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Research and Development Talents Training in China Universities --- Based on the Consideration of Education Management Cost Planning

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Abstract: Research and development (R&D) talents training are asymmetric in China universities and can be of great significance for economic and social sustainable development. For the purpose of making an in-depth analysis in the education management costs for R&D talents training, the belief rule-based (BRB) expert system with data increment and parameter learning is developed to achieve education management cost prediction for the first time. In empirical analysis, based on the BRB expert system, the past investments and future planning of education management costs are analyzed using real education management data from 2001 to 2019 in Chinese 31 provinces. Results show that: 1) the existing education management cost investments have a significant regional difference; 2) the BRB expert system has excellent accuracy over some existing cost prediction models; 3) Without changing the current education management policy and education cost input scheme, the regional differences in China's education management cost input always exist. In addition to the results, the present study is helpful to provide model supports and policy references for decision makers in making well-grounded plans of R&D talents training at universities

Keywords: Research and development; Talents training; Education management; Belief rule-based expert system; Cost planning

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1. Introduction

The development of society and economy has significantly increased the demand for research and development (R&D) talents who are familiar with professional technology and information literacy. How to cultivate R&D talents is being a crucial problem that must be considered in the talents training of colleges and universities. Usually, R&D talents training and education management costs are inseparable. According to the government data at 2020 China Statistical Yearbook [1], the latest China's education financial investment increased over 50% compared with China's education funding in 2011 and the R&D investment intensity of China is higher than most countries. However, the number of R&D talents per 10,000 employees in China is still lower than some developed countries, among which South Korea is the largest one and over seven times of China's R&D researchers. Thus, making an effective education management cost planning is a critical challenge that must be solved for China R&D talents training in new period [2].

In past decades, China ministry of education is constantly increasing the strength of R&D talents training and putting a large amount of funds for technology improvement, whereas the employment rate of R&D talents in universities is much lower and the talent training in universities lacks practical application and platform support. It is necessary to further promote college students to actively engage in R&D-related activities [3], which are inseparable from effective education management cost planning. With the increasing uncertainty of social and economic environment and the emergence of new technologies, traditional cost prediction models are difficult to meet the needs of effective education cost planning [4][5]. Thus, in order to effectively analyze the relationship between R&D talents training and education funding [6], an effective cost prediction model must be selected for education management cost planning.

In this context, the present study pursues the two objectives: 1) the existing education management cost investments are analyzed and investigated to discuss China regional and provincial differences in the representative R&D talents training indicators, so it is able to provide a summary of experience for education manages; 2) an effective cost prediction model is designed to not only achieve accurate education management cost planning, but also take into consideration the existing education and teaching reform goals, so it will enable education manages make visionary planning in future R&D talents training at China colleges and universities.

However, due to the fact that the process of education management cost planning is complex, the prediction outcome should have strong interpretability, and education managers must participate in modeling and prediction process [7][8], all these strict requirements bring a dilemma in selecting system modeling techniques. Among existing techniques, the belief rule-based (BRB) expert system [9] is one of the most advanced decision-support systems in the researches of explainable artificial intelligence and complex system modeling owing to the following advantages:

(1) The BRB expert system takes into consideration the IF-THEN rule with embedding belief structure into THEN part for knowledge representation, in which the IF-THEM rule is one of the most common forms for expressing various types of knowledge [10], so it make the EBRB expert system more powerful in keeping human knowledge. Moreover, the use of belief structure further extends the ability of traditional IF-THEN rules to represent a variety of uncertain information [11].

(2) The BRB expert system is a data-driven, knowledge-driven, or hybrid-driven model and its rule-base is constructed using historical data and expert knowledge. Meanwhile, the BRB expert system takes the ER algorithm [12] as an inference engine for rule reasoning, so it can not only achieve knowledge fusion with uncertain information, but also have transparent rule integration process. All these components form a powerful expert system for handing complex practical problems.

(3) The BRB expert system belongs to a "white box" model, which mainly refers to the visible modeling and inference processes, especially for the fact that domain experts can participate in these processes. The inferential results of the the BRB expert system have good traceability and interpretability so that decision-makers can fully understand and explain its working principle more easily when applying BRB expert systems.

