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RESEARCH ON THE APPLICATION OF PROJECT TEACHING METHOD IN THE NEW MODEL OF SOFTWARE ENGINEERING COURSE

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Abstract. Software engineering course is one of the core courses of computer science. The students trained in the current teaching mode can no longer meet the market demand for high-technology talents. Based on this, the research attempts to optimize the traditional software engineering teaching mode by using the project teaching method (PTM). According to the basic concept of PTM and course characteristics, the reform path of PTM in software engineering course is explored in the experiment. Then in the experiment, the indicators that affect teaching reform effect is selected and a evaluation model is built. And GA-BP algorithm is used to evaluate the effect of the evaluation model. To verify the performance of the built model and the final evaluation effect, the research results are tested from the fitness of the algorithm, error performance, prediction in the data set and other aspects. GA-BP algorithm converged when it iterated to the 18th generation, and the final fitness value was 0.61. The average error square value of GA-BP was 0.35 and the minimum error square sum of GA-BP was 0.48. Its prediction accuracy in test set and training set was 93.4% and 94.1% respectively. The maximum prediction error in the training sample was only 0.015, and the performance of the above data was better than the other three algorithms. To sum up, applying PTM to software engineering curriculum reform can achieve better teaching results.

Key words: Project teaching method; Software engineering; GA-BP; Evaluation model

1. Introduction. Software engineering is one of the core courses of computer colleges in colleges and universities. This requires students to master the relevant theoretical knowledge of software technology in daily learning. And students' engineering awareness and practical hands-on operation design ability need to be cultivated [1]. PTM advocates that under the guidance of the teacher, a relatively independent curriculum project should be handed over to the students themselves. In this process, students' ability to process and collect information, design schemes and successfully implement planned projects can be cultivated [2]. In the process of implementation, there are three prominent features in PTM. The training cycle of the whole teaching process is short, effective and controllable. Students can participate in the project and complete the project design according to the established teaching objectives [3]. BP neural network has many advantages in solving nonlinear problems. In view of the problem that BP neural network is prone to fall into local minimum at the later stage of iteration, many scholars have adopted various algorithms to optimize it [4, 5]. The software engineering teaching in major universities still are concerned about teaching mode and the explanation of basic theoretical knowledge. The whole teaching content is boring. Therefore, students are prone to problems such as boredom, boredom and lack of real participation in learning. About the teaching problems in traditional software engineering courses, the research attempts to reform the traditional software engineering courses with a new teaching method - PTM. GA-BP can evaluate the reformed teaching model, which provides a new reference for innovating the teaching mode of software engineering courses in colleges and universities.

2. Related Works. PTM is to build a real teaching environment around various problems or social issues in life. Under the constructed teaching environment, it can help students turn these issues into driving questions and use them in teaching activities. Given that the current teaching environment is changing, the traditional one-to-one knowledge transfer learning mode no longer meets the requirements of high-quality and high-level talent cultivation [6]. Zak et al. applied the PTM to the teaching and cultivation of engineering students, trying to improve students' learning ability, hands-on ability, cooperation ability, etc. To better show the reform results of PTM applied to engineering teaching, the course completion quality of chemical engineering students was

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evaluated by virtual demonstration and face-to-face demonstration. Students had better performance in the chemical engineering curriculum optimized by the PTM [7]. Vascocelos et al. applied the PTM to the chemical engineering curriculum design project. Students needed to complete the three processes of pre-fermentation, fermentation and distillation in a group cooperation way, and finally report the results before the auditors. In this design project, students and teachers were highly satisfied with the proposed teaching plan [8]. To improve the operation ability of civil engineering students in the actual project design and construction, AMR Pasanda and others carried out optimization experiments on the traditional civil engineering teaching mode. The teaching program combining the PTM and the traditional teaching program were used to teach the students of civil engineering. The teaching scheme combined with the PTM could cultivate more students who have strong movement ability, and their ability to solve problems was also stronger in the actual project operation [9].

Gao et al. used GA-BP to predict the fetal weight. This method aimed to determine whether the fetus could develop healthily and whether the pregnant woman could give birth smoothly. The accurate prediction of fetal weight through the establishment of fetal weight prediction model could provide a new guarantee method for the safety of fetus and pregnant women [10]. Zou M et al. used GA-BP to identify lunar soil's shear parameters, thus providing data support for the path planning, traction control and risk avoidance of the lunar rover. GA-BP algorithm could accurately and effectively identify the shear parameters of lunar soil [11]. Wang Y et al. proposed a model predictive control method combining recurrent back-propagation neural network and genetic algorithm for nonlinear systems with time-delay and uncertainty. In the offline modeling stage, GA-BP network was introduced as the prediction model and used to train parameters. The method proposed in the experiment could effectively reduce the computational load of the nonlinear control system [12].

