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RESEARCH ON THE TEACHING MODEL OF ENGLISH TEACHING QUALITY EVALUATION UNDER THE BACKGROUND OF MOOC

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Abstract. In the context of informatization, online teaching is increasingly favored by people for its convenience and resource richness. Through the Open CourseWar (MOOC) platform, people can easily access learning resources and achieve efficient line length learning. However, currently MOOC online learning cannot provide targeted evaluation for the learning effectiveness of English learners, and there is relatively little research on online English quality assessment. Propose an intelligent MOOC online English teaching evaluation technology. Firstly, analyze the existing English teaching factors and construct a quality evaluation system for online English teaching using Principal Component Analysis (PCA) and expert evaluation method. Considering that the quality of English teaching is influenced by many factors, the evaluation of English teaching quality belongs to a complex nonlinear solving problem. Therefore, the advanced GA-RBF (Genetic Algorithm Radial Basis Function Neural Network, GA-RBF) model is adopted to solve the English teaching quality evaluation model. In teaching quality evaluation, BP and RBF are selected to participate in comparative testing of teaching quality evaluation. In the training loss test of multiple models, the GA-RBF model has the best convergence speed and training performance in the oral sample test, tends to converge after 270 iterations, with a loss value of 0.24. In the evaluation of English proficiency indicators, the BP model has a significant error in testing, with an error of 13 in the evaluation of reading ability scores. The error of RBF in reading ability score evaluation is 4, and the GA-RBF model performs the best. The reading ability evaluation error is 1, and the overall evaluation performance is the best. Through the above research, an intelligent method for evaluating the quality of English teaching is proposed, which will provide important technical references for MOOC online education evaluation and English teaching improvement.

Key words: MOOC; English teaching; PCA; GA-RBF; Quality evaluation

1. Introduction. In the context of informatization, online teaching is increasingly favored by more and more people due to its convenience and abundant resources. Through the Open CourseWar (MOOC) platform, people can easily access learning resources and achieve efficient online learning. MOOC English plays an important role in English teaching. MOOC English teaching provides learners with a comprehensive learning experience through online videos, interactive discussions, online quizzes, and other functions. Learners can learn English listening and speaking skills by watching professional teaching videos [1]. Online lectures provide deeper knowledge learning, allowing learners to understand more English grammar and vocabulary. Forum discussions provide a platform for learners to interact and exchange ideas, allowing them to share their learning experiences and solve problems with other learners [2].

Online assignments and quizzes are used to help learners verify their learning outcomes and deepen their understanding of knowledge. However, there are some shortcomings in the current MOOC online learning. Especially in terms of evaluating the learning outcomes of English learners, targeted evaluations cannot be conducted, and the evaluation results cannot meet the learning requirements of learners [3].

To address the aforementioned issues, a research proposes an intelligent method for evaluating the quality of English teaching. This technology combines expert method and principal component analysis to explore learner influencing factors and construct a teaching quality evaluation system. At the same time, a fusion GA-RBF (Genetic Algorithm Radial Basis Function Neural Network) learning model is introduced to analyze and evaluate data, thereby achieving effective evaluation of MOOC online English teaching. The innovation of this study mainly includes two aspects. Firstly, a quality evaluation system suitable for MOOC English teaching was constructed through principal component analysis and expert evaluation, providing a targeted method for evaluating English learning effectiveness. Secondly, the study adopted the GA-RBF model to solve

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the English teaching quality evaluation model, achieving personalized evaluation of learners and improving accuracy. The significance of this research lies in the proposal of intelligent MOOC online English teaching evaluation technology, which can improve the learning effectiveness and self-learning ability of English learners. Secondly, this study can promote the development and improvement of MOOC English teaching, providing high-quality online learning resources for more learners.

2. Related Work. Good education analysis is the essential to ensure the effective implementation of education. Through effective education and teaching evaluation, it can provide important reference for the optimization and Improving classroom quality. Educators at home and abroad have carried out in-depth research on this. A study on the association between teacher mobility and headmaster effectiveness was conducted by Grissom JA et al. The study found that in actual teaching activities, teachers do not need to be retained equally. On the contrary, more powerful principals will try their best to retain excellent teachers and build a more comprehensive teacher team. Through the analysis and evaluation of the ability system of teachers, it will be found that teachers with high ability have better classroom teaching effect and lower turnover rate. And this study can also provide valuable advice for the evolution of modern education and improve the current educational effect. The research content will significantly improve the teaching quality of the teacher team, optimize the teaching structure, and promote the comprehensive development of education [4].

Han et al. conducted research on the existing education quality evaluation. Due to the imperfect system, classroom teaching evaluation faces many problems. To improve the quality of classroom education, the AHP is used to analyze the physical education in in higher education. to clarify the relevant factors affecting teaching and to build a teaching model. Through specific case analysis, the quality evaluation model constructed according to the existing teaching Can be effectively applied in a sports education environment and improve the teaching effect [5].

Close et al. conducted a study on a student bill promulgated by the US government, which removed the government's assessment of teacher competence. According to various survey data, different regions adopt different evaluation methods to evaluate teachers and students, and gradually reduce the evaluation of student violence. The teacher observation method is used to assess student development, and Meanwhile, it pays attention to the completion of the student's Learning Goals and uses it as the standard for evaluating student development. And this research will strengthen the management of teaching and improve the current teaching environment [6].

Nazari-Shirkouhi et al. analyzed the current teaching management in colleges and universities and found that using performance to adjust teaching functions is conducive to solving teaching problems and implementing more efficient teaching content. Therefore, the existing university management is analyzed, the balanced scorecard is used to determine the university services and activities, and the fuzzy decision-making scheme is used to realize the performance evaluation of the existing university teaching management. Meanwhile, an effective index is put forward as the weight of performance evaluation, which is linked with the cost and policy of education. Through this evaluation model, it can better reflect the management effect of colleges and universities, and help higher education to customize more effective teaching management policies and improve the quality of coursest of higher education [7].

Artificial intelligence and other technologies have been actively used in teaching management and teaching evaluation. Lino A and others found that virtual digital technology has achieved effective results in education and teaching, but due to the influence of teaching characteristics and factors of teaching itself, the existing teaching evaluation methods are facing accuracy problems. To this end, the teaching factors and inferred variable relationships are analyzed, and a new evaluation model is proposed, which uses neural networks to diagnose factor problems. Finally, the proposed evaluation model is applied to a specific teaching scenario. The proposed scheme the influence of complex factors on the evaluation of teaching and learning can be stopped in prediction and evaluation. and Meanwhile greatly Improving productivity [8].