Therefore, in this study, the BRB expert system is used as the modeling basis to construct an advanced cost prediction model for meeting the current demand of education management cost planning to the greatest extent. The construction of the education management cost prediction model is based on the use of the data incremental and parameter learning to enhance the BRB expert system. Owing to the BRB expert system and its improvements, the education management cost prediction model is capable of providing a reference for the policy-making of education management in universities, and also provide an effective prediction tool for the policy implementers and long-term planners of the education management cost to promote the sustainable development of R&D talents training in China.

In order to perform the empirical analysis on China education management costs based on the BRB expert system, real education management data from 2001 to 2019 in Chinese 31 provinces are collected from China Statistical Yearbook. Four representative output indicators and two representative input indicators are collected to investigate and analyze the existing education management cost investment. Furthermore, by using the data from 2001 to 2018 as training data and the data at 2019 as testing data, the performance of the BRB expert system is confirmed in predicting future education management costs. Afterwards, based on the costs of education management predicted by the BRB expert system, the government expenditure on education, technology, and science are further analyzed and discussed to provide policy references for future education management-related cost planning.

The novelties and contributions of the present study [13][14] include: 1) R&D talents training in China universities is studied for the first time based on the consideration of education management cost planning, so that the education managers are able to make well-grounded medium- and long-term plans to guide R&D talents training at colleges and universities; 2) Owing to the advantages of the BRB expert system, the education management cost prediction not only considers the knowledge of education managers, but also is able to provide traceable and understandable prediction process and explainable prediction outcomes; 3) To best of our knowledge, this is the first time that the BRB expert system is applied to the field of R&D talents training in China universities. The empirical analysis on China education management cost prediction confirms the effectiveness of the BRB expert system.

The remainder of this research is structured as follows. Section 2 presents the preliminaries of the study. This is followed by a new education management cost prediction model. The empirical analysis on China education management cost planning is detailed in Section 4. Finally, Sections 5 and 6 present the discussions and conclusions.

2. Preliminaries for Education Management Cost Prediction

In this section, the BRB expert system is reviewed in Section 2.1, and its optimization and inference process are introduced in Sections 2.2 and 2.3 to give the basic knowledge of education management cost prediction.

2.1. Brief review of the BRB expert system

As the rule base of a BRB expert system [9], the BRB has a series of belief rules in the form of IF-THEN rules by embedding belief structures into the THEN part. Normally, the *k*th belief rule in the BRB is written as:

$$\begin{aligned} &R_k : IF\ U_1\ is\ A_1^k \wedge U_2\ is\ A_2^k \wedge \cdots \wedge U_M\ \ is\ A_M^k, THEN\ D\ is \{(D_n, \beta_{n,k}); n=1,...,N\}, \\ &\quad with\ rule\ weight\ \theta_k\ and\ attribute\ \ weights\ \{\delta_1,...,\delta_M\} \end{aligned} \tag{1}$$

where $\{U_m; m=1,\ldots, M\}$ denotes a set of M antecedent attributes; $\{A_m^k; m=1,\ldots, M\}$ denotes a set of referential values used to describe the kth ($k=1,\ldots, L$) belief rule, L is a total number of belief rules in the BRB, A_m^k belongs to $\{A_{m,j}; j=1,\ldots, J_m\}$ that is a complete set of J_m referential values used to describe the mth antecedent attribute; $\{(D_n, \beta_{n,k}); n=1,\ldots, N\}$ denotes belief structure in consequent attribute D, in which $\beta_{n,k}$ is belief degree to which the consequent D_n is believed to be true.