According to previous research, many colleges and universities had applied PTM to engineering teaching [13]. To solve problems such as path planning and risk avoidance through prediction values, many scholars also used GA-BP neural network to build prediction models [14]. Based on this, the research attempts to apply the PTM to the reform of software engineering curriculum, and constructs the corresponding index evaluation model. The results are used to improve the deficiencies in current software engineering teaching.

3. Research on the application of PTM in software engineering courses and the construction of evaluation index system.

3.1. Path exploration of PTM in software engineering curriculum reform. Software engineering course not only needs to cultivate students' engineering awareness, but also needs to cultivate students' practical ability in teaching [15, 16]. Each new teaching model must refer to some previous teaching ideas and theoretical research when it is proposed and applied. The PTM is to build a real teaching environment around various problems or social issues in life, so that students can turn these issues into driving problems and use them in teaching activities under the constructed teaching environment. In the specific project teaching process, students are not only required to study independently, but also need to cooperate. This research carries out path reform and exploration from the following five aspects.

In Figure 3.1, it mainly explores the application mode of PTM in software engineering courses from the five major theories. They are constructivism learning theory, human comprehensive development theory, learning transfer theory, pragmatism learning theory, and the theory of recent development zone. According to the constructivist school, teachers should care about the dynamic characteristics of knowledge in daily teaching. The individual differences of students' experience should be cared about. And students' interactivity, scene and self-construction in classroom learning should be enriched. The PTM also dominates students' autonomous learning in the whole teaching process, so it conforms to the idea of constructivism school. The core idea of pragmatism advocates "learning by doing", with experience as the core, children as the main body and activities as the center. The PTM can not only combine the theory of pragmatism and emphasize the connection between knowledge, but also emphasize the self-development of students. The recent development zone theory believes that when teaching, students' actual and potential development difference must be paid attention. The difference between the two is also called the nearest development zone. The PTM relies on this theory to develop the modern teaching concept in an all-round way. So that every student who is required to take the software engineering course can learn to build their own understanding of the course. Then, under the leadership of the teachers, the level of their own development has been improved. The theory of all-round development of human beings points out that people with all-round development are those who have achieved