Qianna and others conducted research on the existing intelligent teaching, and the evaluation of the quality of intelligent curriculum Education is the key to improving the quality of current education. However, at present, some intelligent education evaluation models are facing the problem of inaccurate predictions, mainly due to the influence of teaching environment factors, which cannot accurately evaluate the teaching status. Aiming at improving the accuracy of Subject Effectiveness Evaluation, the teaching feature information is extracted based on intelligent learning algorithms, and a classroom quality assessment model is constructed based on intelligent algorithms. Applying the proposed scheme to a specific teaching environment, the quality assessment model introduced has good predictive performance and meets the relevant requirements of teaching development [9].

De-kun et al. studied the existing intelligent sports evaluation scheme and found that it ignored the labeling of key teaching tasks, resulting in large errors in the teaching evaluation of the algorithm and a long time-consuming. Therefore, the existing physical education teaching tasks are analyzed, and a brand-new intelligent evaluation scheme is designed, which uses an advanced learning model to mark the teaching objectives and tasks. Meanwhile, through the analysis of relevant factors of sports management, the weight of key factors in teaching is clarified, and a quantitative evaluation model is constructed. Finally, the optimized genetic model is used to solve the question. The final test shows that the proposed solution model has the best performance and is suitable for the current teaching quality requirements [10].

Goli A et al. conducted a study exploring the possibility of achieving educational democratization by increasing enrollment rates. This study investigated the impact of paid certificate purchase options on course content engagement, considering two aspects: certificate effect and sunk cost effect. The study used data from over 70 courses on the Coursera platform and analyzed the participation of individual participants at different milestones. Research has found that the certificate effect and sunk cost effect increase user engagement by approximately 8% -9% and 17% -20%, respectively. The sunk cost effect is short-lived, lasting only a few weeks after payment, while the certificate effect persists until participants reach the level required to qualify for the certificate. This study reveals the important role of price and payment in realizing the potential of MOOC, providing important references for further research and optimization of MOOC education. Compared with the technology studied, this study mainly focuses on the payment preferences of learners and does not fully consider the impact of personalized teaching. Therefore, further research will be conducted on the evaluation of MOOC online education [11].

Luo R et al. conducted a qualitative study aimed at investigating the quality assurance issues of large-scale open online language courses (LMOOC). They adopted a grounded theory approach and analyzed the evaluation of LMOOC quality from the learner's perspective. The study collected evaluation data from 1000 English as a Second Language (ESL) learners on iCourse, the largest MOOC platform in China, and examined the cognitive and perceptual influencing factors of learners towards LMOOC. Based on the research findings, they identified specific quality standards for five types of LMOOC courses, including ESL courses for oral, reading, writing, cultural research, and comprehensive skills. This study provides a foundation for establishing a quality standard framework for LMOOC and designing effective online language courses to meet the needs of different language learners. However, the aforementioned study did not fully consider the impact of English teaching on personalized assessment of learners, and further research will be conducted in the future [12].

Ren et al. proposed a theoretical based method for evaluating the quality of English MOOCs to address the issue of unreasonable weight distribution in existing evaluation indicators. This method constructs a framework for evaluating the quality of English MOOCs and determines the overall teaching objectives. On the basis of selecting MOOC quality evaluation indicators, Analytic Hierarchy Process (AHP) is used to determine the weight values of each evaluation indicator, and fuzzy algorithm is used to evaluate the comprehensive evaluation indicators of each level. Obtain the quality evaluation results of English MOOCs through comprehensive calculation. The quality evaluation method of English MOOC based on grounded theory can provide a reasonable weight distribution and evaluate the quality effect of MOOC. This study provides a feasible and effective method for evaluating the quality of English MOOC, which can help measure and improve the teaching quality of MOOC, thereby providing a better learning experience and outcomes. This study did not fully consider the impact of various factors on learners, and future research will add expert knowledge base to further improve the research [13].

A good teaching assessment will not only clarify the focus and difficulties of teaching. but also provide effective reference for teaching management and teaching planning. Online teaching such as MOOC has been facing problems such as inaccurate teaching evaluation. Innovations in modern educational technology and the spread of smart technology in teaching and learning scenarios are important in improving online English language teaching.

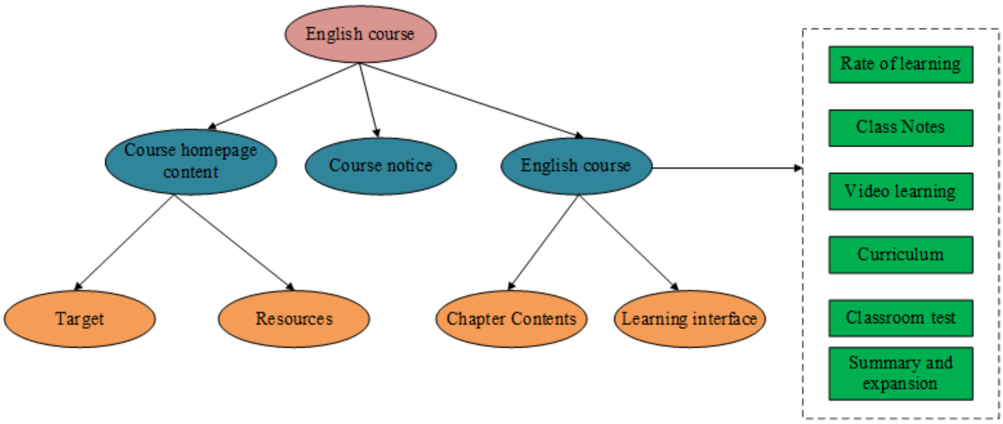


Fig. 3.1: Functional structure of the MOOC English teaching platform

3. Construction of English teaching quality evaluation model under the background of MOOC. With the advent of the information network era, the existing English education is undergoing earth-shaking changes, and the open network MOOC education provides an important technical reference for modern English teaching. Using big data mining technology and intelligent management technology, students and teachers can complete a series of English teaching tasks in MOOC. The functional structure of the open MOOC English teaching platform can be seen in Figure 3.1 [14].

