A Study on Data-Driven Teaching Decision Optimization of Distance Education Platforms

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Abstract—Distance education requires the teachers' teaching decisions to be innovative, thus it's very meaningful to optimize the distance education elements, upgrade the teaching activity quality, and realize sustainable development. Existing studies generally make selections on distance education schemes based on empirical knowledge, however, since the decision parameters are often of poor time-efficient and prone to human caused errors, the efficiency and accuracy of the output decisions can hardly meet requirements. Therefore, to overcome these shortcomings, this paper aims to study the optimization of teaching decisions based on the teaching data of distance education platforms. At first, a hybrid neural network integrating the Bi-directional Long and Short Term Memory (Bi-LSTM) model and the Convolution Neural Network (CNN) was introduced into the Teaching Decision-making Optimization (TDO) model to capture the features of bi-directional time series of teaching decisions and build feature space with stronger expression ability. Then, a multi-objective TDO model was built based on fuzzy logic reasoning, which was then used to solve the problem during teaching decision-making that it's difficult for multiple decision element combinations in distance education to meet standards at the same time. At last, experiments verified the validity and superiority of the proposed model.

Keywords—distance education, teaching behavior data, teaching decision optimization

1 Introduction

During the teaching process of distance education, various internal and external factors of the online classroom would interact with each other [1–6], so each link in the teaching process of distance education is closely related to the teaching quality of online courses, and inappropriate choice of teaching methods or setting of teaching activities would seriously affect students' learning interest and their involvement in learning [7–14]. Teachers are required to carefully and comprehensively predict various factors in each teaching link, make high-quality teaching decisions, formulate reasonable and scientific teaching plans for distance education, select proper teaching methods, and apply suitable teaching tools, and only in this way, can the satisfactory teaching effect be achieved [15–26]. Distance education requires the teachers' teaching decisions to be innovative, thus it's very meaningful to optimize the distance education elements, upgrade the teaching activity quality, and realize sustainable development.

João and Quadrado [27] discussed the role of decision analysis in helping engineers better understand the problems they encounter in this paper, they highlighted the necessity of structured decision analysis and proposed to apply multi-criteria decision analysis to solve sustainability issues with emphasis laid on the MACBETH approach. The authors also provided some insights of a Portuguese summer engineering course for sustainable development and the opinions of students and teachers about the sustainability decision analysis module. Kaliisa et al. [28] explored how teachers make use of social learning analytics as a proxy to understand students' learning processes and help them make wise teaching decisions during the operation process of courses. They used NodeXL, a social network analysis tool, to analyze and visualize students' online learning processes, and used Coh-Metrix to analyze the speech features of students' discussion posts. Aiming at making full use of the massive history data of teaching management in colleges and universities and help make teaching management decisions, He and Chen [29] designed a teaching management decision support system. Based on the requirement analysis of teaching management decisions and the comprehensive application of theory and technology of data warehouse, online analytical processing, and data mining, they designed a four-layer structure for this system. Decision Support System is an effective system used in business and medical fields at present, it allows professionals to make evidence-based decisions and can be applied in the education field for continuous improvement of curriculum and teaching strategies, scholars McEachron and Torres [30] discussed the value of Instructional Decision Support System and its effects on the educational environment. Huang et al. [31] adopted cognitive science method to study the teaching decision-making in engineering education. In the research, engineering teachers were required to determine two memorable recent teaching decisions at two stages of initiation (planning) and interaction (classroom), and the teaching situations, decision-making processes, considered factors, and decision results were introduced.

After carefully reviewing related literatures, it's discovered that the existing studies on teachers' decision-making for distance education generally target on the element optimization of a single or two objectives, and the optimal combination of distance education elements can be attained by decision optimization algorithms. However, few studies have talked about the optimization of the distance education elements of three or more than three objectives. After obtaining the solution set of the decision model, existing studies usually select distance education teaching schemes based on empirical knowledge, however, since the decision parameters are often of poor time-efficient and prone to human caused errors, the efficiency and accuracy of the output decisions can hardly meet requirements. Therefore, to overcome these shortcomings, this paper aims to study the optimization of teaching decisions based on the teaching data of distance education platforms. The second chapter introduced a hybrid neural network integrating Bi-LSTM and CNN into the TDO model to capture the features of bi-directional time series of teachers' teaching decisions and build feature space with stronger expression ability. In the third chapter, a multi-objective TDO model was built based on fuzzy logic reasoning, which could solve the difficulty for multiple decision element combinations in distance education to meet standards at the same time. At last, experiments verified the validity and superiority of the proposed model.