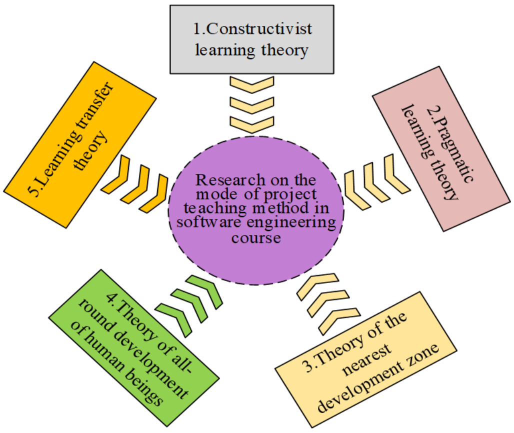


Fig. 3.1: Theoretical basis of PTM in software engineering curriculum reform

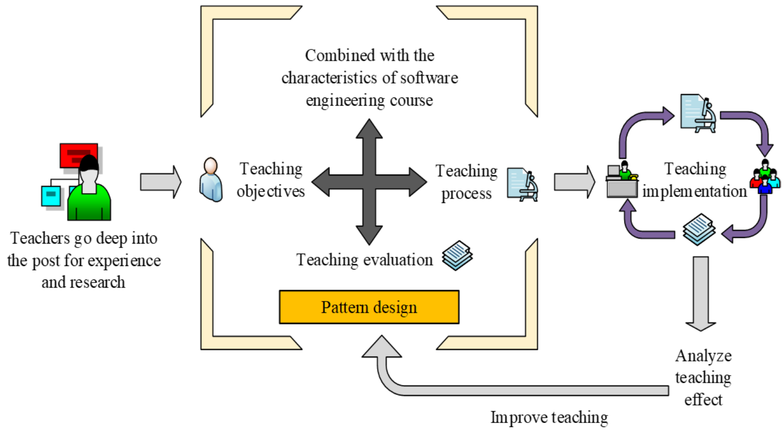


Fig. 3.2: The reform path planning of PTM in software engineering course

coordinated development in physical strength and intelligence. According to this idea, the PTM emphasizes that students should make full use of their potential in all aspects during the teaching process. It should promote students to become people with all-round development of morality, intelligence, physique, beauty and labor in the learning process. The theory of learning transfer believes that, based on the premise of mastering old knowledge, new knowledge's acquisition can be carried out. Because new and old knowledge has a certain transfer function, teachers should consciously give correct guidance to students, and lead them to transferring the knowledge that they have learned in the teaching process. So that a complete knowledge system can be built and students can cultivate their creativity and hands-on ability. Through the above theoretical knowledge, the PTM implementation plan suitable for the software engineering course is formulated. Figure 3.2 shows the reform path planning of PTM in software engineering course.

Before applying PTM to software engineering teaching, it is necessary to investigate the teachers. This is to ensure that teachers have excellent teaching ability, can go deep into the project posts and have sufficient teaching experience. The mode design principle of PTM in software engineering course includes three modules: teaching objectives, teaching process and teaching evaluation. When designing patterns, we should fully combine the characteristics of the software engineering course, so that students can really simulate the development of software under the guidance of teachers. After the model design is completed, it will be applied to the actual

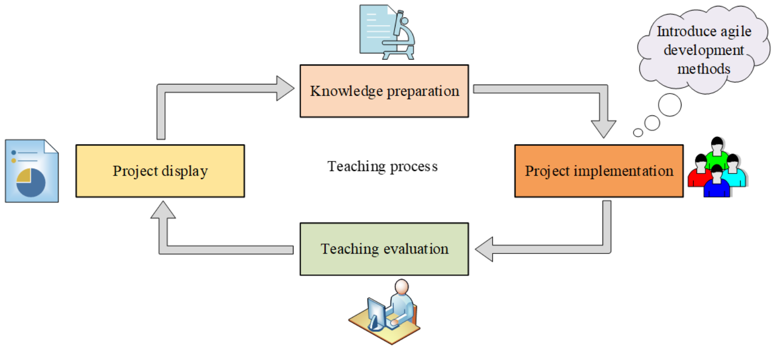


Fig. 3.3: Teaching flow chart of software engineering course combined with PTM

education and teaching. Finally, it will reflect on the teaching results, propose improvement methods for the shortcomings of this teaching, and change the original model design. According to the above reform planning path, the traditional software engineering teaching mode is repeatedly modified until the final teaching model can achieve good evaluation results.

In view of the most important link in the reform path, the construction of teaching process and teaching evaluation index model in the model design is crucial. The construction of teaching evaluation index model will be described in detail in the next section. The design of teaching process is mainly divided into four modules: project presentation, knowledge preparation, project implementation and teaching evaluation. In the project implementation stage, it needs introduce agile development methods to optimize the traditional teaching project implementation methods. The agile development method advocates to focus on research and development, and teaching is only auxiliary. Returning the final R & D results to students can stimulate students' potential for independent learning. At the same time, they can incubate high-quality technical talents for enterprises in advance.

3.2. Construction of PTM used in the software engineering curriculum reform. The last section explored the reform path of PTM in software engineering courses. Next, we will evaluate the implementation effect of PTM by building an evaluation index model. By analyzing the results of the questionnaire and the participation of students, the index factors that affect the PTM in the software engineering curriculum reform are determined.

The evaluation indicators of the PTM used in the software engineering curriculum reform are shown in Table 3.1. Next, the research will optimize the traditional BP neural network, use genetic algorithm to improve the shortcomings of BP neural network, and propose GA-BP neural network model to evaluate the constructed index system. In Figure 3.4, as the basic component of neural network, the structure of artificial neuron is shown [17].

The main components of artificial neural network are the selection of connection weights, summation steps and activation functions in Figure 3.4. The connection weight can combine neurons of different strength. The value of each neuron is weighted and summed by the adder. Finally, the activation functions of different thresholds are set to limit the output amplitude of neurons so that the output signals are consistent.

$$Y_j = f\left\{\left[\sum_{i=1^n} W_{ij}X_i - \theta_j\right]\right\} \tag{3.1}$$

Equation 3.1is the mathematical expression of the basic flow of the above neural network. j and i represent neurons. X_i is neuron input. W_{ij} represents the connection weight value. θ_j is the threshold value. Y_j represents neuron output. $f(\bullet)$ is the activation function. The selection of activation function is generally

Table 3.1: Evaluation index of PTM used in software engineering curriculum reform