Under the MOOC English platform, students can purposefully log in to the MOOC learning interface based on teaching tasks and course arrangements, and complete teaching tasks such as English online teaching and academic testing. However, in the current online MOOC teaching, teaching quality evaluation still faces problems. Traditional evaluation systems cannot adapt to different types of scholars and have poor accuracy in evaluation. Propose an intelligent online English evaluation technology for this [15]. This technology will analyze the factors of online English learning and use PCA method to screen the main influencing factors, thereby constructing an English teaching quality evaluation system. Principal component analysis (PCA) is a technique for simplifying datasets. It maps high-dimensional data to low dimensional space through linear transformation, reducing the dimensionality of the data while preserving as much information as possible, and mining useful data information [16]. PCA is an analytical method that transforms a set of variables into another set of variables through orthogonal transformation, thereby achieving dimensionality reduction of data. The principle is shown in Figure 3.2.

The PCA method is based on the concept of dimensional processing, and the teaching evaluation index is used as the dimension reduction data. For evaluation indicators that are not strongly related to teaching quality, through PCA dimension reduction processing, redundant and overlapping teaching indicator information can be removed, and the most critical indicator data can be retained [17]. Then define the MOOC English teaching index set as X, as shown in formula (3.1).

$$X = (X_1, X_2, ..., X_p) \tag{3.1}$$

In formula (3.1), $X_1, X_2, ..., X_p$ both represent the English teaching index factor and $p$represent the quantity of English teaching index. Due to the large differences in the various evaluation index factors in MOOC English teaching, the accuracy of the final teaching quality evaluation. Therefore, PCA is used to perform dimensionality reduction operations on all English teaching indicators, as seen in formula (3.2).

$$\bar{x}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \tag{3.2}$$

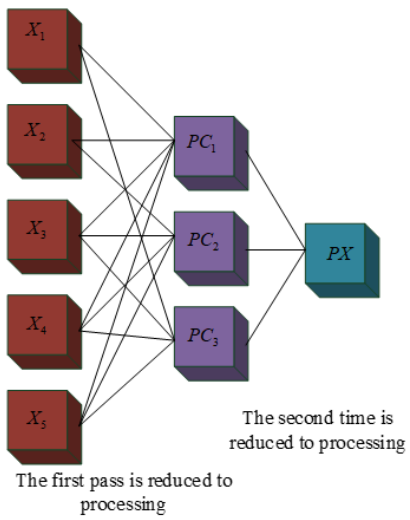


Fig. 3.2: Schematic diagram of PCA dimensionality reduction processing

In formula (3.2), the $\bar{x}_j$ expression is as seen in formula (3.3).

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{3.3}$$

In formula (3.3), it x_{ij} represents the ith teaching index factor of the jth teaching and the s_j expression is as seen in formula (3.4).

$$s_j = \frac{1}{n-1}\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2 \tag{3.4}$$

After standardizing the complex index factors of English teaching, the correlation coefficient matrix between the index and quality is calculated, as shown in formula (3.5).

$$R = (r_{ij})_{p \cdot p} \tag{3.5}$$

In Equation (3.5), it r_{ij} represents the correlation coefficient i of the jth teaching index factor of the th teaching, and the r_{ij} calculation is as seen in Equation (3.6).

$$r_{ij} = \frac{1}{n-1}\sum_{k=1}^{n} \bar{x}_{ki}\bar{x}_{kj} \tag{3.6}$$

In formula (3.6), $\bar{x}_{ki}$ represents the kth i teaching index factor of the th teaching, and $\bar{x}_{kj}$ represents the kth index factor of the th teaching j. After the incidence matrix is solved, the characteristic equation needs to be constructed, as seen in Equation (3.7).

$$\lambda u = Ru \tag{3.7}$$

In formula (3.7), λ denotes the eigenvalue and $u$denotes the eigenvector, then the calculation of the index eigenvalue is as seen in formula (3.8).

$$\lambda = (\lambda_1, \lambda_2, \lambda_3, ..., \lambda_p), \lambda_1 \geq \lambda_2 \geq \lambda_3 \geq ... \geq \lambda_p \geq 0 \tag{3.8}$$

Table 3.1: Evaluation model of Teaching Effectiveness

Evaluation target	Level 1 evaluation index	Secondary evaluation index
MOOC Teaching Effectiveness evaluation	Teaching content	Contact actual
		Full of content
		Depth of knowledge
		Accuracy of theoretical concepts
	Teaching method	Way diversity
		Focus on personality
		Cultivation of innovation consciousness
		Good at inspiring
	Teacher's comprehensive ability	Teacher teaching level
		Professional level
		Teaching objectives are clear
	Teaching effect	Comprehensive quality
		Problem solving ability
		Depth of knowledge
		learning interest

The calculation of index feature vector is seen in formula (3.9).

$$u = (u_1, u_2, u_3, ..., u_p) \tag{3.9}$$

After constructing the characteristic equation, it is necessary to calculate the contribution of the main components of the MOOC English teaching index factor, as seen in formula (3.10).

$$\xi = \sum_{i=1}^{p} a_i \tag{3.10}$$

In formula (3.10), it a_iRepresentative contribution rate. iIn the actual MOOC English education, the selected teaching index factors will be as many as possible, but it will affect the teaching quality evaluation when constructing the teaching evaluation index system [18]. To evaluate the effect of students' Teaching effectiveness more accurately, it is necessary to select the most representative main indicators among the constructed teaching index factors. If the contribution of the sum of the first main components in the $m$construction of the teaching index system is higher than 85%, it can be explained that the selected first $m$index can be used as an evaluation index of teaching quality. After PCA dimensionality reduction, the index factors are more closely related to the teaching quality and can better reflect the actual teaching quality. The MOOC teaching effectiveness evaluation system is shown in Table 3.1.

3.1. GA - RBF solution model construction. The solution of the MOOC English teaching quality evaluation model belongs to a complex nonlinear solving problem. In order to more accurately evaluate the effectiveness of MOOC English teaching quality, the RBF model is adopted to solve the teaching quality evaluation problem [19]. Among them, RBF has the ability of nonlinear mapping, which can map the input space to high-dimensional feature space by introducing nonlinear functions, making linearly inseparable problems linearly separable in high-dimensional space. However, RBF faces parameter configuration issues when dealing with complex data problems. Therefore, the GA algorithm is used to optimize the RBF model and construct the GA-RBF solution model. The RBF model belongs to a type of feedforward deep learning network, which has good non-linear fitting ability and can effectively map complex non-linear relationships in English teaching. At the same time, the model also has good global approximation and generalization ability, which can predict and evaluate the situation of English teaching well [20]. The topology of the RBF model is shown in Figure 3.3.

