Research Article

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Optimal design of neural network-based fuzzy predictive control model for recommending educational resources in the context of information technology

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Abstract: As the information technology develops, educational resource recommendation system has become an indispensable part of the education field. At the same time, people's demand for personalised educational resources is also growing; therefore, how to accurately predict user demand and provide personalised recommendations has become an important issue. In this study, a fuzzy predictive control model on the grounds of neural network is proposed to optimise the design of educational resource recommendation in the context of information technology. After experimental testing, the model recommendation fit reached 95.16 and 92.91% on the two test datasets, which are significantly higher than the control model. The average $F1$ values of the proposed model also reached 95.21 and 88.77%, which are higher than the control model. In other control experiments, the proposed model of this study also has a better performance. The relevant outcomes showcase that the predictive performance and recommendation effect of the model can be further enhanced by improving the structure of the neural network and the parameter optimisation method. Meanwhile, the proposed model has high performance in information overload and personalised demand, which offers a useful reference for the optimal design of educational resource recommendation system.

Keywords: educational resource recommendation, fuzzy predictive control, neural networks, generalised matrix decomposition, rolling optimisation

1 Introduction

With the advent of the information age, the ways in which educational resources are obtained and utilised have undergone tremendous changes. The traditional way of obtaining educational resources can no longer satisfy people's requirements, and the development of information technology provides new opportunities for the establishment and optimisation of educational resource recommendation systems. Although there are various educational resource recommendation systems available on the market, there are still some shortcomings in the current educational resource recommendation systems. First, the problem of information overload makes it difficult for users to find suitable resources among numerous resources, resulting in low efficiency. Second, traditional recommendation algorithms are difficult for satisfying the diverse requirements of users [1,2]. Therefore, how to accurately predict user needs and make personalised recommendations has

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become an important direction of research in educational resource recommendation systems [3]. Neural networks, as a powerful pattern recognition and learning method, can extract useful features from a large amount of data. Especially the generalised matrix factorisation (GMF) algorithm, which has the advantages of general neural networks and can reduce the dimensionality of data [4]. The fuzzy predictive control (FPC) algorithm, on the other hand, is able to deal with uncertainty and ambiguity, improving the robustness and adaptability of the system. Therefore, this research combines GMF and FPC techniques to construct an accurate personalised educational resource recommendation model. There are two innovations in this research: first, the research uses a rolling optimisation algorithm to optimise the FPC algorithm, which solves the problem of the prediction time window limitation; second, using GMF for dimensionality reduction enables the FPC algorithm to maintain high accuracy in processing high-dimensional data. The structure of the article includes four parts, the first part is related work, which looks for a large number of research-related literature to make theoretical preparations for this study; the second part is the methodology, which constructs an educational resource recommendation model through FPC and GMF; the third part is the model performance test, which proposes the application performance of the model through experimental tests; the fourth part is the conclusion, which summarises the achievements and significance of this study, and points out the shortcomings of the research.

2 Related works

FPC is one of the most common types of prediction algorithms, and a number of researchers have conducted in-depth studies and explored this algorithm. For example, Fei and Liu [5] proposed a real-time nonlinear model predictive control method on the grounds of a self-feedback recursive fuzzy neural network estimator. The method integrates the advantages of fuzzy system and recurrent neural network, and significantly improves the dynamic performance through the self-feedback structure. And a gradient descent based optimisation method is utilised for solving the optimal control problem. The relevant outcomes demonstrate that the method has better performance compared to existing methods in both steady state and dynamic states. Shan et al. [6] proposed a predictive voltage and current control strategy for microgrids formed by clusters of shunt-connected distributed generating units in islanded and grid-connected modes of operation. The strategy achieves islanded and grid-connected operation and smooth transition through a unified cost function without changing the control architecture. Test results show that this control strategy outperforms the conventional method. Long et al. [7] presented a new control method that combines fuzzy control with a model predictive controller (MPC). The method makes full use of the regulation capability of the swing equation, and uses the MPC method to modify the optimal power rating of the VSG to enhance the support of the energy storage system (ESS) for power demand. The relevant outcomes verify the effectiveness of the method, which can significantly improve the frequency performance of the system. Zha et al. [8] proposed a hierarchical stability control strategy for the stability problem of four-wheel independent drive (4WID) electric vehicles. The strategy includes a fuzzy controller in the upper level, a torque distribution optimisation controller in the middle level, and a motor torque controller in the lower level. It is validated by a joint simulation platform on the grounds of Carsim and Simulink software, and the outcomes showcase that the proposed control strategy not only meets the driving dynamics requirements, but also improves the stability and security of the 4WID electric vehicle. Gao et al. [9] proposed a trajectory tracking control scheme for solving the lateral motion problem of an unmanned aerial vehicle. The scheme works on the grounds of model predictive control and linearises the nonlinear lateral motion model through small angle approximation. For the lateral motion problem, a new bounded equivalence function is proposed for solving the trajectory tracking control using the vehicle kinematics model and Taylor series expansion. The model predictive control ensures robustness and control accuracy. The relevant outcomes verify the effectiveness of the method in the real environment.

Recently, as the boost of the information technology, neural network-based prediction, and recognition models have been gradually introduced in different aspects, contributing greatly to the advancement of the corresponding industries. A new taxonomy is proposed by researchers such as Zhang et al. [10]. The taxonomy is organised along three dimensions, which are the type of participation, the type of interpretation, and the focus. The taxonomy provides a meaningful three-dimensional view as two of the dimensions are not simply categorised but allow for ordered subcategories. The proposed method is experimentally verified to be significantly useful in black-box attribute classification and effectively improves the efficiency of black-box attribute classification. Cui et al. [11] proposed a feed-forward neural network based battery charging state detection method for solving the problem of effective charging of lithium batteries. The method analyses the charging state of lithium battery in real time through feed-forward on the neural network feature extraction and fitting ability, so as to determine whether there is any abnormality in the charging state. The relevant outcomes proved that the proposed method possess excellent performance and advanced in practical applications. Hizlisoy et al. [12] presented a music emotion recognition method for music recognition and classification. The method provides features obtained by logarithmic Mel filterbank energy and Mel-frequency cepstrum coefficients through the convolutional neural network layer. The classification results show that the best performance is obtained when the new feature set is combined with standard features using long and short-term memory and a deep neural network classifier. Liu et al. [13] proposed a programmable diffractive deep neural network architecture on the grounds of a multilayer array of digitally coded metasurfaces. The architecture acts as an active artificial neuron on the grounds of the integration of each meta-atom on the neuron surface with two amplifier chips, providing a dynamic modulation range of 35 dB (from −22 to 13 dB). The experiment shows that the framework has good dynamic adjustment ability. Hu et al. [14] proposed a solution to process videos using deep neural network visual analytics. The proposed solution aims to detect communication users that can be augmented or substituted in practice activities. The results indicated that this method had great potential in improving the effectiveness of data logging and ultimately enhancing complementarity.