2 Design of the TDO model

The development of Internet technologies has laid a solid foundation for the comprehensive application of distance education, and the deep mining of teaching behavior data has turned into a crucial link in the transformation and upgrading of smart education. For distance education, reasonably choosing the elements of distance education is the crux for achieving high quality and efficiency of distance education, and applying teaching decision optimization algorithms based on the history teaching behavior data of distance education platforms is conductive to improving the comprehensive performance of distance education platforms.

The management of distance education platforms driven by teaching behavior data has received much attention from field scholars in recent years, however, nearly all management methods regard the teachers' teaching decision-making process as a one-way process, and they generally ignored the two-way feature of teaching feedback. Therefore, this paper introduced a hybrid neural network that integrates Bi-LSTM with CNN into the TDO model to capture the features of bi-directional time series of teaching decisions and build feature space with stronger expression ability.

The framework of this TDO model built based on the said hybrid neural network contains three parts: the convolution module, the time series feature module, and the fully connected module. For the convolution module which is consisted of the convolution layer and the pooling layer, its activation function is the ReLU (Rectified Linear Unit) function, and its formula is:

$$\mathrm{Re\,LU}(a) = max(0, a) \tag{1}$$

Assuming: the kernel of two largest pooling layers in the convolution module is of 2*2 dimensions; MP represents the pooling operation, then the output of the pooling layer is:

$$t_i(p) = MP\left(t_{i-1}(p)\right) \tag{2}$$

The coded output of the convolution module will be taken as the input and processed after entering the time series feature module layer.

The time series feature module is a Bi-LSTM network, at first, this paper fused the forward and backward training results of the network. Assuming: a sequence K containing m elements is input into the Bi-LSTM network; $\{K_1, K_2, \ldots, K_{m-1}, K_m\}$ represents the forward network, the backward network is the opposite; FG represents the output of the forward LSTM; FY represents the output of the backward LSTM; ⊗ represents the summation operator, then the fusion process is given by Formula 3:

$$F(p) = F_G(p) \otimes F_Y(m - p + 1) \tag{3}$$

The output of the time series feature module was taken as the input and processed after entering the fully connected module, and the output is the prediction result of teachers' teaching decisions. The fully connected module consisted of two fully connected layers, which could realize the one-dimensional feature vector transformation of the input, the integration of complex features of teaching behavior data extracted by the other two modules, and the mapping of sample mark space. Assuming: F(p) represents the output vector of the time series feature module, then after integration based on groups, the summarized result $F_k(p)$ can be attained by the following formula:

$$F_k(p) = \left\{F_1(p), F_2(p), ..., F_K(p)\right\} \tag{4}$$

The output functions of the two fully connected layers are represented by ξ() and α(), the teachers' teaching decisions could be achieved based on the decoding function of the fully connected module.

$$\Gamma_k(p) = \mathrm{ReLU}\left\{\xi\left[F_k(p)\right]\right\} \tag{5}$$

$$\chi_k(p) = \mathrm{ReLU}\left\{\alpha\left[\Gamma_k(p)\right]\right\} \tag{6}$$

Assuming: $b_k^*(p)$ represents the output of the fully connected module; $Q_k(p)$ and $\varphi_k(p)$ respectively represent the weight vector and the bias vector, then the calculation formula of $b_k^*(p)$ is:

$$b_k^*(p) = sigmoid\left\{Q_k(p) \cdot \chi_k(p) + \phi_k(p)\right\} \tag{7}$$

Assuming: $b_\omega^*(p)$ and $b(p)$ respectively represent the predicted value and the true value; ω represents conventional parameter in gradient descent; β represents the learning rate; $\partial J(\omega)/\partial\omega_j$ represents the partial derivative of the loss function *LOSS* with respect to parameter ω, which could be calculated by the following formula:

$$W = \frac{1}{2}\sum_{p=1}^{P}\left(b_\omega^*(p) - b(p)\right)^2 \tag{8}$$

The training objective of the TDO model is to minimize the errors of $b_\omega^*(p)$ and $b(p)$.