RBF model consists of input, hidden and output three-layer network structure, and the hidden layer is connected by radial basis function. In the test, the English teaching evaluation index data is standardized, and the processed evaluation vector is input into the RBF model And the teaching quality evaluation results

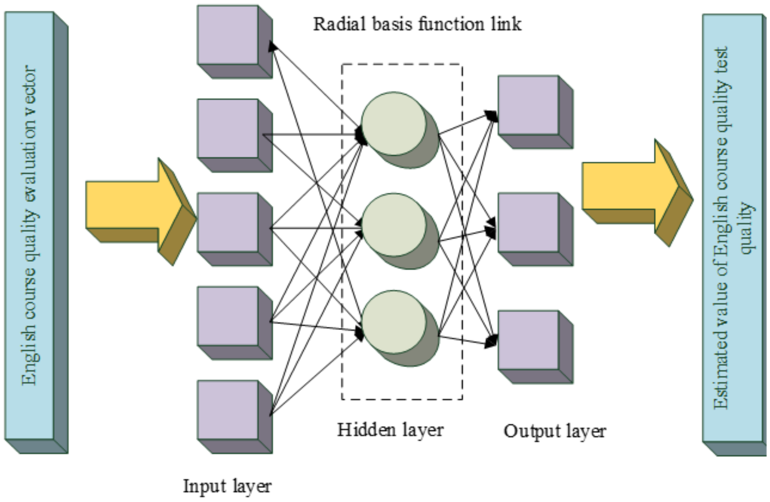


Fig. 3.3: RBF model topology schematic diagram

are obtained through model training. Define the input vector as X_i, and the output vector as Y_i, as seen in formula (3.11).

$$\left\{ \begin{array}{l} X_i = (x_{i1}, x_{i2}, ..., x_{iN}) \\ Y_i = (Y_{i1}, Y_{i2}, ..., Y_{iN}) \end{array} \right. \tag{3.11}$$

Gaussian function is chosen as the activation function in RBF model training, as seen in Equation (3.12).

$$\Phi_i(t) = e^{-t^2/\delta_t^2} \tag{3.12}$$

In formula (3.12), δ_t^2 represents the basis function width, then the first output of the RBF model is $k$as seen in formula (3.14).

$$y_{ik} = \sum_{i=0}^{h} w_{ik} \Phi_i(\|X_j - C_i\|) + b_k \tag{3.13}$$

In formula (3.14), w_{ik} represents the weight of the basis function of the hidden layer, represents b_k the offset of the h model corresponding to the first output, and k represents the number of nodes in the hidden layer. In model training, the number of nodes should be selected to meet the learning rate and model accuracy requirements. In the initial training, select a smaller number of nodes and gradually increase them, and then compare the mean square error between the model output value and the expected value to select the hidden layer. Number of nodes [21]. Then the mean square error is calculated as shown in formula (3.14).

$$fStop = \frac{1}{N.m} \sum_{i=1}^{N} \sum_{j=1}^{m} (Y_{i,j} - y_{i,j})^2 \tag{3.14}$$

In formula (3.14), N represents the number of model training samples, Y_{ij} and y_{ij} respectively represents the i expected value and actual value m after the fitting operation of the first sample, and represents the $j$total number of nodes in the output layer.

RBF model faces the problem of model parameter setting during training, so the GA algorithm is used to optimize the RBF model. The GA algorithm is a kind of heuristic algorithm. The principle is to simulate

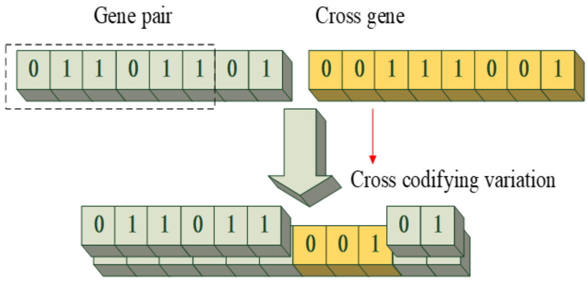


Fig. 3.4: Cross process of GA algorithm

the rules of biological evolution, and find the optimal solution from the population through the population's selection, crossover and mutation of chromosomes. In the study, the common roulette method was chosen to calculate the total chromosome fitness of the genetic population, and the proportion of the fitness of a single chromosome was calculated as the probability of chromosome selection, and finally the algorithm operation was completed by using roulette. Since RBF model parameter setting is a continuous parameter optimization problem, floating-point encoding is used to ensure the accuracy of model training, so as to avoid decoding problems in the GA algorithm selection operation. The expression is as seen in formula (3.15).

$$E = 1/\sum_{Kl=1}^{N}(T_l - Y_l) \tag{3.15}$$

In formula (3.15), Trepresents the expected output value of the Y model, represents the actual output value of the model, and N is the total number of chromosomes. Using roulette to calculate and sort the fitness of a single chromosome, the probability of a single chromosome being selected is shown in formula (3.16).

$$p(b_i) = E_{bi}/E \tag{3.16}$$

In formula (3.16), it E_{bi} represents when chromosome fitness. According to the probability of each chromosome being selected, the chromosome with a higher probability of being selected is subjected to evolutionary operation. The crossover operation is to exchange some genes of two chromosome pairs, and a new chromosome pair appears. The principle is shown in Figure 3.4.

In the population crossover operation, the population is selected for crossover operation many times during the evolution, resulting in a larger chromosome fitness value. Therefore, To improve the optimization effect of the algorithm, it is necessary to reconfigure the crossover rate, and increase the probability of chromosome crossover with a small probability after the number of iterations increases. After completing the crossover operation, carry out the genetic variation operation [22]. The mutation operation is a mutation of a certain gene position of a chromosome to generate a new chromosome, as shown in Figure 3.5.