In summary, the education resource recommendation model on the grounds of neural networks and FPC has great potential in improving the learning effectiveness of learners and meeting personalised needs, but further research and improvement are still essential for enhancing the accuracy, practicality, and adaptability of the model. Therefore, this study attempts to introduce new methods to improve FPC and GMF technologies, aiming to construct an efficient and accurate educational resource recommendation model.

3 Construction of an education resource recommendation model on the ground of GMF and FPC

In the current education sector, recommender systems play an important role in helping students access personalised educational resources. However, traditional recommendation methods often fail to accurately capture students' interests and needs. Therefore, this research uses advanced generalised matrix decomposition techniques and FPC models to upgrade the educational resource recommendation model.

3.1 Research on personalised recommendation model on the ground of FPC

The demand for education has diverse and personalised characteristics, and the existing educational resources are showing an explosive growth trend. Its query efficiency and recommendation efficiency face many challenges. FPC algorithm plays a crucial role in educational resource recommendation, and its feedback correction mechanism can continuously update the correction prediction values during the process of educational resource recommendation, achieving good recommendation results [15]. The basic idea of FPC algorithm is to describe the dynamic behaviour by constructing a fuzzy rule base and to use fuzzy inference and fuzzy controller for prediction and control. The construction of FPC model requires the definition of fuzzy set, where each element has a certain degree of affiliation within a particular range of variables [16]. Therefore, the study chose FPC as the main method to explore the key challenges in educational resource recommendation systems.

FPC, with its ability to handle system uncertainty and ambiguity, provides effective solutions for diverse educational needs. The RO algorithm overcomes the prediction time window limitation by optimising FPC, thereby enhancing the robustness of the system. The combination of FPC and RO enables the system to more accurately predict user needs, achieve personalised educational resource recommendations, and provide higher quality educational resource services. The construction of the FPC model requires the definition of a fuzzy set, which refers to a specific range of variables where each element has a certain degree of membership [17]. The degree of affiliation indicates how similar an element is to that fuzzy set and is usually expressed as a real value between 0 and 1. The value of the degree of affiliation is determined by the affiliation function and the expression defining the affiliation function of a fuzzy set is shown in equation (1).

$$\mu_{\mathrm{a}}, \mu_{\mathrm{a}} : U \to [0, 1], \tag{1}$$

where U serves as the domain of the set; μ_a serves as the affiliation function of the fuzzy set, which represents the degree to which the elements belong to the set. Therefore, the mathematical expression of the fuzzy set A is showcased in equation (2).

$$A = \frac{\mu_{\mathrm{a}}(x_1)}{x_1} + \frac{\mu_{\mathrm{a}}(x_2)}{x_2} + \cdots + \frac{\mu_{\mathrm{a}}(x_n)}{x_n}, \tag{2}$$

where x denotes the elements of the fuzzy set; A denotes the fuzzy set; $\frac{\mu_{\mathrm{a}}(x_n)}{x_n}$ serves as the correspondence between the element x_n and the degree of affiliation $\mu_{\mathrm{a}}(x_n)$; n denotes the total number of elements. After the fuzzy set is constructed, we need to consider the construction of prediction model, which is the core of FPC algorithm. In FPC algorithm, the role of predictive model is for forecasting the future behaviour of the system. By building a suitable predictive model, the future output and behaviour of the system can be estimated on the grounds of the current inputs and states, thus providing a basis for the controller to make decisions. If the current input is a single-point fuzzy function, the prediction model will set the fitness function for the given input, and the mathematical expression of the fitness function is showcased in equation (3).

$$\alpha_j = \mu_{\mathrm{a}_1^j}(x_1) + \mu_{\mathrm{a}_2^j}(x_2) + \ldots + \mu_{\mathrm{a}_n^j}(x_n), \tag{3}$$

where α_j represents the fitness of each rule; A_i^j represents the jth language variable value of x_i. The fitness function should be on the grounds of the characteristics of the problem and the weights should be chosen reasonably to reflect the key requirements of the problem. The output expression of the original prediction model for a single element x is showcased in equation (4).

$$\delta(z^{-1})y(x) = \varphi(z^{-1})u(x - 1) + \chi(z^{-1})\frac{\xi(x)}{\Delta}, \tag{4}$$

where $\Delta = 1 - z^{-1}$; $y(x)$, $u(x - 1)$, $\xi(x)$ are the input, output, and noise sequence with mean value 0, respectively; δ, φ, and χ all represent polynomials of z^{-1}. This output formula has many defects such as high data requirement, difficulty in parameter adjustment, and limitation of prediction time window. In order to accurately recommend educational resources, this study uses rolling optimisation (RO) algorithm to optimise the prediction model. RO algorithm is an optimisation method on the grounds of consecutive time windows, which performs local optimisation in each time window according to the objective function, and constantly updates and adjusts the optimisation strategy by means of rolling windows. The basic idea of rolling optimisation is to divide the optimisation problem into a series of consecutive time windows, and perform local optimisation within each time window to obtain a set of optimal solutions [18]. Then, according to the characteristics of the problem and the optimisation objective, the optimal solution is passed to the next time window by means of the rolling window, which is used as the initial condition for the next local optimisation. In this way, the problem can be iterated continuously, and the overall solution of the problem can be optimised step by step by continuously updating and adjusting the optimisation strategy. The expression of the objective function of the RO algorithm is shown in equation (5).