Evaluation system	**Main indicators**	**Secondary indicators**	**Indicator code**
PBL used in software engineering curriculum reform	Teacher indicators	Teaching experience	Q1
		Teaching style	Q2
		Knowledge mastery and familiarity	Q3
	Student indicators	Learning attitude	Q4
		learning interest	Q5
		Daily attendance	Q6
		Proficiency in using relevant software	Q7
		Ability to use the theoretical knowledge of software engineering course for hands-on design	Q8
		Ability to apply theoretical knowledge of software engineering course	Q9
		Thinking ability	Q10
		Communication ability	Q11
		Software project design effect	Q12
	Content of courses	Theoretical knowledge learning	Q13
		Structured design	Q14
		Software project management	Q15
		After-class Q&A	Q16
	Teaching equipment	Multi-functional media device	Q17

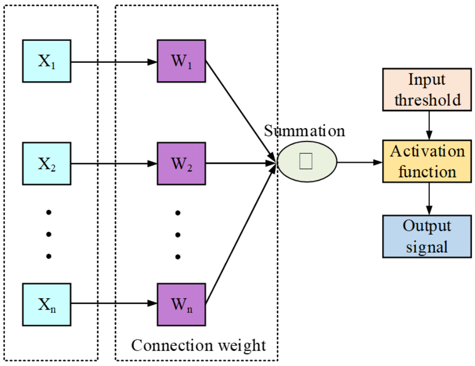


Fig. 3.4: Structure of artificial neuron

divided into threshold function, piecewise linear function and sigmoid function.

$$f(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{3.2}$$

Equation 3.2 is the expression of threshold function. Its function is to map the input value to two output values. When $x \geq 0$, its mapping output value is 1, which means that the corresponding neuron is in an excited

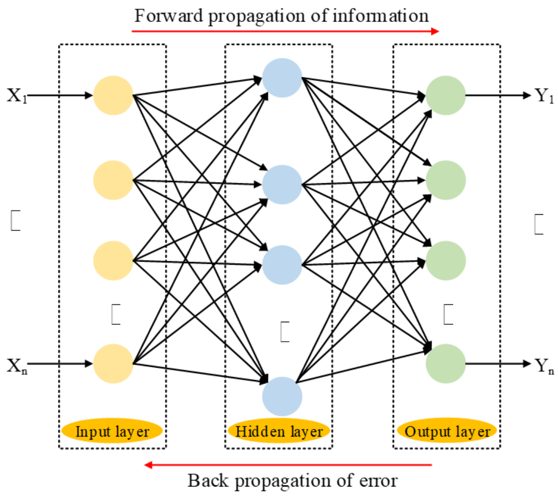


Fig. 3.5: BP neural network structure

state. When $x < 0$, its mapping output value is 0, and the neuron is in the inhibition state.

$$f(x)=\begin{cases}1, x \geq 1\\ x, -1 < x < 1\\ -1, x \leq 1\end{cases} \tag{3.3}$$

Equation 3.3 is the expression of piecewise linear function. The linear function can amplify the input signal according to the neuron model. In the interval (- 1,1), the linear function can be used as a linear combiner. When the coefficient in the linear interval is infinitely amplified, the linear coefficient becomes a threshold function.

$$f(x)=\frac{1}{1+e^{-x}} \tag{3.4}$$

Equation 3.4 is the expression of the sigmoid function. Because of its smooth and easy derivation, it can reduce the amount of model calculation and is often used as the activation function [18, 19]. BP has strong learning ability and can be used to solve nonlinear problems with complex internal mechanism. It can still work normally in case of local damage and can correctly classify the objectives. So, it is widely used to solve problems in different fields.

Figure 3.5shows the general structure of BP neural network, which is mainly composed of three layers. BP neural network's training process includes: forward propagation of information and back propagation of error. When the output result is not within the error range, the model will be automatically transferred back. The output error is reduced by modifying weight and threshold. The model will not stop training until the error finally meets the predetermined range. A three-layer BP is taken, and it needs be initialized first. The number of neurons in the input layer is set as . The number of neurons in the hidden layer is set as n . The number of neurons in the output layer is set as q . After setting the error function, it needs calculate the precision value and the maximum learning times. And the random number within the weight (- 1,1) range is given.

$$\begin{cases}X(k)=(X_1(k),X_2(k),\ldots,X_n(k))\\ D_o(k)=(D_1(k),D_2(k),\ldots,D_q(k))\end{cases} \tag{3.5}$$

