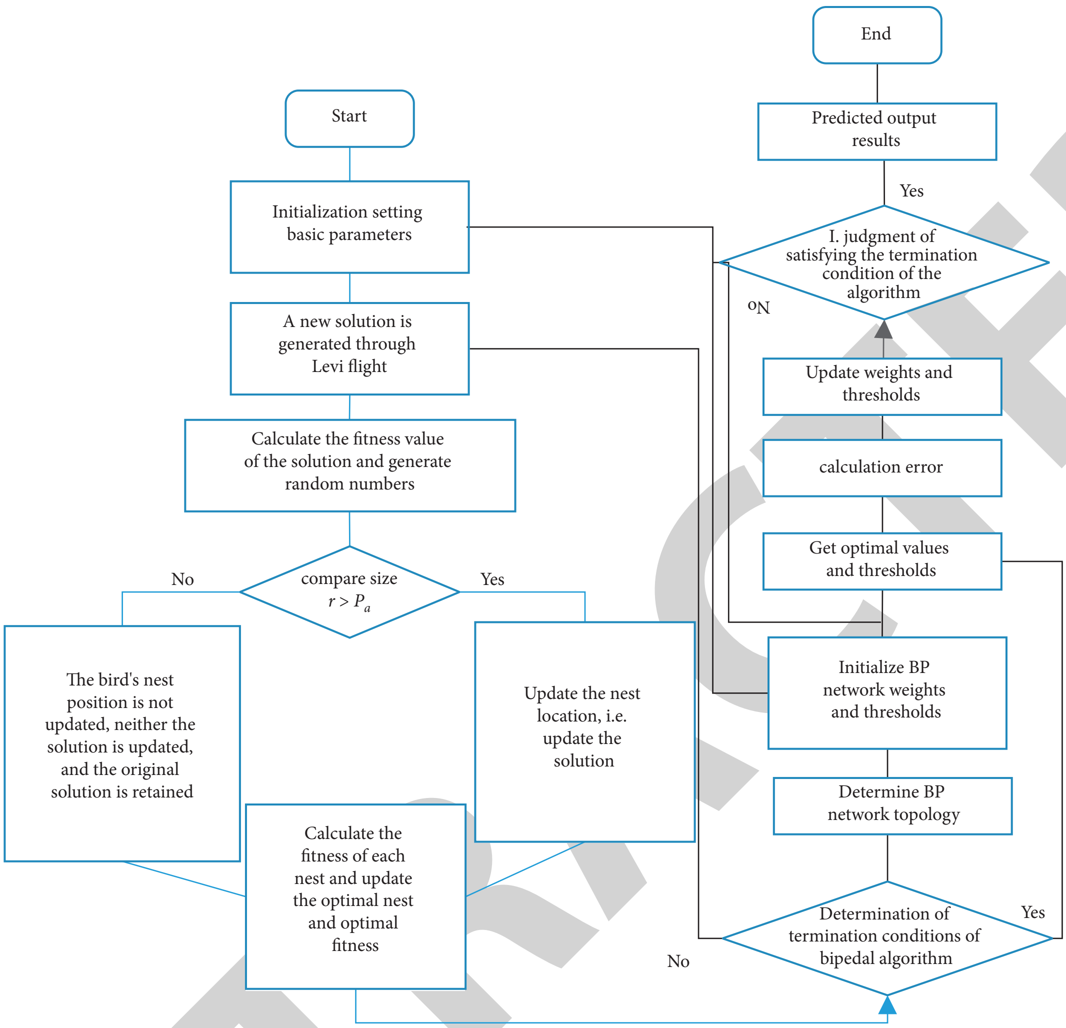

Figure 2: Estimating student classroom status based on IMOCS-BP neural network.

centre the data so that the average value of the data is close to 0.5, whereas the transit function with arbitrary input and output between −1 and 1 will make the average value of the data closer to 0. Therefore, except for the binary classification case where the performance of the sigmoid is better, the tuning function is more applicable and performs better. Therefore, the tansy function $f(x) = 2/1 + e^{-2x} - 1$ is used as the transfer function in the implicit layer, and the linear transfer function purely function $g(y) = y$ is used in the output layer [23].

(9) The battery data samples are divided into a training set and a test set, and the algorithm is trained with the first segment data as the training set, and the latter segment test set data are used for prediction and comparison [24].