$$J = \sum_{J=1}^{m} [y(x + 1) - \mu_{\mathrm{a}}(x + j)]^2 + \sum_{j=1}^{o} \lambda(j)[\mu'(x + j - 1)]^2, \tag{5}$$

where $\lambda(j)$ denotes the weighting coefficient, which is usually a constant greater than 0; m serves as the maximum value of the predicted length; o denotes the control length, which should be smaller than the maximum value of the predicted length; and $\mu'(.)$ denotes the weighted subordinate function. After optimisation, the output of the fuzzy system is the weighted average of the output of each input element. The final output is shown in equation (6).

$$y = \frac{\sum_{j=1}^{N} \alpha_j y_j}{\sum_{j=1}^{n} \alpha_j} = \sum_{j=1}^{N} \bar{\alpha}_j y_j, \tag{6}$$

where y_j serves as the weighted output of the prediction model for the elements of x_j; N represents the total number of elements; $\bar{\alpha}_j$ serves as the fitness coefficient of α_j, and the computational expression for taking the average value of α_j is showcased in equation (7).

$$\bar{\alpha}_j = \frac{\alpha_j}{\sum_{i=1}^{n} \alpha_i}, \tag{7}$$

Feedback correction is also an important module of the FPC algorithm, which measures and compares the output of the system, and adjusts and corrects the input of the system according to the measurement results for making the output close to the desired value. The feedback correction module contains two parts: the feedback control loop and the feed-forward positive path, and its structure is shown in Figure 1.

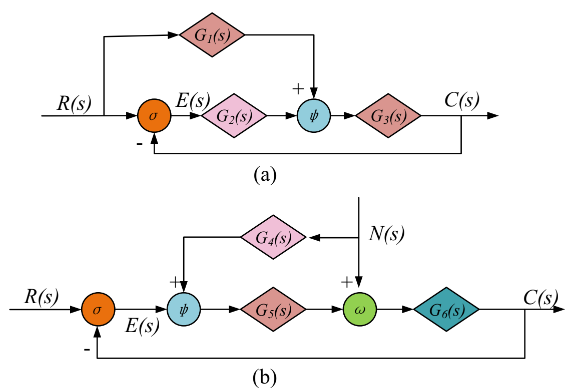

Figure 1: Structural diagram of feedback correction module. (a) Feedback control loop. (b) Feedforward positive path.

The feedback correction module possesses an essential influence on control systems. It can not only significantly enhance the performance of the control system and make it more comfortable in the face of uncertainty and change but also broaden the utilisation areas of the control system. The addition of the feedback correction module effectively alleviates the problem of information overload in the educational resources recommendation model. After adding the feedback correction, the construction of a more complete FPC model is basically completed, and the structure is showcased in Figure 2.

Since the FPC model cannot handle high-dimensional data, the output accuracy of the algorithm often fails to meet the needs of personalised recommendation when facing multi-attribute optimal selection. To address the above shortcomings, the FPC model also needs to be improved by dimensionality reduction.

3.2 Construction of FPC education resource recommendation model integrating GMF algorithm

The GMF algorithm is a technique for dimensionality reduction of high-dimensional matrices, which disassembles the original high-dimensional matrix into the product of multiple matrices for achieving the influence

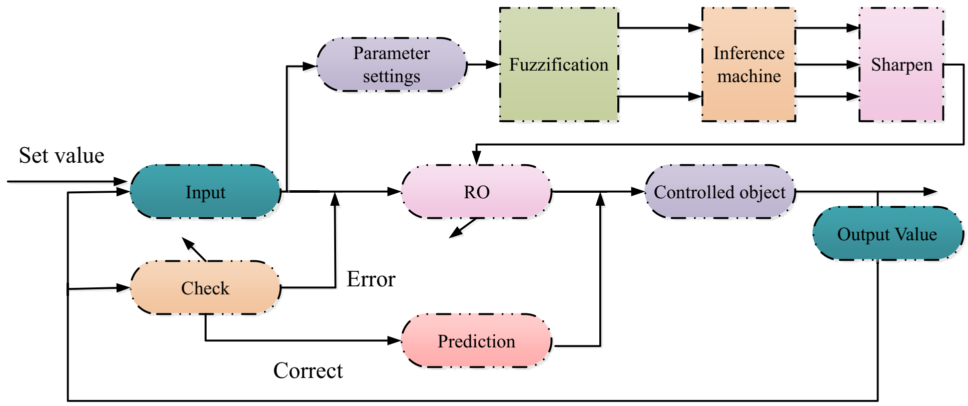

Figure 2: Structure diagram of FPC model.

of dimensionality reduction [19]. Therefore, the study uses the GMF algorithm to improve the FPC model and thus reach the influence of dimensionality reduction. Matrix decomposition is an important concept in linear algebra, which has an extensive range of applications in many fields [20]. Among the many matrix decomposition methods, singular value decomposition, eigenvalue decomposition, and Cholesky decomposition are well known and widely used. However, these traditional matrix decomposition methods are significantly different from the decomposition of GMF algorithm. The matrix decomposition of GMF algorithm is showcased in Figure 3.

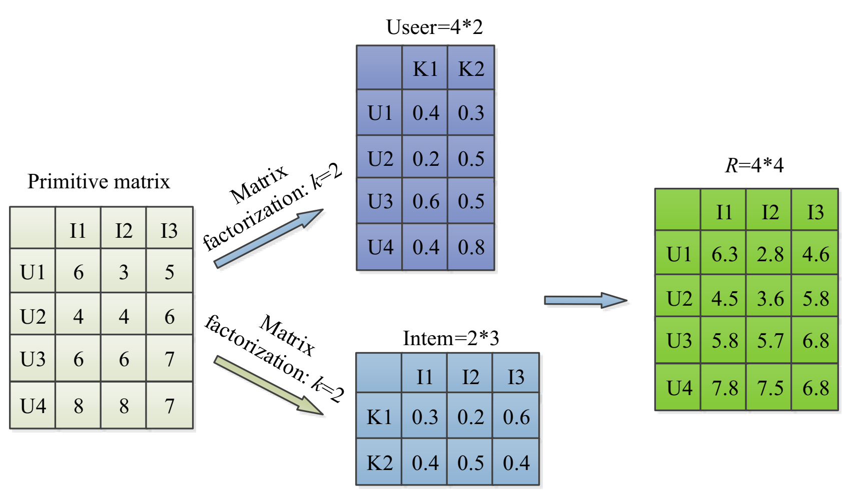

Figure 3: Matrix decomposition process of GMF algorithm.