Equation 3.5 shows the input sample X_k of input layer k and the expected output $D_o(k)$ corresponding to each input sample.

$$\begin{cases}H_h(k)=\sum_{i=1}^{n} W_{ih}X_i(k)-b_h\\ H_h'(k)=f(H_h(k))\end{cases} \tag{3.6}$$

Equation 3.6 shows the expression formula of hidden layer input vector and output vector. $H_h(k)$ represents hidden layer's input sample, and $H'_h(k)$ represents hidden layer's output.W_{ih} represents input and hidden layer's connection weight. b_h represents the threshold value of the hidden layer.

$$\begin{cases} I_o(k) = \sum_{H=1}^{P} W_{ho}H_i(k) - b_o \\ I'_o(k) = f(I_o(k)) \end{cases} \tag{3.7}$$

$I_o(k)$ represents output layer's input sample, and $I'_o(k)$ represents output layer's output sample. W_{ho} represents hidden and output layer's connection weight. b_o represents the threshold value of the output layer.

$$e = \frac{1}{2}\sum_{o=1}^{q}(D_o(k) - I'_o(k))^2 \tag{3.8}$$

Equation 3.8 is the expression of error function e. The partial derivatives of the hidden layer and the output layer can be calculated through the error function.

$$\delta_o(k) = (D_o(k) - I'_o(k)f'(I_o)k) \tag{3.9}$$

Equation 3.9 is the calculation formula of partial derivative of output layer weight $\delta_o(k)$.

$$\delta_h(k) = -(\sum_{o=1}^{q}\delta_o(k))W_{ho}f'(H_h(k)) \tag{3.10}$$

Equation 3.10 is the calculation formula of partial derivative of hidden layer weight $\delta_h(k)$. Combining formula 3.9 and 3.10 can correct W_{ho} and b_o .

$$W_{ho}^{(N+1)}(k) = W_{ho}^{N}(k) + \eta\delta_o(k)H'_o(k) \tag{3.11}$$

Equation 3.11 is the calculation formula of the corrected connection weight $W_{ho}^{(N+1)}$. η represents the learning step. $W_{ho}^{N}(k)$ is the value before correction.

$$b_o^{(N+1)}(k) = b_o^{N}(k) + \eta\delta_o(k) \tag{3.12}$$

Equation 3.12 represents the calculation formula of corrected threshold $b_o^{(N+1)}(k)$. $b_o^{N}(k)$ is the threshold value before correction. Wih and b_h are modified in the same way, and the global error is calculated at last.

$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(D_o(k) - I'_o(k))^2 \tag{3.13}$$

Equation 3.13 is the calculation formula of global error, and m represents the learning times. If the final global error result reaches the set accuracy value or its learning times exceed the maximum learning times, the algorithm will stop running. Otherwise, new samples will be selected for the next round of learning. Although BP neural network has many advantages in solving nonlinear problems, it is easy to have local minimum problems due to the use of gradient descent algorithm for training. The method to optimize BP neural network is a algorithm which has strong global optimization probability, namely genetic algorithm (GA). It can optimize BP neural network's weight and threshold. And it can accelerate the convergence speed of the whole model by optimizing the individuals in BP neural network.

Genetic algorithm is an optimization tool that simulates biological evolution, the algorithm simulates the collective evolutionary behavior of a population where each individual represents an approximate solution to the search space of the problem. Starting from an arbitrary initial population, genetic algorithm effectively implements a stable and optimized breeding and selection process through individual inheritance and mutation, so that the population evolves to a better range of search space. Genetic algorithm optimization of BP neural network is mainly divided into the following three parts. The first is to use the algorithm to determine the