5. Simulation and Analysis

5.1. Simulation Data. In this study, the experimental test data of English classrooms in colleges and universities were used to simulate the SOH prediction of BP neural network [13, 25], MOCS-BP neural network, and IMOCS-BP neural network. The selected three groups of English classrooms were evaluated by students' learning efficiency, ability, and status; their learning methods were the same all with 1.5 min learning status and ended with 2 min learning, 5#, 6# and 7# students stopped at 2.7, 2.5, and 2.2 min, respectively, and finally the classroom optimization parameters were obtained by learning effect measurement.

The actual change in SOH is nonlinear and fluctuating, not simply declining, because the number of ELLs [26] increases and the change in student learning outcomes becomes more dramatic, as verified in Figure 3. Because the SOH of ELL cannot be measured directly due to multiple factors, a health factor (HI) [8, 27] is needed to characterize the change in SOH. In general, the most intuitive observation of the decline in ELL performance is characterized by a decline in capacity, and it is most accurate to use the change in capacity as a direct HI. The actual measurement of capacity is usually done using destructive intrusion measurements, which makes it difficult to achieve online application of SOH, so this

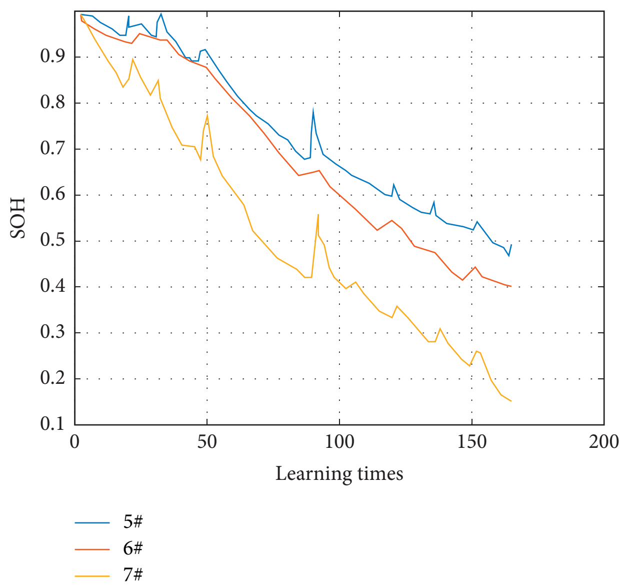

Figure 3: Learning measurement data.

study used classroom effects as an indirect HI input algorithm for student learning, with SOH defined by the capacity method as the output. Three groups of student data, #5, #6, and #7 student, are used for simulation using BP, MOCS-BP, and IMOCS-BP algorithms, respectively, and the data are divided into two segments for training and testing, respectively.

5.2. Evaluation Indicators. In this study, three metrics, mean square error (MSE), mean absolute error (MAE), and mean relative error (MAPE) [7, 28] are selected to evaluate the performance of the above three algorithms. The three metrics are shown in the following equations (5)–(7), respectively.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i' - Y_i\right)^2,$$
$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i' - Y_i\right|, \quad (5)$$

where, Y_i' is the output prediction, Y_i is the true value, and N is the number of predicted samples.

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\frac{\left|Y_i' - Y_i\right|}{Y_i}. \quad (6)$$

It is worth noting that the range of MAPE is $[0, +\infty]$, and the larger the MAPE tends to 0%, the stronger the performance of the model, and conversely, the larger the MAPE is, the worse the performance.

5.3. Simulation Design. When setting up a BP neural network, its performance is easily influenced by the number of hidden layers. The empirical formula for the implicit layer setting problem can be referred to as shown in the following equation:

$$M_{\mathrm{mum}} = \sqrt{M_{\mathrm{in}} + M_{\mathrm{out}}} + a. \quad (7)$$

The number of nodes in the hidden layer is M_{mum}, the number of nodes in the input layer is M_{in}, the number of nodes in the output layer is M_{out}, and a is a constant between 0 and 10. In this study, the performance of BP neural network algorithms with different number of hidden layers was evaluated using MSE, MAE, and MAPE, and the most powerful 4-layer BP neural network was selected for comparison with the other two methods, and the evaluation results are shown in Table 2.