The decomposition expression of the GMF algorithm is showcased in equation (8).

$$R = P^{\mathrm{T}} \cdot Q = \hat{R}, \tag{8}$$

where R denotes the matrix involved in the decomposition calculation; P^{T} denotes the transpose of P matrix; P, Q denote the matrix obtained after R decomposition. The matrix P consists of the correspondences of the elements of n to the subjects of k, and the matrix Q consists of the correspondences of the subjects of k to the targets of θ. The expression for calculating the values of the elements in the decomposition matrix is shown in equation (9).

$$\hat{r}_{ij} = \sum_{i=1}^{k}\sum_{j=1}^{k} p_{ik} \cdot q_{kj}, \tag{9}$$

where $\hat{r}_{ij}$ denotes the value of the element in the i row and j column of the $\hat{R}$ matrix; p_{ik} denotes the element in the i row and k column of the P matrix; and q_{kj} denotes the element in the k row and j column of the Q matrix. The loss function (LF) is often used to judge the merits of matrix decomposition methods, and in this study, the LF is utilised for calculating the minimum value of the sum of each element, which is used to judge whether the matrix decomposition meets the requirements or not [21]. The mathematical calculation is demonstrated in equation (10).

$$e_{ij}^2 = (r_{ij} - \hat{r}_{ij}) = \left(r_{ij} - \sum_{i=1}^{k}\sum_{j=1}^{k} p_{ik} \cdot q_{kj} \right), \tag{10}$$

where e_{ij} denotes the sum of each element in the matrix; r_{ij} denotes the elements of the matrix before decomposition. The concept of negative gradient exists for the LF, for calculating the negative gradient of the LF, equation (11) is used in this study.

$$\begin{cases} \dfrac{\partial}{\partial p_{ik}} e_{ij}^2 = -2(r_{ij} - \hat{r}_{ij})(q_{kj}) = -2e_{ij} \cdot q_{kj} \\ \dfrac{\partial}{\partial q_{kj}} e_{ij}^2 = -2(r_{ij} - \hat{r}_{ij})(p_{ik}) = -2e_{ij} \cdot p_{ik}, \end{cases} \tag{11}$$

where $\frac{\partial}{\partial p_{ik}} e_{ij}^2$ and $\frac{\partial}{\partial q_{kj}} e_{ij}^2$ denote the derivatives of e_{ij}^2 with respect to p_{ik} and q_{kj}. The GMF algorithm is a kind of machine learning algorithm, so the algorithm carries a regular term in its operation. The role of the regular term is used to avoid overfitting and improve the generalisation ability, the LF representation formula carrying the regular term is shown in equation (12).

$$e_{ij}^2 = \left(y_{ij} - \sum_{i,j=1}^{k} p_{ik} \cdot q_{kj} \right)^2 + \frac{\alpha}{2} \sum_{i,j=1}^{k} (||P||^2 + ||Q||^2), \tag{12}$$

where α denotes the correction parameter; and $||.||$ denotes the inner product operation. The updating of the elements in the matrix needs to be done through the direction of change in the negative gradient, so the expression of the updated matrix elements is shown in equation (13).

$$\begin{cases} p'_{ik} = p_{ik} + \varepsilon(2e_{ij}q_{kj} - \alpha p_{ik}) \\ q'_{kj} = q_{kj} + \varepsilon(2e_{ij}q_{kj} - \alpha q_{kj}), \end{cases} \tag{13}$$

where ε represents the learning rate, the larger the learning rate, the faster the iteration speed and the faster the descending gradient; p'_{ik} and q'_{kj} represent the updated matrix elements. The matrix gradually converges after several updates, and the output value of the algorithm is basically stable. The expression of the output value after stabilisation is shown in equation (14).

$$Y = p(i,1) \cdot q(1,j) + p(i,2) \cdot q(2,j) + \ldots + p(i,k) \cdot q(k,j), \tag{14}$$

where Y denotes the fit of the ith element to the jth target. In the personalised recommendation of educational resources, the above matrix decomposition process can not only reduce the computational dimension but also derive and refine the feature information of users and educational resources. The refinement process of feature information is shown in Figure 4.

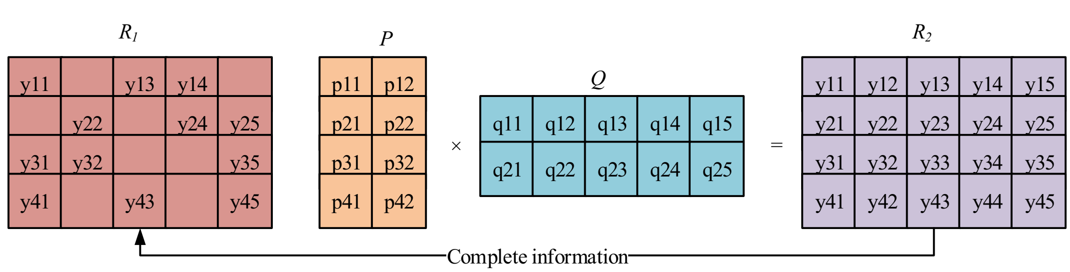

Figure 4: Process of improving feature information.

Aiming at obtaining the predicted values in the user and educational resource scarcity matrices in Figure 4, it is necessary to decompose the matrix R into a user feature matrix P^{T} and an educational resource feature matrix Q, and the decomposition process is described in the above calculation. After several iterations, the vacant feature information can be filled in. Therefore, the final output expression of the FPC educational resource recommendation model incorporating the GMF algorithm is shown in equation (15).

$$y_{\mu,r} = f(\mu, r|P, Q) = P_{\mu}^{\mathrm{T}} \cdot Q_r, \tag{15}$$

where P_{μ}^{T} denotes the fuzzy matrix generated by user preference; Q_r denotes the fuzzy matrix generated by the characteristics of educational resources; $y_{\mu,r}$ denotes the correlation degree of user preference and characteristics of educational resources, and the higher the correlation degree is, the higher the recommendation index of the resource is. At this point, the fuzzy predictive control educational resource recommendation model (G-FPC) incorporating GMF algorithm is built, and the technical framework diagram is showcased in Figure 5.