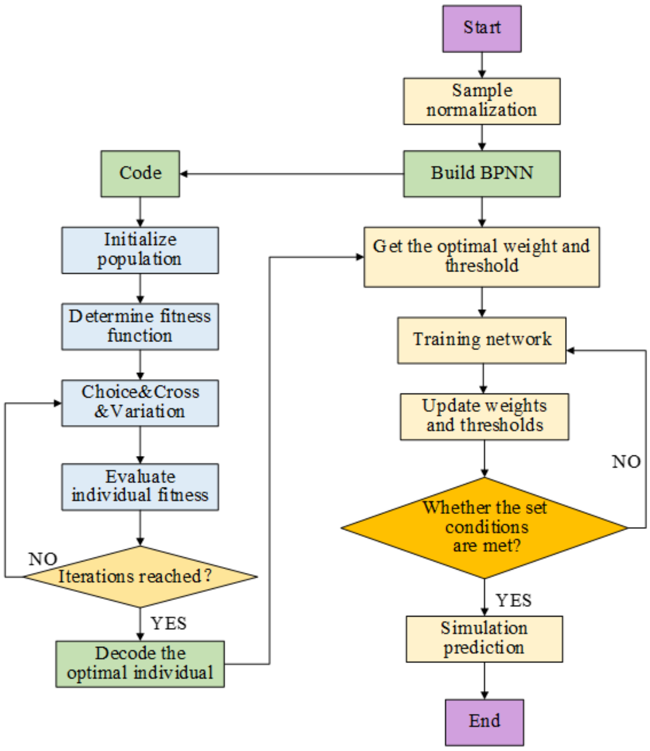


Fig. 3.6: Flow chart of GA-BP optimization algorithm

specific structure of the BP neural network, including the number of nodes in the final input layer as well as the number of neurons in the output layer ultimately determined according to the evaluation results. The second is to use the algorithm to optimize the weights and thresholds of the BP neural network. The algorithm is capable of randomly generating a population whose individuals represent the network weights and thresholds, and then the fitness function is utilized to calculate the fitness value, and finally the optimal individuals are found through selection, crossover and mutation operations. Finally, BP neural network (Genetic Algorithm- Back propagation, GA-BP) under GA optimization is used for prediction. After initialization with the optimal individuals, the weights and thresholds of the BP neural network can be locally optimized again during the training process, thus making the GA-BP neural network have better prediction accuracy and prediction efficiency. The indicators in the evaluation index system are used as the input of GA-BP, and after a series of operations, the predicted value of the model can be obtained. Comparing the predicted values of each index, we can get the degree of influence of each factor on the software engineering teaching mode, so as to assist colleges and universities to take corresponding measures to carry out educational reform.The operation flow chart of the GA-BP algorithm is shown in Figure 3.6.

The flowchart of the optimized GA-BP algorithm operation is shown in Figure 3.6. The positive and negative propagation mode of BP neural network can adjust the neuron weight and threshold. Therefore, the model will evaluate the effect of PTM applied to software engineering curriculum reform according to the algorithm process [20]. The evaluation results of the model can determine the factors that have a greater impact on the software engineering curriculum reform by using PTM. The teaching model can be further improved by modifying the relevant indicators.

4. Evaluation effect of PTM in software engineering curriculum reform. The result analysis part evaluated the effect of the PTM used in the software engineering curriculum reform. The performance of the index evaluation model was tested first. Through Matlab, the PTM using GA-BP optimization algorithm was

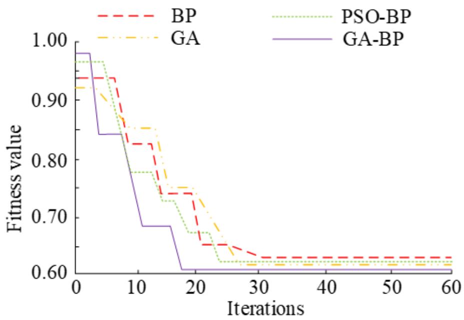
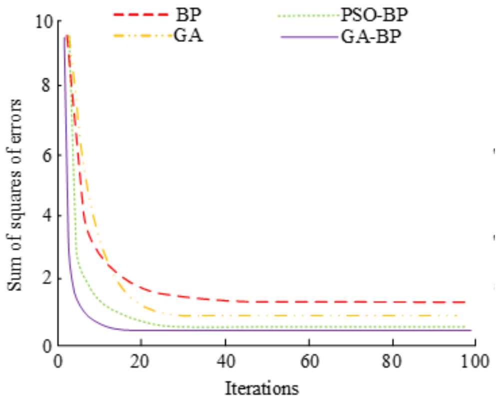
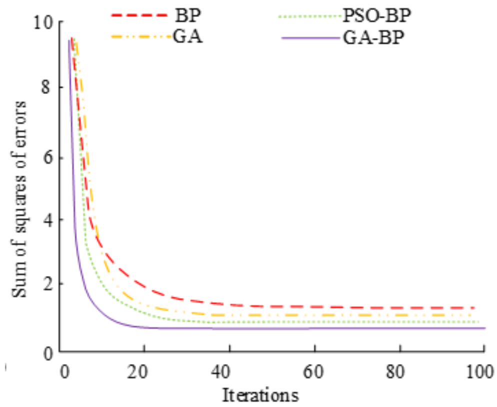