Table 1. Example of a complete BRB regarding education management cost prediction

Rule No.	Rule weight	Antecedent attributes (weights)		Belief distribution of consequent attribute		
		TMTV (δ_1)	NNP (δ_2)	*Low*	*Middle*	*High*
R_1	θ_1	*Low*	*Low*	$\beta_{1,1}$	$\beta_{2,1}$	$\beta_{3,1}$
R_2	θ_2	*Low*	*Middle*	$\beta_{1,2}$	$\beta_{2,2}$	$\beta_{3,2}$
R_3	θ_3	*Low*	*High*	$\beta_{1,3}$	$\beta_{2,3}$	$\beta_{3,3}$
R_4	θ_4	*Middle*	*Low*	$\beta_{1,4}$	$\beta_{2,4}$	$\beta_{3,4}$
R_5	θ_5	*Middle*	*Middle*	$\beta_{1,5}$	$\beta_{2,5}$	$\beta_{3,5}$
R_6	θ_6	*Middle*	*High*	$\beta_{1,6}$	$\beta_{2,6}$	$\beta_{3,6}$
R_7	θ_7	*High*	*Low*	$\beta_{1,7}$	$\beta_{2,7}$	$\beta_{3,7}$
R_8	θ_8	*High*	*Middle*	$\beta_{1,8}$	$\beta_{2,8}$	$\beta_{3,8}$
R_9	θ_9	*High*	*High*	$\beta_{1,9}$	$\beta_{2,9}$	$\beta_{3,9}$

Taking education management cost prediction for an example, suppose that government expenditure on education (GEE) is related to technical market transaction volume (TMTV) and number of new products (NNP). Thus, TMTV and NNP are regarded as two antecedent attributes and GEE is as consequent attribute. When each of the three attributes is described by three referential values: *Low*, *Middle*, and *High*, a complete BRB for education management cost prediction is illustrated in Table 1.

2.2. Optimization of BRB expert system

In order to obtain the optimal values for the parameters used in a BRB, *i.e.*, rule weights, attribute weights, belief degrees shown in Table 1, parameter learning should be applied to extract useful information from historical data to assign the parameters value of the BRB. Usually, a global parameter learning model can be written as follows:

$$Min \sum_{t=1}^{T} | f(\boldsymbol{x_t}) - y_t |, \tag{2a}$$

$$s.t. \sum_{n=1}^{N} \beta_{n,k} = 1, k = 1,..., L \ , \tag{2b}$$

$$0 \le \beta_{n,k} \le 1, \ n = 1,..., N; k = 1,..., L , \tag{2c}$$

$$0 \le \theta_k \le 1, k = 1,..., L , \tag{2d}$$

$$0 \le \delta_i \le 1, i = 1,..., M , \tag{2e}$$

$$u(A_{m,j}) < u(A_{m,j+1}), m = 1,..., M; \ j = 1,..., J_m - 1 , \tag{2f}$$

$$u(A_i^1) = lb_i , u(A_i^L) = ub_i , i = 1,..., M , \tag{2g}$$

$$u(D_n) < u(D_{n+1}), n = 1,..., N - 1 , \tag{2h}$$

$$u(D_1) = lb, u(D_N) = ub \ , \tag{2i}$$

where $f(\boldsymbol{x_t})$ denotes the inference output of a BRB expert system to predict the input data $\boldsymbol{x_t}$, here $\boldsymbol{x_t}$ =(x_{1t}, x_{2t}, …, x_{Mt}); y_t is the actual output of the input data $\boldsymbol{x_t}$; T is the total number of historical data used to train the BRB expert system; Eqs. (2b) - (2c) are constraints on the belief degree; Eqs. (2d) - (2e) are constraints on the antecedent attribute weights and the rule weights, respectively; and Eqs. (2f) - (2i) are the constraint on the utility values of the referential values used for antecedent attributes and the consequents used for consequent attribute. Note that the global parameter learning model can be solved by using the MATLAB optimization toolbox [15], clonal selection algorithm [16], and differential evolution algorithm [17].

2.3. Inference of BRB expert system

After constructing a BRB expert system based on parameter learning, it means that the BRB expert system is able to have an excellent performance for predicting any given input data. Suppose that $\boldsymbol{x}$=(x_1, x_2,…, x_M) is the input vector and x_i denotes the input data of the *i*th antecedent attribute, The following steps should be performed to obtain an inference output.