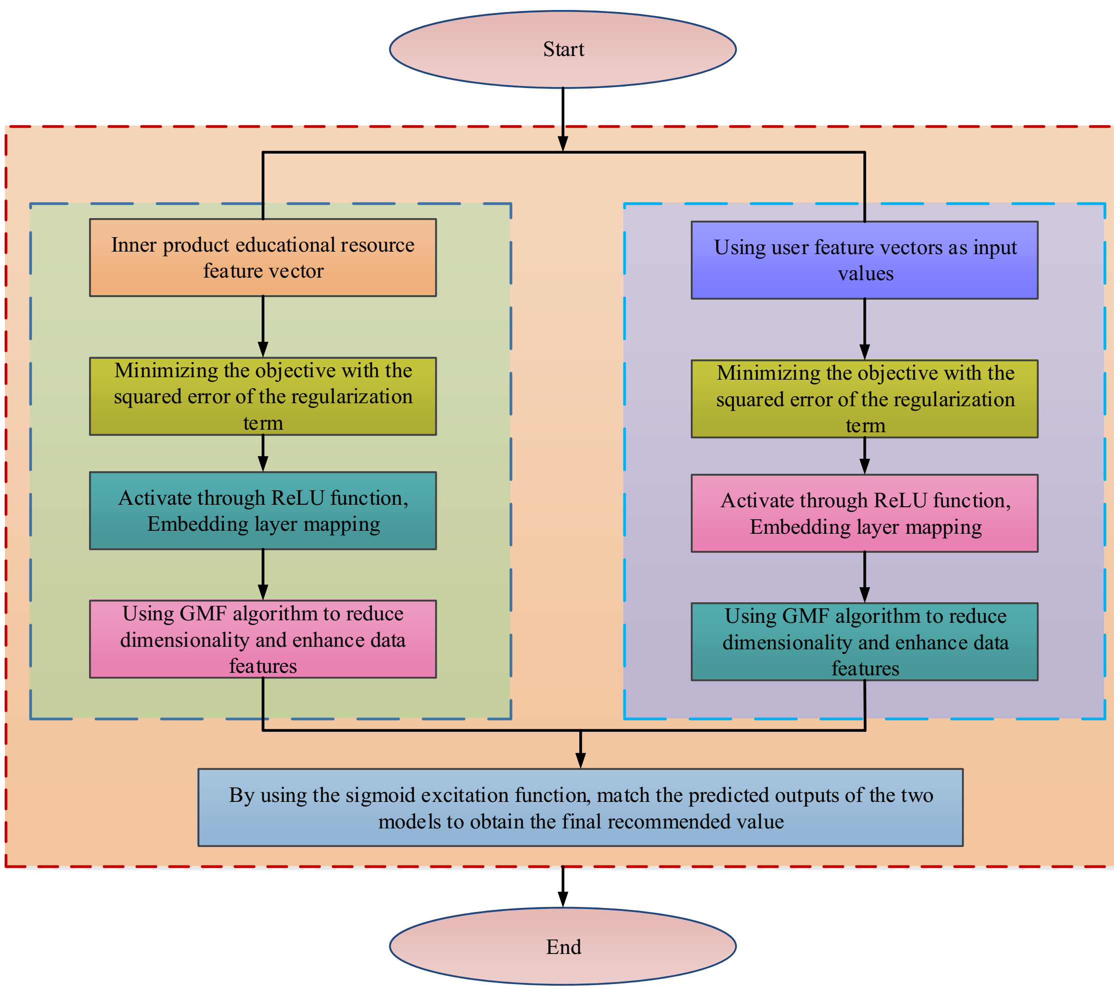

Figure 5: Technical framework of G-FPC model.

4 Performance analysis of G-FPC model

The study comprehensively analyses the performance of content-based recommendation (CBR), G-FPC, and collaborative filtering (CF) models on the air quality and energy efficiency datasets to evaluate the effectiveness of different models in recommendation systems. The indicators involved in the experiment include model fit, loss rate, recall rate, time complexity, $F1$ value, and root mean square error (RMSE). The selected comparison models include CF and CBR.

4.1 Analysis of G-FPC model classification performance and loss rate

The equipment used for this experiment is a desktop computer with 16GB of operating memory, i7-13700K CPU, and GeForce GTX 470 graphics card; the system resource is Windows 11; the data processing and analysis tool is Pandas; the editor is PyCharm; the experimental datasets are air quality and energy efficiency dataset; the control models are CF, CBR. The fit between the recommended resources output from the models and the actual user preferences is the core index of this study. This experiment takes the air quality and energy efficiency datasets as inputs, and compares the fit between the recommended resources output from the three models CBR, G-FPC, and CF and the actual user preferences, and the outcomes are showcased in Figure 6. Figure 6(a) represents the relation in the fit of each model on the air quality dataset and the number of training times. Figure 6(b) represents the relationship between the fit of each model on the energy efficiency dataset and the number of training times. The figure indicates that the fit of the G-FPC model outperforms the control model on both datasets, and the fit of the G-FPC model on the air quality dataset reaches a maximum of 95.16%, and that on the energy efficiency dataset reaches a maximum of 92.91%.