Fig. 4.1: Adaptability changes of different algorithms under different iterations



(a) Sum of squares of average errors of different algorithms



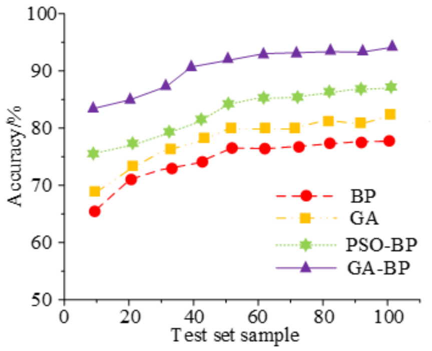
(b) Sum of squares of minimum errors of different algorithms

Fig. 4.2: Error performance of different algorithms

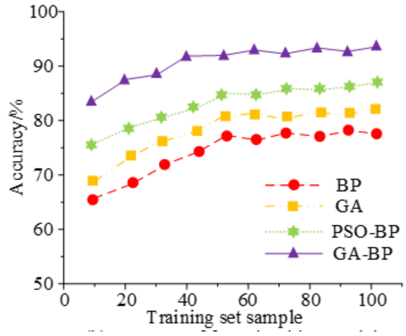
used to simulate the effect of software engineering curriculum reform.The performance of the algorithms was tested using a home-made dataset, which was divided into a training dataset and a test dataset in a ratio of 9:1, to train and test each algorithm.

Figure 4.1 showed the fitness changes of the four algorithms under different iterations. The GA-BP algorithm used in this study was compared with the traditional BP neural network, the GA algorithm, and the improved BP network based on PSO algorithm (PSO-BP). With the increase of the number of iterations, the four algorithms could finally converge to a stable state. Among them, the GA-BP algorithm began to converge at the 18th generation, and the final fitness value was 0.61. The BP neural network began to converge in about 32 generations, and its final stability fitness value was 0.64. The iteration of GA algorithm was better than that of BP neural network. It started to converge after 28 iterations, and the final fitness value remained at 0.62. PSO-BP algorithm began to converge around 24 generations, and its fitness value was 0.63 when it converged to a stable state. Comparing the fitness values of four different algorithms, we could find that GA-BP algorithm could converge to the optimal fitness value as soon as possible. This showed that the algorithm has better optimization ability, and could better avoid the model falling into the local optimal solution when other three algorithms are compared with it.

Figure 4.2 showed four algorithms' error performance in the iteration process. Figure 4.2a showed the square sum of the average errors of the four algorithms. Figure 4.2b showed the sum of squares of the minimum



(a) Accuracy of four algorithm models in test set samples



(b) Accuracy of four algorithm models in training set samples

Fig. 4.3: Prediction of different algorithms in test set and training set

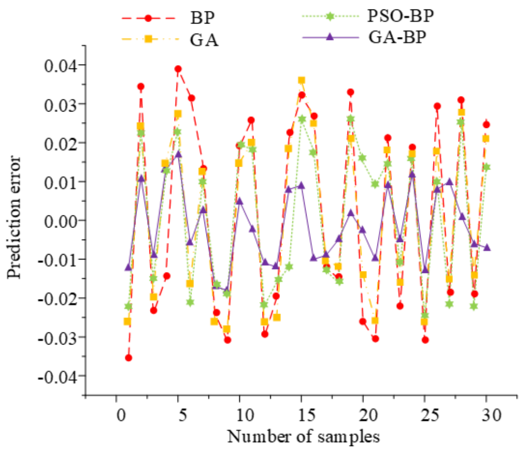


Fig. 4.4: Evaluation error results of different algorithms in training samples

errors of the four algorithms. According to the iteration curves of the four algorithms, we could see that GA-BP can iterate to convergence state faster. The final average error square value and the minimum error square sum of the convergence state were 0.35 and 0.48, respectively. The error performance of the GA-BP algorithm was far better than the other algorithms, so the GA-BP algorithm had better global optimization ability at runtime.

Figure 4.3a showed the prediction of the four algorithms in the test set. Figure 4.3b showed the prediction of the four algorithms in the training set. When the samples number increased, the prediction accuracy of the four algorithms in the test set and the training set had increased and could eventually become stable. When the stable prediction accuracy was reached, the optimal prediction accuracy of BP, GA, PSO-BP and GA-BP in the test sample set was 74.6%, 80.5%, 85.1% and 93.4% respectively. The optimal prediction accuracy of BP, GA, PSO-BP and GA-BP in the training sample set was 75.2%, 80.8%, 86.2% and 94.1% respectively. Whether in the test set or in the training set, the prediction accuracy of GA-BP algorithm was higher.