$$\omega_j \leftarrow \omega_j - \beta\frac{\partial}{\partial\omega_j}J(\omega) \tag{9}$$

Compared with the conventional stochastic gradient descent algorithms which use a unified learning rate to update the weight during network training, this paper applied an adaptive learning rate optimization method to the network model, that is, to use the adaptive moment estimation method to estimate the first and second moments of the gradient of the stochastic gradient descent algorithm, and further update all weights of the network. Figure 1 shows the execution process of the TDO model.

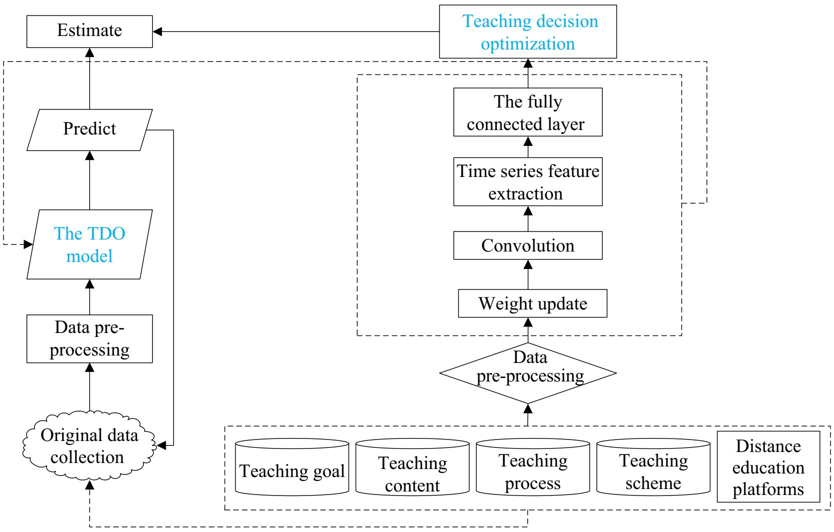

Fig. 1. Execution process of the TDO model

3 Optimization of decision element combinations in distance education

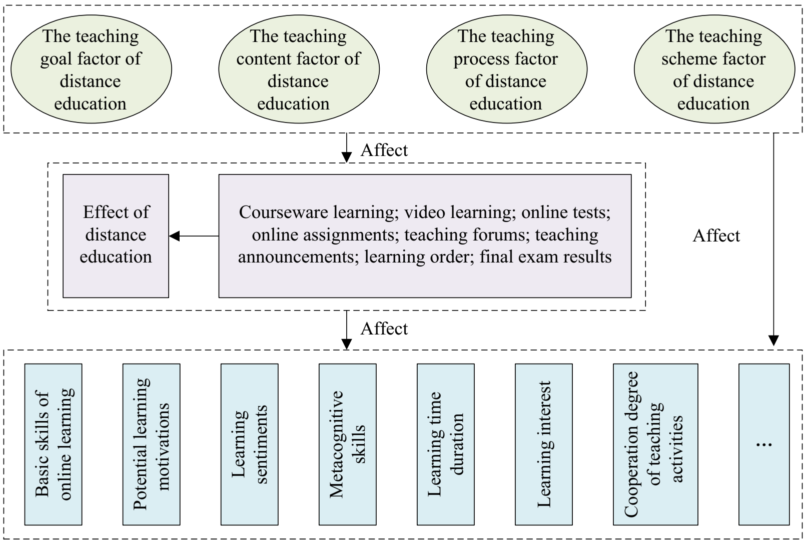

Fig. 2. Influencing factors of teaching decisions

Considering that distance education is a continuous process of making various decisions before, during, and after interaction with students, this paper divided the factors of distance education into four aspects, as shown in Figure 2, that is, to clarify the teaching goal of distance education, determine the teaching content of distance education, control the teaching process of distance education, and reflect on the teaching schemes of distance education. To enable the decision element combinations of distance education to reach standards stably, this paper constructed a fuzzy reasoning system based on the grey relational coefficient, so as to provide suggestions for distance education platforms to make optimal teaching decisions. Usually, the teaching decision results need to meet the standards of multiple element combinations of distance education, so the conventional fuzzy reasoning systems could not be applied directly. Therefore, this paper constructed a multi-objective TDO model based on fuzzy reasoning. At first, according to the TDO model built based on hybrid neural network in the previous chapter, an orthogonal test matrix was constructed to normalize the teaching decision optimization goals. Then, the grey relational coefficients of reference goals and each optimization goal were calculated and subjected to grey fuzzy reasoning value transformation. After that, the attained transformed grey fuzzy reasoning values were subject to mean value analysis to get the optimal teaching decision element combination for distance education platforms and to solve the problem during decision-making process that it's hard for multiple decision element combinations to reach standards at the same time. Figure 3 gives the execution process of the fuzzy reasoning system.