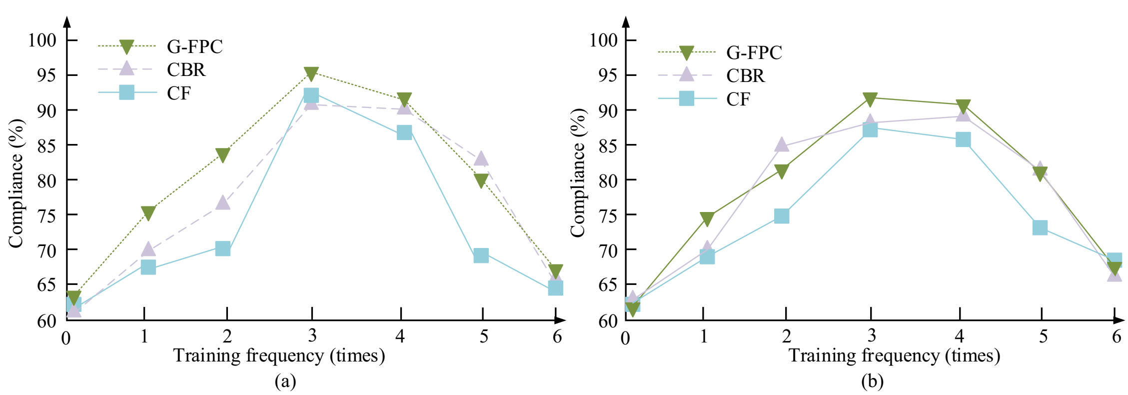

Figure 6: Comparison of fit between different models. (a) The fit of the model on the air quality dataset. (b) The fit of the model on the energy efficiency dataset.

Aiming at verifying the classification effect on educational resources, this experiment assumes various types of data in the energy efficiency dataset as different types of educational resources as inputs, and compares the classification effects of the CBR model and the G-FPC model. The outcomes are showcased in Figure 7. Figure 7(a) represents the classification effect of the CBR model, which has a low classification density and an error in the locating classification centre after classification. Figure 7(b) represents the classification performance of the CF model, which can have better classification performance compared to CBR, but also has the disadvantages of inaccurate classification centre position and low classification density. Figure 7(c) shows the classification effect of the G-FPC model, which classifies with high density and also locates the classification centre more accurately.

In order to analyse the relationship between the loss rate and the number of iterative steps, this experiment uses the air quality dataset as input and compares the loss rate of the CBR and G-FPC models and the average loss rate calculated after three experiments, and the outcomes are showcased in Figure 8. Figure 8(a) represents the relation in the loss rate and the number of iteration steps for the first experiment of the CBR and G-FPC model; Figure 8(b) represents the relation in the average loss rate and the number of iteration steps after repeating the three experiments. From the figure, it can be seen that the trend of the change in the loss rate and the change in the average loss rate of the first experiment are basically the same. The G-FPC model

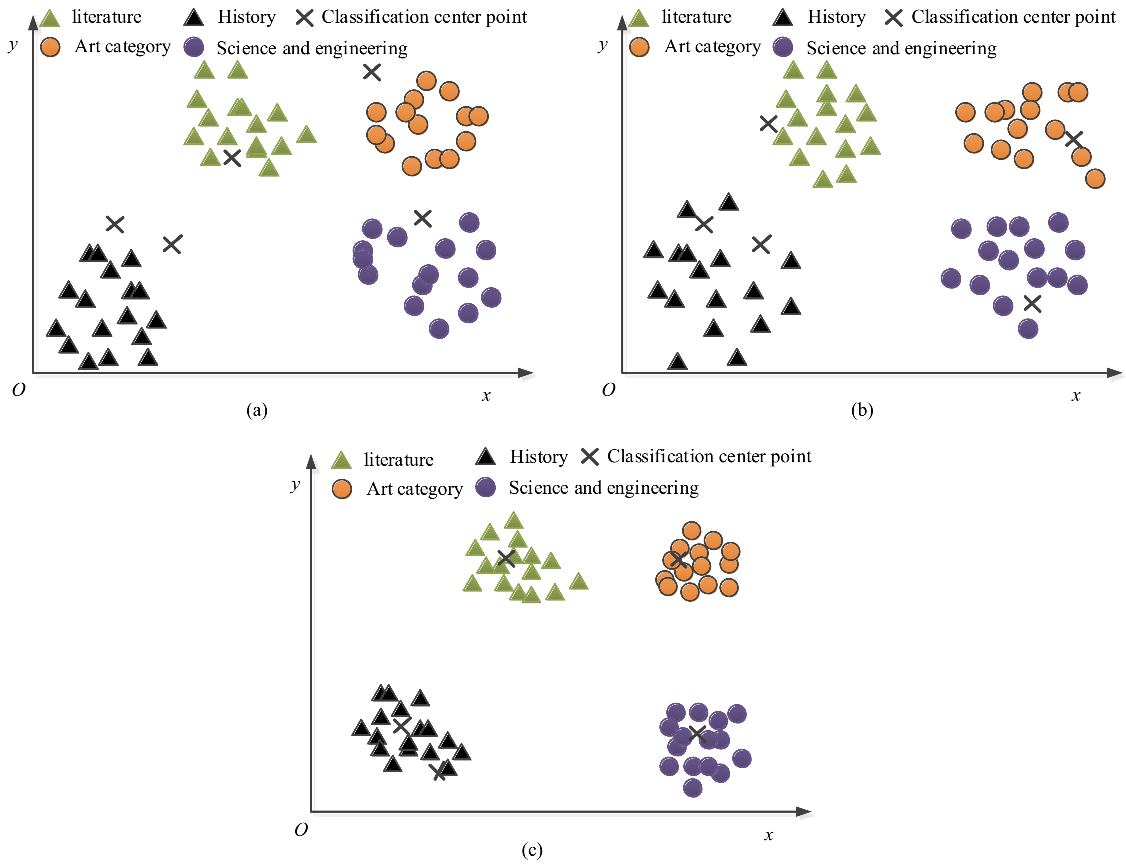

Figure 7: Comparison of model classification effects. (a) CBR model classification performance. (b) CF model classification performance. (c) G-FPC model classification performance.