The population generates new chromosomes through mutation operations, which is one of the important processes of GA model optimization. Meanwhile, in the mutation operation, it is necessary to set an appropriate mutation rate. When the mutation rate is large, it can expand the optimization range of the model and enhance the global optimization effect of the model [23]. However, if the mutation rate is too large, it will affect the effect of chromosome selection and crossover, while a small mutation rate is conducive to retaining excellent chromosomes. Therefore, the mutation rate is dynamically set between 0.001 and 0.1, and when the chromosome fitness value is smaller than the average value in the early stage, the mutation rate takes a smaller value. When the chromosome fitness value is higher than the average value, the model mutation rate is gradually increased to ensure the optimization effect of the model. Then the working principle of the whole GA - RBF model can be seen in Figure 3.6.

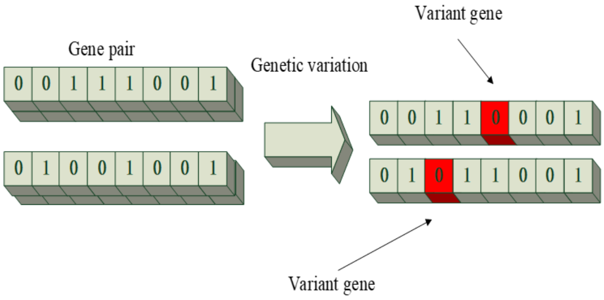


Fig. 3.5: Variation process of population

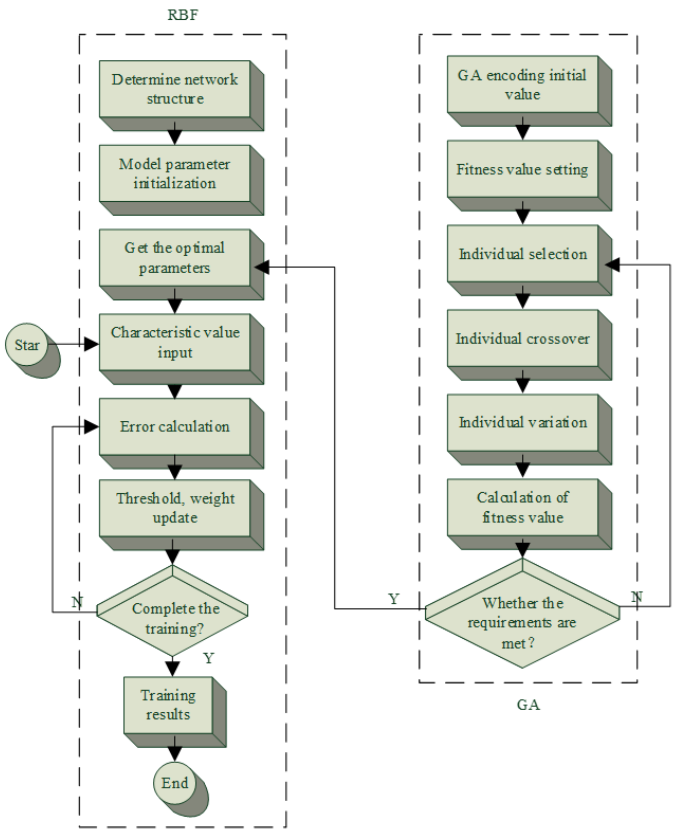


Fig. 3.6: GA - RBF model training flow chart

4. Algorithm model simulation test and analysis. To test the performance effect of the proposed GA - RBF algorithm model, the traditional BP (back propa GA tion, BP) algorithm model and the traditional RBF model will be selected to participate in the performance comparison. The test platform is win10 64-bit system, memory 64g, processor is intel i7. GA - RBF test model parameters are seen in Table 4.1.

The MOOC Teaching Effectiveness evaluation data is selected as the model test data, and the main 15 teaching evaluation index factors are obtained on the basis of the PCA method. Choose 10 for experts in the field of education to score the Teaching Effectiveness index system, and get the weight of each index system,

Table 4.1: GA - RBF model initial parameter values

Model initialization parameters	Parameter value
GA population size	30
Mutation probability	0.4
Number of evolution iterations	10
Crossover probability	0.6
Training step length	1500
learning rate	0.2

Table 4.2: MOOC English teaching weight index system

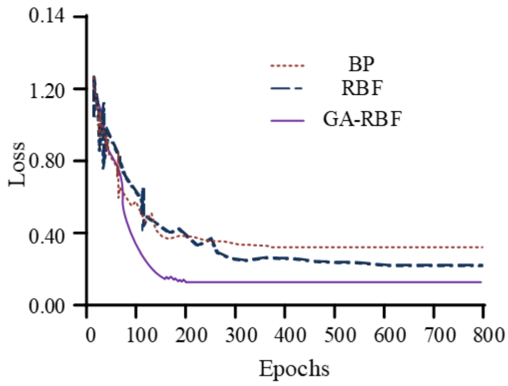
Level 1 evaluation index	Secondary evaluation index	Indicator weight score
teaching content	Contact actual	0.08
	Full of content	0.05
	Depth of knowledge	0.06
	Accuracy of theoretical concepts	0.04
Teaching method	Way diversity	0.04
	Focus on personality	0.05
	Cultivation of innovation consciousness	0.06
	Good at inspiring	0.04
Teacher's comprehensive ability	Teacher teaching level	0.05
	Professional level	0.08
	Teaching objectives are clear	0.05
Teaching effect	Comprehensive quality	0.08
	Problem solving ability	0.12
	Depth of knowledge	0.12
	learning interest	0.08

as shown in Table 4.3.

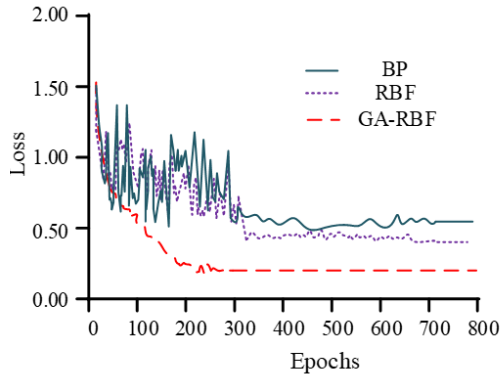
To further evaluate the quality and effect of MOOC English teaching, the MOOC English teaching in a university is selected as the research object, the relevant quality evaluation data are collected from the 15 indicators in Table 3, and 200 English teaching test samples are obtained by scoring by experts. All test sample data are normalized to obtain the model training loss results, as shown in Figure 4.1.