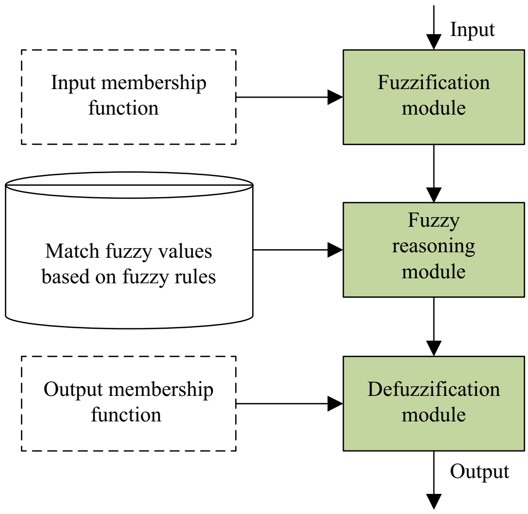

Fig. 3. Execution process of the fuzzy reasoning system

The fuzzy reasoning system constructed in this paper consisted of three parts: fuzzification module, fuzzy reasoning module, and defuzzification module.

The fuzzification module constructed in this paper adopted three kinds of fuzzy membership functions, and the expression of the triangular membership function is given by the following formula:

$$Tri\,(a) = \begin{cases} 0, a \le x \\ \dfrac{a-x}{b-a}, x < a \le y \\ \dfrac{d-a}{d-y}, y < a \le d \\ 0, a > d \end{cases} \tag{10}$$

The trapezoid membership function can be expressed as:

$$Trap\,(a) = \begin{cases} 0, a \le x \\ \dfrac{a-x}{y-x}, x < a \le y \\ 1, y < a \le d \\ \dfrac{c-a}{c-d}, d < a \le c \\ 0, a > c \end{cases} \tag{11}$$

The Gaussian membership function is given by:

$$Gauss(a) = o^{-\left(\frac{a-o}{\varepsilon}\right)2} \tag{12}$$

Logical reasoning is realized by matching the fuzzy values based on fuzzy rules, so this paper defined the main functions of the constructed fuzzy reasoning module as the formulation of fuzzy reasoning rules and the realization of fuzzy reasoning. Language type, table type, and formula type are common expression forms of the fuzzy rule library. Language-type fuzzy rules consisted by several fuzzy conditional statements are expressed in the "IF-THEN" form; assuming "a is L" represents the input of the module; "b is P" represents the output of the module; then the expression of the fuzzy system at this time is given by the formula below:

$$S_k\text{: } IF\ a_1\ is\ L_{1,k}\ and \ldots and\ a_m\ is\ L_{m,k} \tag{13}$$

$$THENIF\ b_1\ is\ M_{1,k}\ and \ldots and\ b_m\ is\ M_{m,k}, k = 1, 2, \ldots, s \tag{14}$$

For fuzzy rules with a reasoning type of "IF a is A" and… and "b is B" THEN "c is C", the fuzzy system rules are given by the following formulas:

$$S_1 : IF\ a\ is\ X_1\ and\ b\ is\ Y_1\ THEN\ c\ is\ D_1 \tag{15}$$

$$also\ S_2 : IF\ a\ is\ X_2\ and\ b\ is\ Y_2\ THEN\ c\ is\ D_2 \tag{16}$$

$$also\ S_m : IF\ a\ is\ X_m\ and\ b\ is\ Y_m\ THEN\ c\ is\ D_m \tag{17}$$

The commonly used Mamdani reasoning method was adopted as the fuzzy reasoning method of the fuzzy reasoning module.