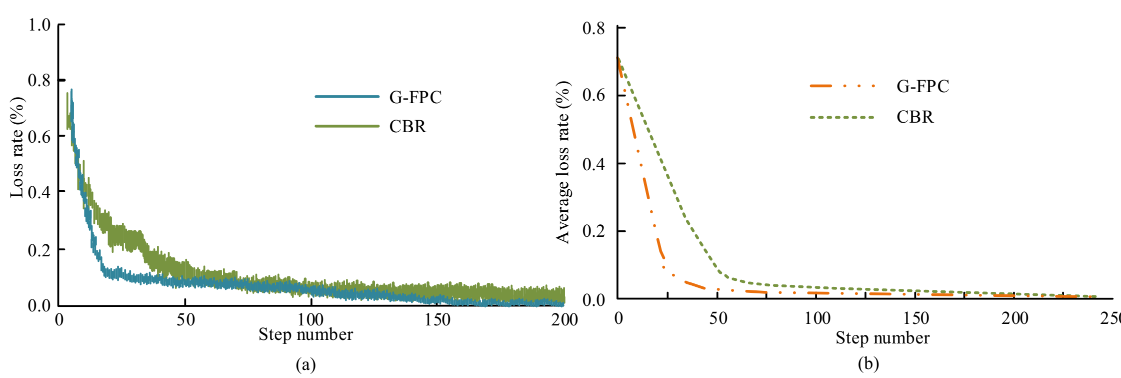

Figure 8: Comparison of loss rates of various models. (a) Loss rate. (b) Average loss rate.

possesses a lower loss rate with the same number of iterative steps, and at the same time, the number of convergence steps of the G-FPC model is smaller than that of the CBR model.

4.2 Training and application analysis of G-FPC Model

Recall is a metric that reflects the relationship between positive and negative samples in a model run, and is one of the metrics commonly used in machine learning class of algorithms. This experiment uses the air quality dataset as input, and compares the recall and average recall of the three models CBR, G-FPC, and CF, and the outcomes are showcased in Figure 9. Figure 9(a) represents the relation in the recall and the number of training times for the three models CBR, G-FPC, and CF; Figure 9(b) represents the average recall of the three models for multiple training times. The figure reveals that the recall of the G-FPC model exceeds the control model except for the second training. In addition, the average recalls of the three models CBR, G-FPC and CF are 88.71, 93.09, and 79.24%, respectively, so the G-FPC model performs better than the control model in the *F*1 test.

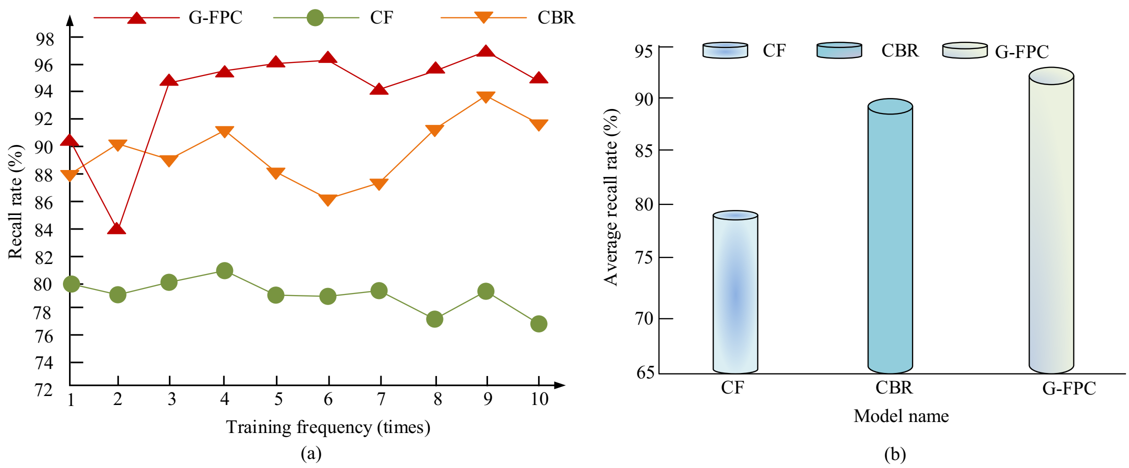

Figure 9: Comparison of recall rates among different models. (a) Comparison chart of recall rates among different models. (b) Comparison of *F*1 values among different models.

Time complexity is a measure used in algorithm analysis of how fast the execution time of an algorithm grows with the size of the input. It describes the relationship between the algorithm running time and the problem size. Aiming at verifying the time complexity, this experiment uses two datasets, air quality and energy efficiency, as inputs to compare the relationship between the number of information and time complexity of the three models, CBR, G-FPC, and CF, and the outcomes are showcased in Figure 10. Figure 10(a) represents the time complexity comparison of each model on the air quality dataset; Figure 10(b) represents the time complexity comparison of each model on the energy efficiency dataset. The figure reveals that the time complexity of G-FPC model is below other control models on both datasets, so the G-FPC model is advanced in terms of time complexity, and also verifies the advantage of high computational efficiency of G-FPC model from the side.

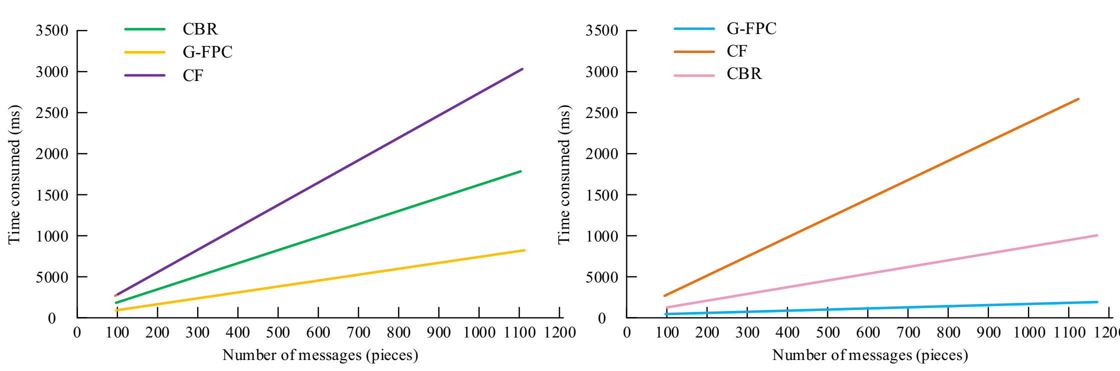

Figure 10: Comparison of time complexity of various models. (a) Comparison of time complexity on the air quality dataset. (b) Comparison of time complexity on the energy efficiency dataset.