Step 1: To calculate individual matching degrees. The individual matching degree can be transformed from the input data $\boldsymbol{x}$ using utility-based equivalence transformation techniques, *i.e.*, the individual matching degrees of x_i are calculated by

$$\alpha_{i,j} = \frac{u(A_{i,j+1}) - x_i}{u(A_{i,j+1}) - u(A_{i,j})} \text{ and } \alpha_{i,j+1} = 1 - \alpha_{i,j}, \text{ if } u(A_{i,j}) \le x_i \le u(A_{i,j+1}), \tag{3}$$

$$\alpha_{i,k} = 0, \text{ for } k = 1,..., J_i \text{ and } k \ne j, j+1 , \tag{4}$$

where $A_{i,j}$ represents the jth referential value for the ith antecedent attribute, $u(A_{i,j})$ represents the utility value of $A_{i,j}$, $\alpha_{i,j}$ represents the individual matching degree of the given input x_i to $A_{i,j}$. As a result, the distribution of the individual matching degree for the ith antecedent attribute is represented as follows:

$$S(x_i) = \{(A_{i,j}, \alpha_{i,j}); j = 1,..., J_i\}, \tag{5}$$

Step 2: To calculate activation weights. While the BRB expert system is constructed under the conjunctive assumption, the activation weight for the kth belief rule is calculated as follows:

$$w_k = \frac{\theta_k \prod_{i=1}^{M} (\alpha_i^k)^{\bar{\delta}_i}}{\sum_{l=1}^{L} (\theta_l \prod_{i=1}^{M} (\alpha_i^l)^{\bar{\delta}_i})}. \tag{6}$$

where α_i^k is the individual matching degree to the ith antecedent attribute in the kth rule, and

$$\bar{\delta}_i = \frac{\delta_i}{\max_{i=1,\dots,M}\{\delta_i\}}, \tag{7}$$

where θ_k is the rule weight of the kth belief rule, δ_i is the attribute weight of the ith antecedent attribute.

Step 3: To integrate belief rules for producing an inference output. After calculating activation weights for all belief rules in the BRB, the combined belief degree β_i can be calculated using the ER algorithm:

$$\beta_i = \frac{\prod_{k=1}^{L}\left(w_k\beta_{i,k} + 1 - w_k\sum_{n=1}^{N}\beta_{n,k}\right) - \prod_{k=1}^{L}\left(1 - w_k\sum_{n=1}^{N}\beta_{n,k}\right)}{\sum_{n=1}^{N}\prod_{k=1}^{L}\left(w_k\beta_{n,k} + 1 - w_k\sum_{j=1}^{N}\beta_{j,k}\right) - (N-1)\prod_{k=1}^{L}\left(1 - w_k\sum_{j=1}^{N}\beta_{j,k}\right) - \prod_{k=1}^{L}(1 - w_k)} \tag{8}$$

Next, the inference output of the BRB expert system $f(\boldsymbol{x})$ can be obtained as follows:

$$f(\boldsymbol{x}) = \sum_{i=1}^{N}\left(u(D_i)\beta_i\right) + \frac{\left(u(D_1) + u(D_N)\right)}{2}\left(1 - \sum_{i=1}^{N}\beta_i\right). \tag{9}$$

where $u(D_i)$ denotes the utility value of the consequent D_i.

3. Education Management Cost Prediction based on the BRB Expert System

For education management cost prediction, the historical input and output data always grow over years. However, the inference output of a BRB expert system is limited by the minimum and maximum utility values, which are given based on the lower and upper bound of historical data, leading to the dilemma that the BRB expert system fails to predict the cost of education management. For example, the lower and upper bound of historical data x_t (t=1,…, T) is $x_t \in$[100, 200], which also means that the input data needed to predict must be $x \in$[100, 200]. In other words, the BRB expert system can not produce an inference output for the input data x=210 because of 210 > 200.