When the traditional MOCS-BP algorithm is used, the experimental results with different parameters show that it is better to set the hidden layer to 3 layers. The structure of the BP neural network is 5-3-1, so the number of weights and thresholds of the BP neural network to be optimized can be determined, and the 22 parameters of the neural network structure are optimized for both the MOCS and IMOCS algorithms. The optimal weights and thresholds are assigned to the initial weights and thresholds of the BP neural network, and then, the prediction of SOH by the BP neural network is achieved. From the best results of multiple trials, we determine the probability of random egg abandonment by the host $P_a = 0.25$, the number of nests $n = 25$, the lower limit of global search $nd = 22$, and the number of iterations itertotal = 100.

Unlike the MOCS-BP algorithm, the other parameters remain unchanged when setting up the IMOCS-BP algorithm and are additionally set $p_{a\max} = 0.5$, $p_{a\min} = 0.1$ [29].

6. Simulation Results and Analysis

The prediction results of the above three methods were tested using three test sets of battery data, and the prediction results of the algorithms are shown in Figures 4–6.

The error plots of the three SOH prediction algorithms for the 5# students are shown in Figure 7. The minimum value of the BP neural network-based prediction error is 1.8, and it increases with the number of iterations, whereas the prediction errors of the two cuckoo optimization algorithms are much lower and do not fluctuate significantly with the increase in the number of iterations [30]. SOH errors of the MOCS-BP algorithm range from −0.012 to 0.004, whereas the IMOCS-BP algorithm is in the range of −0.011 to 0.0038, which further reduces the errors. The performance of the three algorithms is evaluated using the evaluation metrics, and the results are shown in Table 3.

In summary, the IMOCS-BP neural network algorithm has lower error and better performance to meet the prediction requirements of energy storage English learning.

7. Conclusions

According to the different degrees of combination of existing teaching modes and PBL teaching mode, this study firstly constructed a “four-step” teaching mode of PBL to realize the innovative application of PBL teaching mode in the

Table 2: Evaluation indexes of BP neural network with different number of hidden layer layers.

Number of hidden layers	MSE	MAE	MAPE (%)
2nd floor	8.0951	2.7979	139.34
3rd floor	7.2204	2.6490	142.88
4th floor	7.2039	2.6448	143.12
5th floor	8.0319	2.7876	139.52
6th floor	7.2549	2.6538	142.88
7th floor	7.4835	2.6927	141.98
8th floor	7.4585	2.6899	141.89
9th floor	7.8264	2.7573	140.25
10th floor	7.3098	2.3342	142.53
11th floor	8.5723	2.8803	137.12
12th floor	7.6117	0.7159	141.29

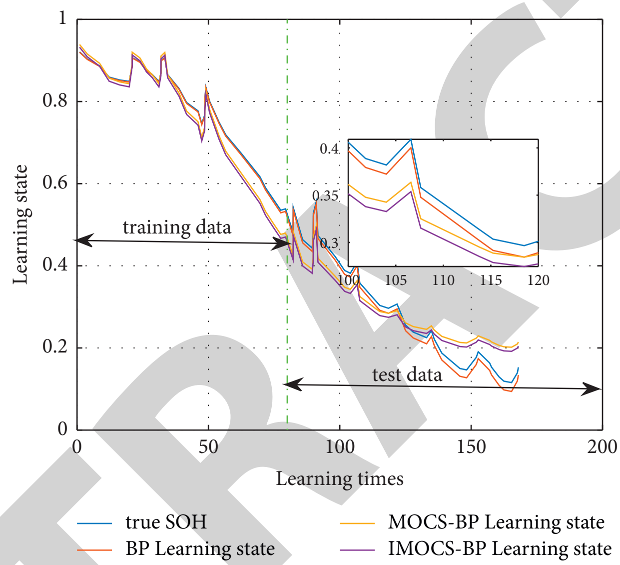

Figure 4: Prediction of SOH of students 5# by BP, MOCS-BP, and IMOCS-BP.

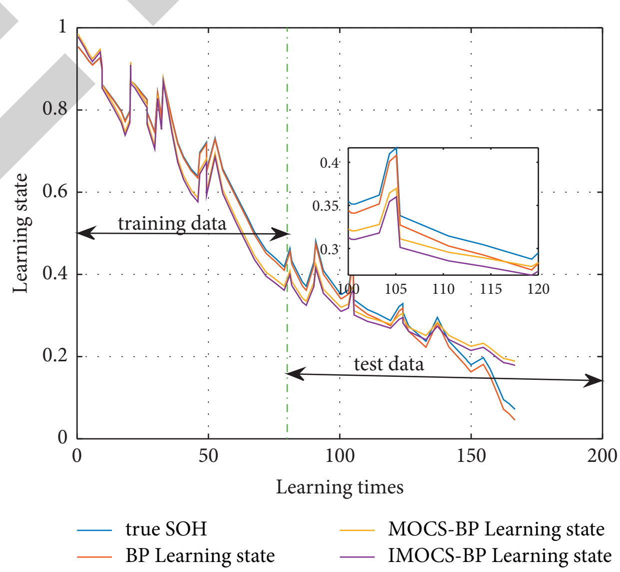

Figure 5: Prediction of SOH of students 6# by BP, MOCS-BP, and IMOCS-BP.