The grey correlation analysis of reference goals and each optimization goal of teaching decisions included five specific steps: the analysis of the teaching behavior data sequences of distance education platforms, data normalization, the calculation of grey relational coefficients, the calculation of relational degrees, and the sorting of relational degrees. The details are given below:

STEP 1: Determine the reference sequence that can reflect the features of the teaching behavior data of distance education platforms and the comparative sequence of the influencing factors of the teaching behavior of distance education platforms. The reference sequence is denoted as $\{A^*\}=\{a_{E1}(l), a_{E2}(l), \ldots, a_{Em}(l)\}$, and the comparative sequence is denoted as $\{A\} = \{a_{i1}(l), a_{i2}(l), \ldots, a_{im}(l)\}$.

STEP 2: Normalize the data of $\{A^*\} = \{a_{E1}(l), a_{E2}(l), \ldots, a_{Em}(l)\}$ and $\{A\} = \{a_{i1}(l), a_{i2}(l), \ldots, a_{im}(l)\}$ to ensure that the volumes of the teaching behavior data participated in the calculation of grey relational coefficients are comparable and the results of the optimal teaching decision element combination are scientific and rigorous.

STEP 3: Calculate the grey relational coefficient of $\{A^*\} = \{a_{E1}(l), a_{E2}(l), \ldots, a_{Em}(l)\}$ and $\{A\} = \{a_{i1}(l), a_{i2}(l), \ldots, a_{im}(l)\}$. The greater the value of grey relational coefficient, the higher the correlation between $\{A^*\}$ and $\{A\}$. Assuming: $\gamma_{0i}(l)$ represents the grey relational coefficient of a_i and a_0 at point l; σ represents the distinguishing coefficient, then there is:

$$\delta_{0i}(l) = \frac{\min_i \min_j \left|a_0(l) - a_i(l)\right| + \sigma \max_i \max_j \left|a_0(l) - a_i(l)\right|}{\left|a_0(l) - a_i(l)\right| + \sigma \max_i \max_j \left|a_0(l) - a_i(l)\right|} \tag{18}$$

STEP 4: Since the relational coefficient is the degree of correlation between teaching decision sequences attained after getting the feedback of distance education of different moments, it'll be difficult to obtain result if the teaching feedback information is too scattered, so this paper averaged the relational coefficients attained from STEP 3, and the calculation formula of the relational degree is:

$$\alpha_i = \frac{1}{M}\sum_{l=1}^{M} \delta_{i0}(l) \tag{19}$$

STEP 5: Sort out the relational degrees based on the results of above formula, and finally attain the optimal teaching decision element combination of distance education platforms.

4 Experimental results and analysis

Figure 4 shows the influence of decision-making factors on the implementation effect of decision scheme. Specifically, Figure 4-1 shows the changes of the target value of decision optimization with the number of iterations; Figure 4-2 shows the changes of the distance from the target value of decision optimization to the optimal value with the number of iterations; Figure 4-3 shows the changes of the bias of the target value of decision optimization with the number of iterations; Figure 4-4 shows the changes of the bias of the distance from the target value of decision optimization to the optimal value with the number of iterations. In the figure, $a1$ and $a2$ are two decision-making factors; $O1$ and $O2$ are the bias values of the implementation effects of two decision schemes. As can be seen from the figure, the target value of decision optimization converged at the 20-th iteration, which indicated that the iteration process of the constructed TDO model was developing toward to correct direction. Considering that the multiple optimization objectives of teaching schemes would affect each other, at this time, the global optimal position of the model converged to a non-zero position, indicating that the output results of the TDO model were effective and the convergence speed was satisfactory.