In order to overcome the dilemma, the data increment is introduced to improve the prediction performance of the BRB expert system. According to [18], the definition of data increment is given as follows:

Definition 1 (Data increment). Consider a case of a M-dimensional function $y=f(\boldsymbol{x})$ with $\boldsymbol{x}=\{x_1,\dots,x_M\}$ and its definition domain [$\boldsymbol{a}$, $\boldsymbol{b}$], where $\boldsymbol{a}$ and $\boldsymbol{b}$ are all M-ary vectors, respectively. When there exists an input-output data pair <$\boldsymbol{x}_0$, $\boldsymbol{y}_0$> in the function $y=f(\boldsymbol{x})$, for any $\boldsymbol{x}_1 \in [\boldsymbol{a}, \boldsymbol{b}]$, the data increment regarding the input and output data can be written as $\Delta\boldsymbol{x}=\boldsymbol{x}_1-\boldsymbol{x}_0$ and $\Delta y = f(\boldsymbol{x}_1)-f(\boldsymbol{x}_0)=f(\boldsymbol{x}_0+\Delta\boldsymbol{x})-f(\boldsymbol{x}_0)$, respectively.

According to ***Definition 1***, the lower bound and the upper bound of historical data increment are $\Delta x_{t,l}=x_t-x_l$ and $\Delta x_{t,l} \in$ [-100, 100] (t, l=1,…, T) for historical data x_t and x_l, so it is possible for BRB expert system to produce an inference output when x=210 because data increment is $\Delta x=x-x_t$ and $\Delta x \in$ [-100, 100]. Based on the above viewpoint, Fig. 1 provides a framework of the BRB expert system for education management cost prediction.

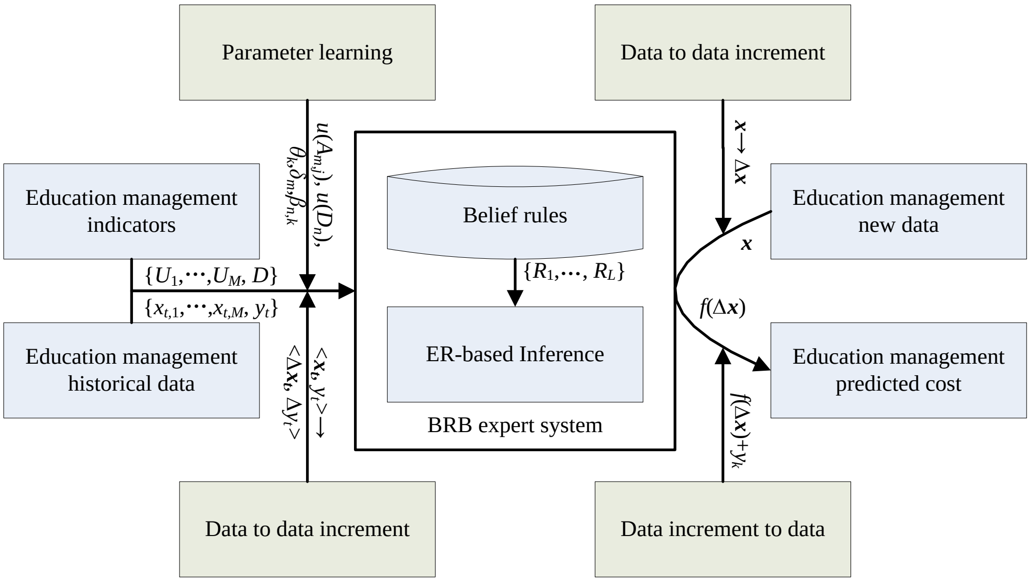

Figure 1. Framework of BRB expert system in education management cost prediction

From Fig. 1, the steps of using BRB expert system to predict education management costs are introduced as follows:

Step 1: To determine antecedent and consequent attributes. Suppose that one certain education management cost D is related with M education management indicators $\{U_i; i=1,\ldots, M\}$. In order to construct a BRB expert system, all these D and U_i are regarded as antecedent and consequent attributes of the BRB expert system. Moreover, gives J_i referential values $\{A_{i,j}; j=1,\ldots, J_i\}$ for the ith antecedent attribute and N consequents $\{D_n; n=1,\ldots, N\}$ for consequent attribute.