Figure 4.4 showed the evaluation error performance of the four algorithms in training samples. The four algorithms could evaluate the given training samples, but the evaluation effect of GA-BP algorithm was far better. The prediction error of GA-BP algorithm could be controlled within, so it had good prediction accuracy.

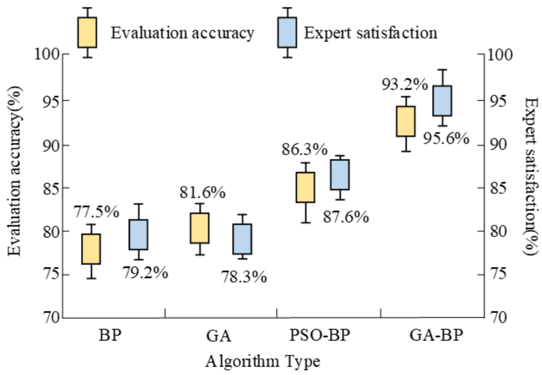


Fig. 4.5: Accuracy and student satisfaction of different algorithms in the evaluation model of PTM reform

The maximum prediction error of GA-BP algorithm was only 0.015. The prediction effect of BP neural network was the worst, its prediction error is within, and the maximum prediction error was 0.37. The prediction effect of GA algorithm was second only to BP neural network, its prediction error could be controlled within, and the maximum prediction error value was 0.035. Although the prediction effect of PSO-BP algorithm was better, its control of prediction error range is still insufficient. The prediction error of PSO-BP algorithm is within , and PSO-BP algorithm's highest prediction error is 0.024. According to the results in Figure 4.3and Figure 4.4, GA-BP algorithm had a good prediction effect in the sample data set. Next, it is used to evaluation model's construction of PTM reform, and the actual evaluation effect of different algorithms used in the PTM reform software engineering teaching is observed.

Figure 4.5 showed the accuracy rate and student satisfaction of the four algorithms in the evaluation model of PTM reform. Four algorithms were used in the evaluation model of PTM reform. According to the evaluation results, GA-BP algorithm had the best evaluation accuracy and could accurately evaluate the parameters and indicators that affected the teaching reform, with the evaluation accuracy of 93.2%. The evaluation accuracy of BP, GA and PSO-BP were 77.5%, 81.6% and 86.3% respectively. In addition, we also collected the satisfaction of software engineering students with the evaluation results of the four algorithm models. Student satisfaction could provide more effective ideas for the follow-up curriculum reform. The degree of satisfaction of software engineering students with BP, GA, PSO-BP and GA-BP was 79.2%, 78.3%, 87.6% and 95.6% respectively. According to the satisfaction results, students were most satisfied with the evaluation effect of using GA-BP algorithm in the evaluation model.

5. Conclusion. In view of a series of problems existing in the current teaching mode of software engineering course, the PTM is proposed to reform the software engineering course. And an effect evaluation model is built to verify reformed course's teaching effect. About BP neural network's defects, genetic algorithm is used to optimize it. And the optimized GA-BP algorithm is used in the index evaluation model to test the teaching method of the project and the reform effect of the software engineering course. To prove the performance of GA-BP algorithm and the effect of its application in the evaluation index model, a series of algorithm comparison experiments are set up and the comparison results are analyzed. Compared with BP, GA and PSO-BP, GA-BP has better convergence effect. When the algorithm is iterated to 18 generations, the fitness value of GA-BP algorithm reaches a stable value of 0.61. In addition, GA-BP algorithm has smaller average error square value and minimum error square sum value, which are 0.35 and 0.48 respectively. In the test set and training set, the prediction accuracy of the four algorithms is tested. The prediction accuracy of GA-BP algorithm is as high as 93.4% and 94.1%, and its prediction error range is also smaller, and the final control is within. Finally, four algorithms are used to evaluate the evaluation accuracy and student satisfaction of the test model in the evaluation model. The evaluation accuracy of BP, GA, PSO-BP and GA-BP are 77.5%, 81.6%, 86.3% and 93.2% respectively, and the student satisfaction is 79.2%, 78.3%, 87.6% and 95.6% respectively. The above experimental results prove the role of project-based learning in software engineering curriculum reform.

However, since the determination of evaluation indicators is often affected by many factors, there is still room for modification in the selection of indicators of the evaluation model.

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