Figure 4.1a Loss test results of multiple models trained on English grammar samples. Formthe graph data that different models have different loss performance in the English grammar sample test. The BP model tends to converge after 400 iterations, and the loss value at this moment is 0.39. The RBF model tends to converge after 600 iterations, and the loss value at this moment is 0.32. The best performance is the GA - RBF model, which tends to converge after 200 iterations, and the loss loss value at this moment is 0.23. From a comprehensive comparison, the BP model has more advantages in the convergence speed than the RBF model, but the accuracy is not as good as the RBF model. Figure 4.1b Loss test results of multi-model training on spoken English samples. Since the characteristic data of spoken language samples are more complex, the effect of the model on data processing is tested. Formthe data in the figure that the test results of the BP model are the worst in terms of convergence speed and model training accuracy. Compared with the BP model, the RBF model has more advantages in the convergence speed, tends to converge after 700 iterations, and the loss loss value at this moment is 0.47. The proposed GA - RBF model has the best comprehensive performance in the oral English sample test, and tends to converge after 270 iterations, and the loss value at this moment is 0.24. It can be seen that the GA - RBF model has the best comprehensive performance in the English sample test. Still choose English grammar and spoken English samples to test the teaching quality evaluation accuracy of each model, with a total of 10 sample data in each group, the results are shown in Figure 4.2.

Figure 4.2a Quality evaluation results of multiple models on English grammar samples. According to the

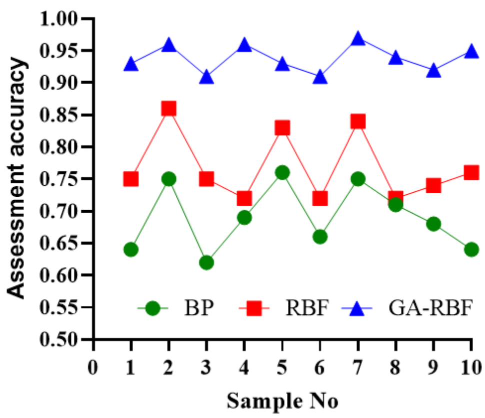


(a) English Grammar Teaching Test

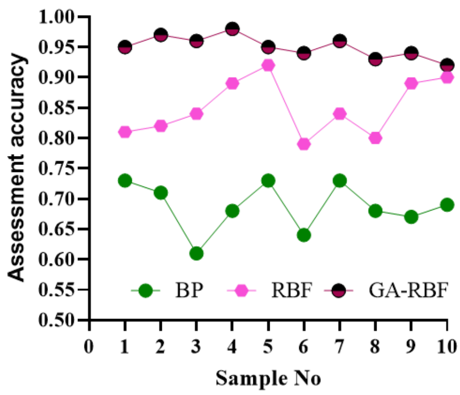


(b) Oral English Teaching Test

Fig. 4.1: Model training loss test results



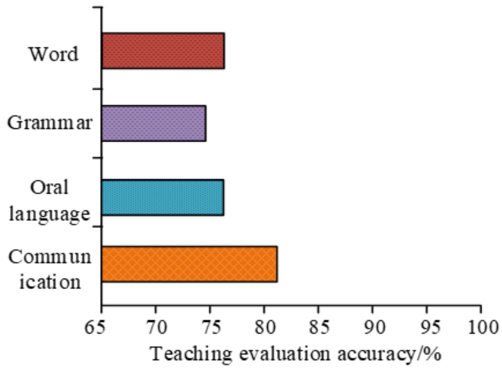
(a) English Grammar



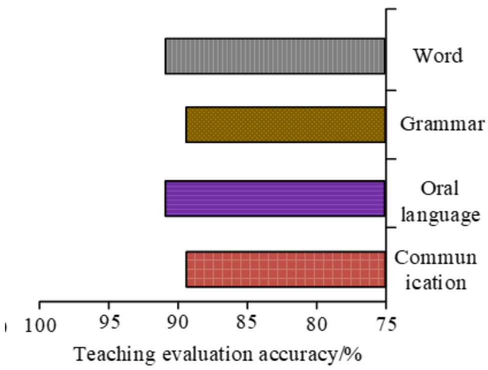
(b) Oral English

Fig. 4.2: Evaluation accuracy tests

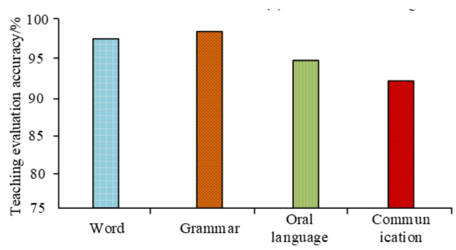
data, the three quality evaluation models have large accuracy differences in the quality evaluation of different samples. The BP model has low accuracy in evaluating the quality of a single English grammar sample, for example, the quality evaluation accuracy of sample 3 and sample 10 are 0.61 and 0.64 respectively. Compared with the BP model, the overall quality evaluation accuracy of the RBF model is higher. In the quality evaluation of sample 3 and sample 10, the evaluation accuracy is 0.74 and 0.76, respectively. The proposed GA - RBF model has the best performance in English grammar quality evaluation, and the quality evaluation accuracy is above 0.90. Figure 4.2b Quality evaluation results of multi-model in spoken English samples. The quality evaluation accuracies of BP model in sample 3, sample 6, and sample 9 are 0.61, 0.64, and 0.67, respectively. The quality evaluation accuracies of RBF model in sample 3, sample 6, and sample 9 are 0.84, 0.78, and 0.90, respectively. The quality evaluation accuracies of GA - RBF model in sample 3, sample 6, and sample 9 are 0.96, 0.94, and 0.91, respectively. It can be seen that the GA - RBF model has excellent evaluation accuracy in English quality evaluation. The teaching content of the four aspects of MOOC English teaching, vocabulary teaching, grammar teaching, oral language teaching and social environment, is selected for testing, and the



(a) BP model teaching evaluation accuracy



(b) RBF model teaching evaluation accuracy



(c) GA-RBF model teaching evaluation accuracys

Fig. 4.3: Evaluation accuracy results of MOOC English content

results are shown in Figure 4.3.