Step 2: To generate data increments. Suppose that there are S input-output education management data pairs $<\boldsymbol{x}_t, y_t>$ ($t=1,\ldots, S$) for the M antecedent attributes $\{U_i; i=1,\ldots, M\}$ and consequent attribute D, where $\boldsymbol{x}_t=\{x_{t,1},\ldots, x_{t,M}\}$. Based on ***Definition 1***, the data increments of any two input-output data pairs, *e.g.*, $<\boldsymbol{x}_t, y_t>$ and $<\boldsymbol{x}_s, y_s>$ ($t, s=1,\ldots, S; t\neq s$), are generated as follows:

$$\Delta \boldsymbol{x}_{t,s} = \boldsymbol{x}_t - \boldsymbol{x}_s \tag{10}$$

$$\Delta y_{t,s} = y_t - y_s \tag{11}$$

where the new set of training data has $S\times(S-1)$ input-output data increment pairs. For the sake of descriptions, these $S\times(S-1)$ data increment pairs are denoted as $<\Delta\boldsymbol{x}_k, \Delta y_k>$ ($k=1,\ldots, T$; $T= S\times(S-1)$).

Step 3: To train parameter value of BRB expert system. Based on the parameter learning model shown in Section 2.2 and the T input data increment pairs shown in Eqs. (10) - (11), the parameters of the BRB expert system, including rule weights, attribute weights, belief degrees, and utility values, can be trained to obtain their optimal values, so the resulting BRB expert system is able to accurately predict the cost of education management.

Step 4: To predict education management cost for any given input data. Suppose that there are a new input data $\boldsymbol{x}=\{x_i; i=1,\ldots, M\}$ and a recent input-output historical data pair $<\boldsymbol{x}_k, y_k>$. Hence, the data increment of $\boldsymbol{x}$ and $\boldsymbol{x}_k$ can be calculated and it is denoted as $\Delta\boldsymbol{x}=\{\Delta x_i; i=1,\ldots, M\}$. Furthermore, based on the three steps detailed in Section 2.3, an inference output of the BRB expert system $f(\Delta\boldsymbol{x})$ can be obtained to produce a final predicted education management cost by $y_k+ f(\Delta\boldsymbol{x})$.

For the above-mentioned steps, the case detailed in Section 2.1 is used to describe how to predict education management costs using the BRB expert system as follows:

Firstly, a total of 9 belief rules can be constructed by combining all the referential values of each antecedent attributes, as shown in Table 1, where the parameter values of all these belief belief may be inaccurate because they are usually given by only according to expert knowledge. Secondly, suppose that there are 3 historical data $<\boldsymbol{x}_1, y_1>=<x_{1,1}=$ 12142, $x_{1,2}=$ 5695.28, y_1=1137.18>, $<\boldsymbol{x}_2, y_2>=<x_{2,1}$=11010, $x_{2,2}$=4957.82, y_2=1025.51> and $<\boldsymbol{x}_3, y_3>=$ $<x_{3,1}$=10490, $x_{3,2}$=4486.89, y_3= 964.62>, the resulting data increments can be calculated and they are $<\Delta x_{1,1}$=1132, $\Delta x_{1,1}$=737.46, Δy_1=111.67>, $<\Delta x_{2,1}$= -1132, $\Delta x_{2,1}$=-737.46, Δy_2= -111.67>, $<\Delta x_{3,1}$=1652, $\Delta x_{3,1}$=1208.39, Δy_3=172.56>, $<\Delta x_{4,1}$=-1652, $\Delta x_{4,1}$=-1208.39, Δy_4=-172.56>, $<\Delta x_{5,1}$= 520, $\Delta x_{5,1}$=470.93, Δy_5=60.89>, and $<\Delta x_{6,1}$=520, $\Delta x_{6,1}$=470.93, Δy_6=60.89>. Thirdly, all these 6 data increments are used to optimize the parameter values of 9 belief rules to improve the performance of the BRB expert system, in which the parameter learning model is introduced in Section 2.2. Finally, when a new input data $\boldsymbol{x}=<x_1$ = 13142, x_2=6695.28> is given, the data increment regarding $<\boldsymbol{x}_1, y_1>$ should be calculated by Δx_1=13142-12142=1000 and Δx_2=6695.28-5695.28=1000. Afterwards, the three steps detailed in Section 2.3 is used to produce $f(\Delta \boldsymbol{x})$, *e.g.*, $f(\Delta \boldsymbol{x})$=300, and the final predicted cost is $f(\boldsymbol{x})$=300+1137.18=1437.18.