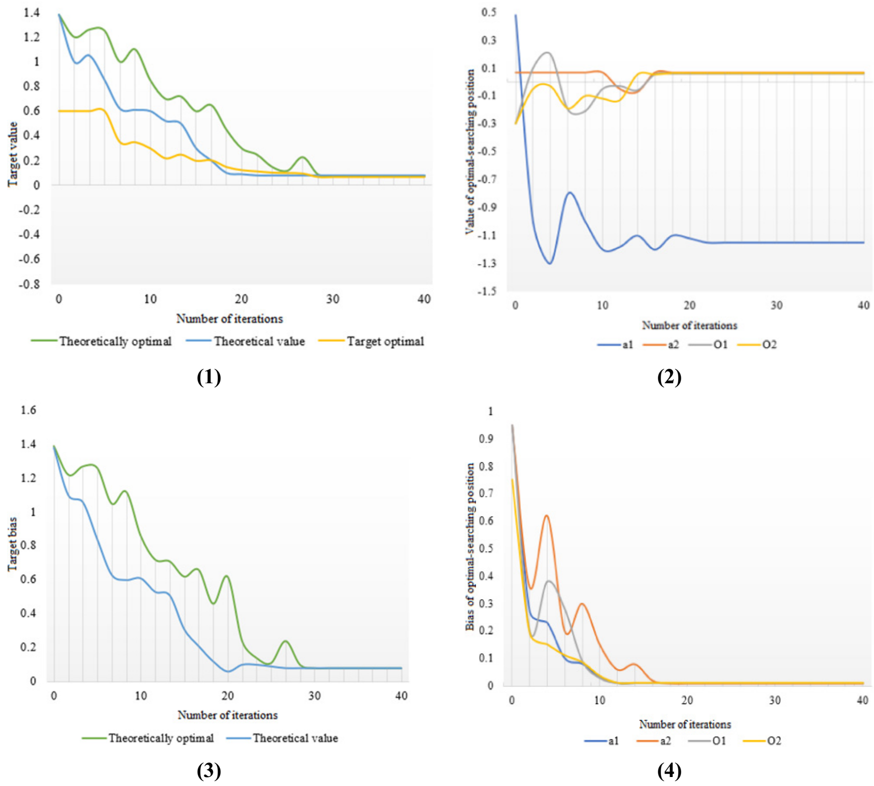

Fig. 4. Influence of decision-making factors on the implementation effect of decision scheme

Table 1 is the performance evaluation of the four decision-making factors of the constructed TDO model, namely clarifying the teaching goal of distance education, determining the teaching content of distance education, controlling the teaching process of distance education, and reflecting on the teaching scheme of distance education. For different factors of the model, there're certain differences in their four evaluation indexes, namely *MAE*, *RMSE*, *MAPF*, and R^2. The *MAE* and *RMSE* of the prediction of teaching goal were slightly greater than those of the prediction of teaching content, teaching process, and teaching scheme; and the *MAE* and *RMSE* values of the teaching process were obviously smaller than those of the other three factors. The *MAPE* values of the prediction of teaching goal, teaching process, and teaching scheme were all around 30%; the *MAPE* value of the teaching goal was the smallest, and the *MAPE* value of the teaching content was the largest. In terms of the R^2 value of the four factors, there're not much differences. The R^2 value of the teaching goal was the highest, indicating that this factor was best fitted; the R^2 value of the teaching process was the lowest of 50.62%, indicating that there's only a small difference between the true value and the predicted value of this factor.