Figure 4.3a BP model Teaching Effectiveness evaluation results. Formthe figure data that in vocabulary teaching, grammar teaching, oral language teaching and social environment, the quality evaluation accuracy of BP model is 77%, 75%, 73% and 81% respectively. Figure 4.3b RBF model Teaching Effectiveness evaluation results. Formthe figure data that in word teaching, grammar teaching, oral language teaching and social environment, the quality evaluation accuracy of BP model is 92%, 88%, 92% and 89% respectively. Figure 4.3c GA - RBF model Teaching Effectiveness evaluation results. Formthe figure data that in word teaching, grammar teaching, oral language teaching and social environment, the quality evaluation accuracy of GA - RBF model is 97%, 98%, 94% and 93%, respectively. Formthe data results that the GA - RBF model has more accurate evaluation accuracy in English content evaluation. Finally, the seven ability indicators in English teaching are selected for prediction, and the average scores are taken. The results are shown in Table 4.3.

Form the test results in Table 3 that the BP model performed worst in the performance prediction of English proficiency indicators, and there was a large error between the predicted performance and the actual performance. For example, in the reading ability test, the predicted score is 85, the actual score is 98, and the error is 13. The best performing model is the GA - RBF model, which has excellent performance in speaking ability, reading ability, and comprehensive ability prediction. It can be seen that the GA - RBF model has excellent performance in the evaluation of MOOC Teaching Effectiveness and meets the development requirements of English education.

5. Discussion. MOOC (Massive Open Online Courses) is an emerging educational model that provides open and free online courses through the internet, providing people with convenient learning opportunities. With the popularization and development of MOOC, the evaluation of its teaching quality has become particularly important. Educational evaluation can help research and understand teaching effectiveness, optimize

Table 4.3: Evaluation results of English teaching ability indicators

Evaluation model	Test capacity	Predicted grades	Actual performance	difference
BP	Speaking ability	84	89	5
	Basic ability	94	90	4
	Problem solving ability	84	88	4
	Reading ability	85	98	13
	Writing ability	72	80	8
	Word memory ability	86	80	6
	Comprehensive ability	83	88	5
RBF	Speaking ability	86	89	3
	Basic ability	87	90	3
	Problem solving ability	90	88	2
	Reading ability	94	98	4
	Writing ability	79	80	1
	Word memory ability	82	80	2
	Comprehensive ability	90	88	2
GA-RBF	Speaking ability	90	89	1
	Basic ability	90	90	0
	Problem solving ability	90	88	2
	Reading ability	97	98	1
	Writing ability	82	80	2
	Word memory ability	82	80	2
	Comprehensive ability	87	88	1

curriculum design, and improve teaching quality, thereby providing better learning experiences and outcomes. In the past, traditional educational evaluation methods mainly relied on the subjective evaluation of teachers and the academic performance of students for evaluation. However, this evaluation method has issues such as strong subjectivity and inconsistent evaluation standards. With the continuous development of technology, evaluation methods based on data analysis are gradually being applied. MOOC English teaching quality assessment is no exception. By collecting and analyzing learner data, teaching effectiveness can be more objectively evaluated, providing accurate feedback and improvement suggestions. This study is based on the Principal Component Analysis (PCA) method, selecting 15 main teaching evaluation indicators in the evaluation of MOOC English teaching quality, and determining the weight indicators through expert scoring. After normalization, model training and loss testing were conducted on 200 English teaching samples.

In this study, the GA-RBF model was chosen as the main evaluation model. Compared with traditional BP models, the GA-RBF model has advantages in convergence speed and accuracy. In English grammar sample training, the GA-RBF model tends to converge after 200 iterations, while the BP model requires 400 iterations to converge. In English speaking sample training, the GA-RBF model converges after 270 iterations, while the BP model requires 700 iterations to converge. This indicates that the GA-RBF model has a faster convergence speed. Secondly, the study also compared the differences in the accuracy of English teaching content evaluation among different models. The results show that the GA-RBF model has higher accuracy than the BP and RBF models in word teaching, grammar teaching, oral teaching, and social environment evaluation. This indicates that the GA-RBF model is more accurate in evaluating MOOC English teaching content. Finally, the study also used a model to predict the scores of English teaching ability indicators. The results showed that the GA-RBF model performed the best in predicting performance indicators, with a small error between the predicted results and actual scores. In contrast, the prediction accuracy of the BP model is lower.

Finally, the proposed technology was compared with literature [12] and literature [13]. Compared with previous research, this study introduced PCA and expert methods in the evaluation of MOOC English teaching quality, and selected the main teaching evaluation index factors. The weight index was determined through expert scoring. Compared with other technologies, it has stronger targeting and is suitable for English learners in more fields. At the same time, the GA-BP model was introduced to optimize the linear data, further improving the overall evaluation of the model. Compared to references [12] and [13], there is a significant improvement in the accuracy of the target audience and evaluation quality.

In summary, MOOC English teaching quality assessment is crucial for improving teaching quality and learning outcomes. This study provides an effective evaluation method by introducing PCA method and GA-RBF model, and has achieved excellent performance in experiments. However, further research and improvement are needed, such as the evaluation model only targeting online English learners, and an offline evaluation system can be added in the future. Strengthening consideration of learner emotions and other factors can further enhance the evaluation effectiveness of the model.

6. Conclusion. Network teaching has become an important development direction of modern education. Taking MOOC English teaching as the research background, a more comprehensive quality evaluation of MOOC English teaching is carried out. Therefore, this paper studies the current situation of MOOC English teaching using the PCA method to reduce the dimensionality of the existing Teaching Effectiveness factors, selects the main English quality evaluation index factors, and constructs the Teaching Effectiveness evaluation system. Considering the complexity of English quality evaluation, the GA-RBF model is used to solve the Teaching Effectiveness evaluation model. In the multi-model quality evaluation accuracy test, the GA-RBF model has the best evaluation accuracy in the oral English quality evaluation, and the quality evaluation accuracy in sample 3, sample 6, and sample 9 are 0.96, 0.94, and 0.91, respectively, which are better than BP model and RBF model. In the MOOC English content evaluation accuracy test, the quality evaluation accuracy of the BP model in vocabulary teaching, grammar teaching, oral language teaching, and social environment is 77%, 75%, 73%, and 81%, respectively. The RBF model is 92%, 88% respectively, and the GA-RBF model is 97%, 98%, 94%, 93%, respectively. It can be seen that the GA-RBF model has an excellent performance in quality assessment. Compared with BP and RBF, GA-RBF is more accurate in predicting the performance of English indicators in the evaluation test of teaching ability indicators. For example, in the reading ability test of BP, the predicted score is 85, the actual score is 98, and the error is 13. The GA-RBF estimated score is 97, the actual score is 98, and the error is 1. It can be seen that the proposed GA-RBF model performs the best in MOOC teaching effectiveness evaluation. Compared with similar evaluation models, it has higher accuracy and better adaptability, which meets the requirements of English teaching. However, there are also shortcomings in the research. The evaluation of English teaching quality mainly relies on algorithmic model solving, and the preset parameters of the model have a significant impact on the evaluation of teaching quality. It is necessary to choose training parameters reasonably to meet the requirements of model training. Meanwhile, in the future, offline evaluation systems can be added. Strengthening consideration of learner emotions and other factors can further enhance the evaluation effectiveness of the model.