4. Empirical Analysis on China Education Management Cost Planning

In this section, based on the cost prediction method detailed in Section 3, actual education management data derived from 31 provinces in mainland China are used to perform an empirical case study.

4.1. Data collection and indicator explanation

In empirical analysis, the education management data related with 31 Chinese provinces from 2001 to 2019 are derived from China Statistical Yearbook, which is the most commonly used and reliable public database for the study of education management cost planning in China, and a total of four education management output indicators and two education management input indicators are collected based on literature summary, the reality of education management, data availability in China Statistical Yearbook, and the requirement of complex system modeling[2][3][9], respectively, to analyze the past and future education management cost planning. The specific interpretations of these indicators are shown in Table 2.

Table 2. Introduction of indicators in education management cost planning

Indicator name	Abbr.	Corresponding relationship
Number of R&D employees	NRDE	Antecedent
Number of new products	NNP	Antecedent
Number of invention patent applications	NIPA	Antecedent
Technical market transaction volume	TMTV	Antecedent
Government expenditure on education	GEE	Consequent
Government expenditure on science and technology	GEST	Consequent

From Table 1, the four indicators, namely number of R&D employees, number of new products, number of invention patent applications, and technical market transaction volume, are used as the antecedent attributes of the BRB expert system, respectively. Correspondingly, two indicators, namely government expenditure on education and government expenditure on science and technology, are used as the consequent attributes of the BRB expert system, respectively. Additionally, due to the education management data related with 31 provinces, a total of 31 BRB expert systems need to be constructed for each year while investigating education management cost planning. Additionally, the BRB expert system within this study is implemented by Microsoft Visual C++ 6.0 in Windows 7 Ultimate (64-bit Operating System) with Intel (R) Core (TM) i5-4300 CPU @1.90GHz 2.50GHz and 4GB RAM.

4.2. Analysis of education management cost investments during 2001-2019

In this subsection, the past education management cost investments during 2001 - 2019 are analyzed based on the education management data collected from 31 provinces in China, so that the existing differences among Chinese provinces can be illustrated to establish the basis of predicting future education management cost planning.

Firstly, Figs. 2 - 7 show the data of different education management costs and the R&D talents training of different provinces. From Figs. 2 and 3, it can be found that the number of R&D employees and number of new products have significantly regional differences, in which the number of R&D employees and number of new products in most eastern provinces are much higher than that of western provinces in China. The regional differences of R&D level in China are not only related to the differences of physical and geographical environment in the central and western regions, but also closely related to the number of universities in various provinces and the local financial support. Compared with the western region, universities in the eastern region are more densely distributed, and the employment opportunities of scientific and technological talents in the eastern region are also higher than those in the western region. Especially, the eastern economic circle is a high-tech industry concentration area, and the R&D support and the number of new product production in these provinces are significantly higher than those in other regions.