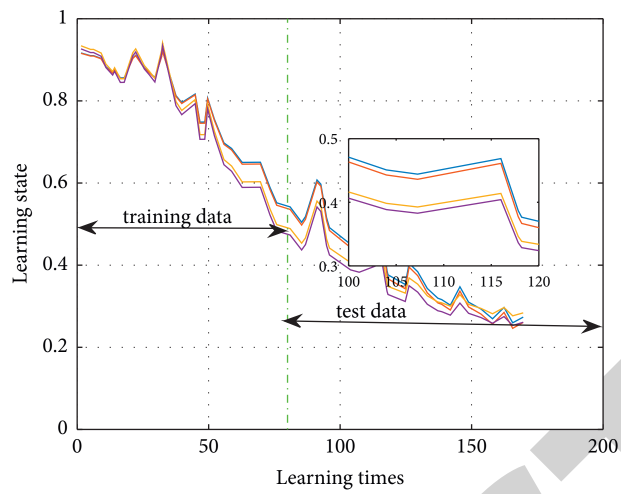

FIGURE 6: Prediction of SOH of students 7# by BP, MOCS-BP, and IMOCS-BP.

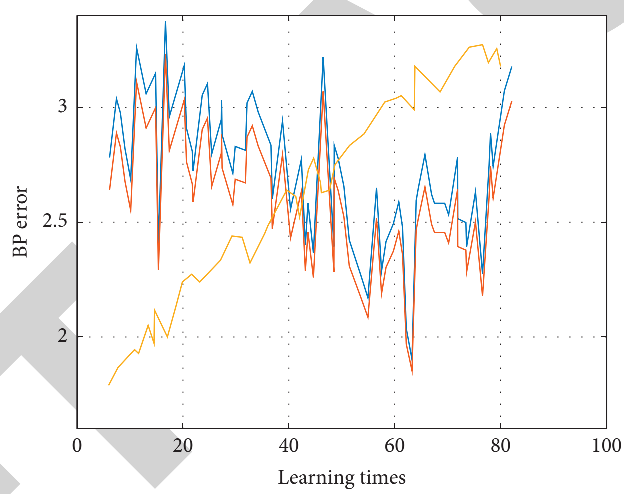

FIGURE 7: Comparison of the prediction errors of BP, MOCS-BP, and IMOCS-BP.

TABLE 3: Algorithm evaluation metrics.

Battery number	Evaluating indicator	MSE	MAE	MAPE
	BP	7.2023	2.6448	143.12%
5#	MOCS-BP	2.1781×10^{-5}	0.0039	0.54%
	I MOCS-BP	1.5202×10^{-5}	0.0032	0.43%
	BP	4.9398	2.1890	147.09%
6#	MOCS-BP	5.2855×10^{-5}	0.0048	0.80%
	I MOCS-BP	1.9847×10^{-5}	0.0032	0.525
	BP	7.4596	2.6842	145.335
7#	MOCS-BP	1.5933×10^{-5}	0.0031%	0.40%
	I MOCS-BP	6.9364×10^{-5}	0.0021	0.27%

teaching of English majors in new universities in a step-by-step manner. Then, we designed a method of English classroom resource optimization based on IMOCS-BP neural network, and then, the classroom resource optimization reconstructed the teaching process with unique connotation essence. The introduction of a neural network approach to English classroom resource optimization in English grammar teaching has positive implications in optimizing English grammar teaching. The experiments show that the BL "four-step" teaching model and the designed neural network optimize the English classroom resources.

In the future, one needs to discuss the stability of the algorithm, optimize the classroom resources to reconstruct the teaching process, and then explore its unique connotation essence. Some functions of the algorithm should be improved to further optimize the "four-order" teaching mode and the neural network designed to further optimize English classroom resources.

Data Availability

The data set used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Acknowledgments

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