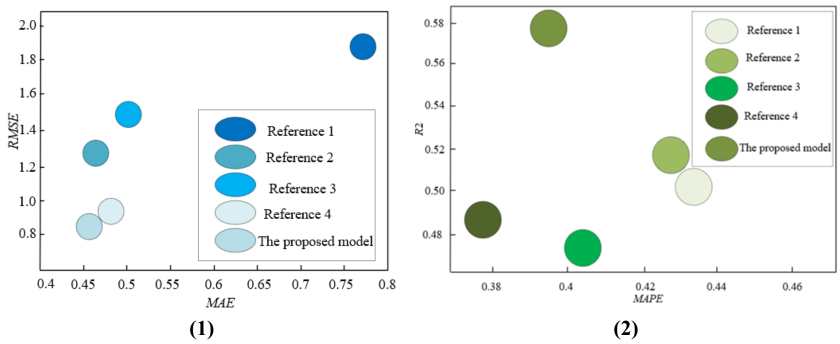

Fig. 5. Comparison of the decision optimization performance of different models

Table 1. Performance evaluation of the TDO Model

Evaluation Index	*MAE*	*RMSE*	*MAPF*	R^2
Teaching goal	1.528 1.528	3.629 3.629	28.39% 28.39%	58.58% 58.58%
Teaching content	0.639 0.639	0.847 0.847	74.51% 74.51%	52.35% 52.35%
Teaching process	0.051 0.051	0.035 0.035	35.28% 35.28%	50.62% 50.62%
Teaching scheme	0.857 0.857	1.352 1.352	36.51% 36.51%	55.19% 55.19%

Figure 5 compares the decision optimization performance of different models. In Figure 5-1, the horizontal and vertical axes are respectively the MAE value and the RMSE value, and the blue circles represent the MAE-RMSE value combinations. In Figure 5-2, the horizontal and vertical axes are respectively the MAPE value and the R^2 value, and the green circles represent the MAPE-R^2 value combinations. The closer the blue circles are to the origin, the better the decision optimization effect. The closer the green circles are to the upper left corner of the figure, the better the fitting effect of the decision optimization model. The references models are MLP, CNN, LSTM, and CNN-LSTM. As can be seen from the figure, the MAE-RMSE value of the proposed model was closer to the origin than that of the other models, and the MAPE-R^2 value of the model was closer to upper left corner than that of the other models, therefore, it's known that the proposed TDO model outperformed the others in terms of accuracy and performance.

Figure 6 shows the changes of teaching quality in different semesters after the teaching decision optimization of distance education. The distance education platform had been studied could focus on sustainable development and optimize the teaching decisions. According to the figure, as the teaching quality improved constantly, the execution effect of decision scheme also showed an upward trend, suggesting that the teaching decision optimization of distant education was highly effective.

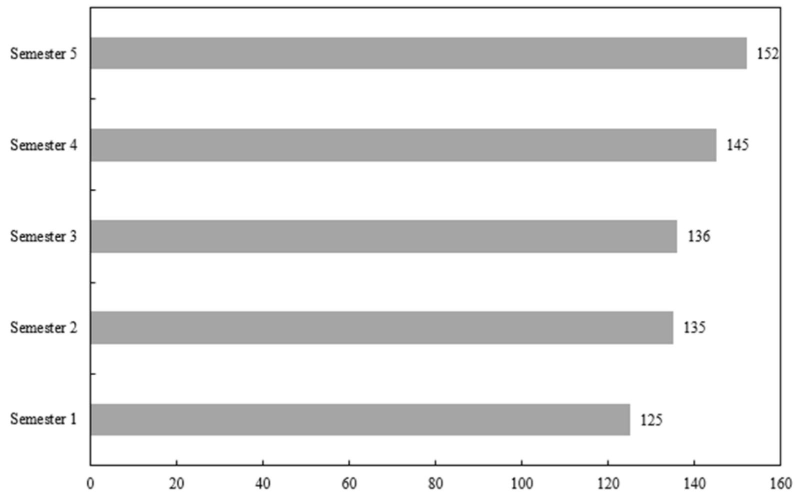

Fig. 6. Teaching quality in different semesters

5 Conclusion

This paper studied the topic of data-driven teaching decision optimization of distant education platforms. At first, it introduced a hybrid neural network integrating Bi-LSTM and CNN into the TDO model to capture the features of bi-directional time series of teaching decisions and build feature space with stronger expression ability. Then, this paper built a multi-objective TDO model based on logic reasoning, which could solve the difficulty for multiple decision element combinations in distance education to meet standards at the same time. Experimental results revealed the influence of decision-making factors on the execution effect of decision scheme, and verified that the output results of the proposed TDO model were effective and the convergence speed was satisfactory. Moreover, this paper gave the evaluation results of the performance the proposed TDO model in predicting the four decision-making factors, compared the decision optimization performance of different models, and the results showed that the proposed TDO model outperformed the others in terms of accuracy and performance. At last, this paper examined the changes of teaching quality in different semesters after the teaching decision optimization of distance education, and verified the effectiveness of the proposed method.

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