REFERENCES

[1] Yuan, L., Xiaofei, Z. & Yiyu, Q. Evaluation model of art internal auxiliary teaching quality based on artificial intelligence under the influence of COVID-19. *Journal Of Intelligent & Fuzzy Systems.* **39**, 8713-8721 (2020)

[2] Sun, Z., Anbarasan, M. & Praveen Kumar, D. Design of online intelligent English teaching platform based on artificial intelligence techniques. *Computational Intelligence.* **37**, 1166-1180 (2021)

[3] Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L. & Takiyama, H. Accurate and interpretable evaluation of surgical skills from kinematic data using fully convolutional neural networks. *International Journal Of Computer Assisted Radiology And Surgery.* **14**, 1611-1617 (2019)

[4] Grissom, J. & Retention, B. Principal effectiveness and teacher turnover in multiple-measure teacher evaluation systems. *American Educational Research Journal.* **56**, 514-555 (2019)

[5] Han, K. Evaluation of teaching quality of college physical education based on analytic hierarchy process. *International Journal Of Emerging Technologies In Learning (iJET).* **15**, 86-99 (2020)

[6] Close, K., Amrein-Beardsley, A. & Mapping, C. America's teacher evaluation plans under ESSA. *Phi Delta Kappan.* **101**, 22-26 (2019)

[7] Nazari-Shirkouhi, S., Mousakhani, S., Tavakoli, M. & AAffiliation M, Affiliation J. Importance-performance analysis based balanced scorecard for performance evaluation in higher education institutions: an integrated fuzzy approach. *Journal Of Business.* **21**, 647-678 (2020)

[8] Lino, A., Rocha, Á. & Sizo, A. Virtual teaching and learning environments: automatic evaluation with artificial neural networks. *Cluster Computing.* **22**, 7217-7227 (2019)

[9] Qianna, S. Evaluation model of classroom teaching quality based on improved RVM algorithm and knowledge recommendation. *Journal Of Intelligent & Fuzzy Systems.* **40**, 2457-2467 (2021)

[10] De-kun, J. & Memon, F. Design of mobile intelligent evaluation algorithm in physical education teaching. *Mobile Networks And Applications.* **27**, 527-534 (2022)
[11] Goli, A., Chintagunta, P. & Sriram, S. Effects of payment on user engagement in online courses. *Journal Of Marketing Research.* **59**, 11-34 (2022)
[12] Luo, R. & Ye, Z. What makes a good-quality language MOOC?. *An Empirical Study Of Criteria To Evaluate The Quality Of Online Language Courses From Learners' Perspectives ReCALL.* **33**, 177-192 (2021)
[13] Ren, S. & Yu, B. The evaluation method for English MOOC quality based on grounded theory International Journal of Continuing Engineering Education and Life Long Learning. *32(2):*. pp. 143-158 (2022)
[14] Goli, A., Ala, A. & Mirjalili, S. A robust possibilistic programming framework for designing an organ transplant supply chain under uncertainty Annals of Operations Research. *328(1):*. pp. 493-530 (2023)
[15] Goli, A., Ala, A. & Hajiaghaei-Keshteli, M. Efficient multi-objective meta-heuristic algorithms for energy-aware non-permutation flow-shop scheduling problem Expert Systems with Applications. *213:*. **119077** (2023)
[16] Shichijo, S., Endo, Y., Aoyama, K., Ozawa, T. & Bianchi, D. Application of convolutional neural networks for evaluating Helicobacter pylori infection status on the basis of endoscopic images. *Scandinavian Journal Of Gastroenterology.* **54**, 158-163 (2019)
[17] Yang, C., Xie, L., Qiao, S. & Yuille, A. Training deep neural networks in generations: A more tolerant teacher educates better students[C]//Proceedings of the AAAI Conference on Artificial Intelligence. *33(01):*. pp. 5628-5635 (2019)
[18] Zavoli, A., Maria Zolla, P., Federici, L., Migliorino, M. & Bianchi, D. Surrogate Neural Network for Rapid Flight Performance Evaluation of Hybrid Rocket Engines. *Journal Of Spacecraft And Rockets.* **2022**, 6
[19] Funke, I., Mees, S., Weitz, J. & Speidel, S. Video-based surgical skill assessment using 3D convolutional neural networks. *International Journal Of Computer Assisted Radiology And Surgery.* **14**, 1217-1225 (2019)
[20] Gao, Y., Kim, Y. & Doan, B. Design and evaluation of a multi-domain trojan detection method on deep neural networks. *IEEE Transactions On Dependable And Secure Computing.* **19**, 2349-2364 (2021)
[21] Saito, T., Watanobe, Y. & Zhang, Z. Learning path recommendation system for programming education based on neural networks. *International Journal Of Distance Education Technologies (IJDET).* **18**, 36-64 (2020)
[22] Abrishami, A. & Aliakbary, S. Predicting citation counts based on deep neural network learning techniques. *Journal Of Informetrics.* **13**, 485-499 (2019)
[23] Schöller, C., Aravantinos, V., Lay, F. & Knoll, A. What the constant velocity model can teach us about pedestrian motion prediction. *IEEE Robotics And Automation Letters.* **5**, 1696-1703 (2020)
[24] Hasanpour, R., Rostami, J., Schmitt, J., Ozcelik, Y. & Sohrabiane, B. Prediction of TBM jamming risk in squeezing grounds using Bayesian and artificial neural networks. *Journal Of Rock Mechanics And Geotechnical Engineering.* **12**, 21-31 (2020)

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