The $F1$ value is a comprehensive indicator that takes into account both accuracy and recall, and is also one of the commonly used indicators for model evaluation. This experiment compares the $F1$ values of the three models CBR, G-FPC, and CF on the air quality and energy efficiency datasets, and the experiment will be repeated three times for avoiding the influence of chance factors. The relevant outcomes are showcased in Figure 11. Figure 11(a) represents the $F1$ values of the models on the air quality dataset; Figure 11(b) represents the $F1$ values of the models on the energy efficiency dataset. The figure reveals that the $F1$ values on the air quality and energy efficiency datasets are G-FPC model, CBR model, and CF model in descending order. The average $F1$ of the proposed model on the two datasets of air quality and energy efficiency is 95.21 and 88.77%, respectively.

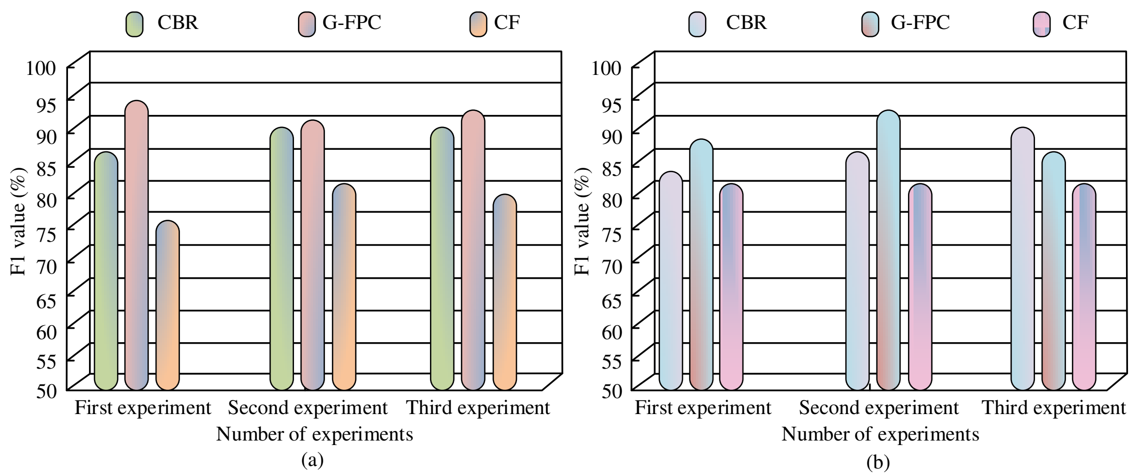

Figure 11: Comparison of $F1$ values among different models. (a) Comparison of $F1$ values on the air quality dataset. (b) Comparison of $F1$ values on the energy efficiency dataset.

RMSE is a commonly utilised statistical measure of the degree of difference between predicted and observed values. In this experiment, the air quality and energy efficiency datasets are used as inputs to compare the RMSE of the two models G-FPC and CF, and the outcomes are showcased in Figure 12. Figure 12(a) serves as the RMSE values of the models on the air quality dataset; Figure 12(b) serves as the RMSE values of the models on the energy efficiency dataset. The trends of the RMSE values of the models on the two datasets are generally the same, but the fluctuation of the RMSE values on the energy efficiency dataset is more obvious. The RMSE values of the two models, G-FPC and CF, on the air quality dataset are 0.131 and 0.186,

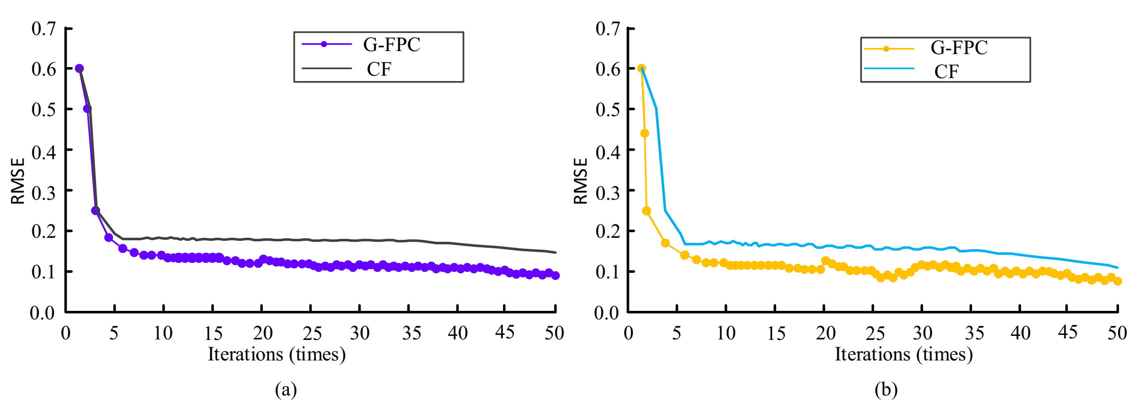

Figure 12: Comparison of RMSE values of various models. (a) RMSE comparison on the air quality dataset. (b) RMSE comparison on the energy efficiency dataset.

respectively, after the models have reached a stable level, while the RMSE values of the energy efficiency dataset are 0.134 and 0.20, respectively, after the models have reached a stable level.

5 Conclusion

In today's education field, people are facing a massive amount of educational resources, which cover multiple sources such as schools, online platforms, and training institutions. Due to the lack of fully functional classification recommendation systems on the market, how to quickly and efficiently recommend personalised educational courses from these chaotic and diverse resources has been an urgent issue that the industry needs to solve. Consequently, this study presents a personalised education resource recommendation model that incorporates the GMF algorithm and FPC, and designs experiments for validating its performance. The relevant outcomes showcase that the proposed model achieves a recommendation fit of 95.16 and 92.91% on the test dataset, an average $F1$ value of 95.21 and 88.77%, and a recall rate of 93.09%. These data indicate that the proposed model possesses high accuracy and recall in recommendation tasks and can effectively provide personalised recommendation services to users. In addition, the proposed model demonstrated a low RMSE on the test dataset, proving its high prediction accuracy. Meanwhile, this means that the model can accurately predict user behaviour and interests, providing users with more accurate recommendations and ensuring a good user experience. During the experiment, it was also found that the proposed model had shortcomings, such as slow convergence and poor performance in processing complex data. The subsequent research can decrease the complexity of the input data by pre-processing the data before inputting it, so as to improve the efficiency of the model recommendation.

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