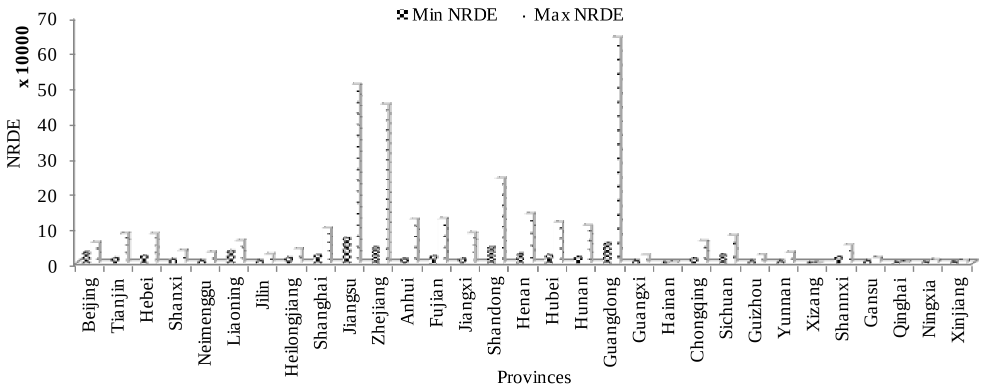

Figure 2. NRDE for 31 Chinese provinces during 2001 – 2019

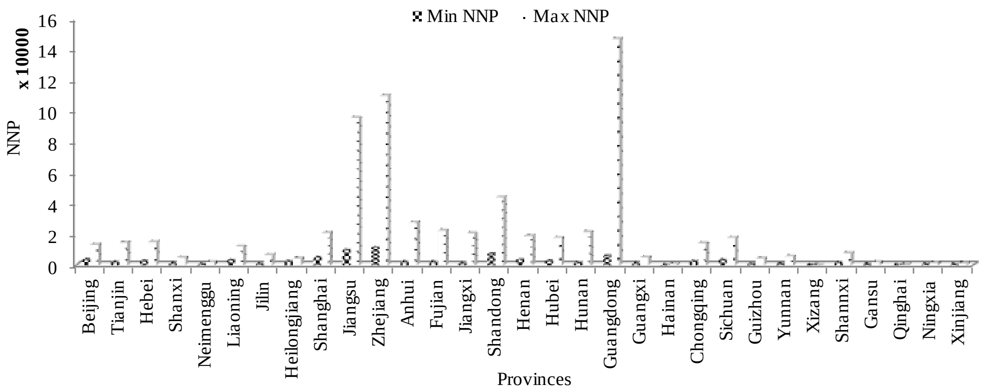

Figure 3. NNP for 31 Chinese provinces during 2001 – 2019

Compared to the regional differences of the number of R&D employees and new products, the number of invention patent applications and technical market transaction volume in Figs. 4 and 5 show that the province with highest value of technical market transaction volume is Beijing, and the highest number of invention patent applications is in Guangdong province. As China's political center, Beijing has natural policy advantages in science and technology market transactions, and it is also the center of China's international exchanges and exhibitions. Therefore, considering the special political position of Beijing, it can effectively bring certain convenience to science and technology market transactions. It is worth noting that except for some coastal areas such as Guangdong, Zhejiang and Jiangsu, the R&D capacity of most provinces needs to be improved. The reason is that there are many achievements in scientific research management with few patents applied in actual economic activities, and the conversion rate of scientific research achievements is often lower in most provinces, which also leads to the lack of guidance in talents training based on the combination of professional knowledge teaching and practical social practice [19]. Moreover, the strength of scientific research talents is relatively scattered in China's current talents training and it is difficult to effectively integrate different teams and resources for new products and patterns innovation.

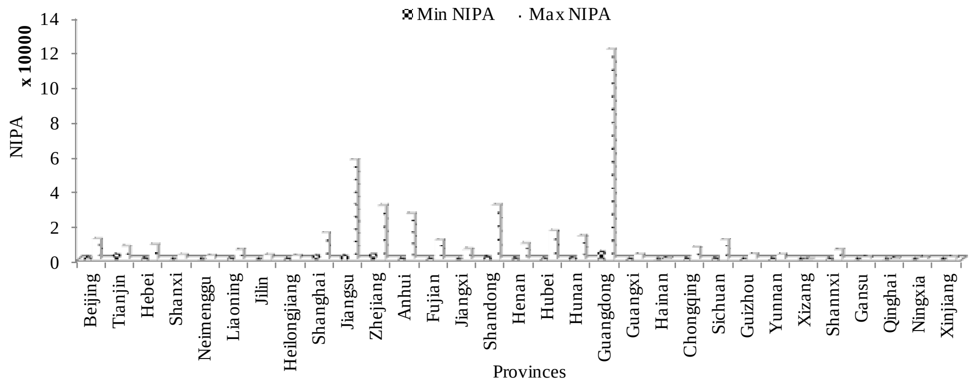

Figure 4. NIPA for 31 Chinese provinces during 2001 - 2019

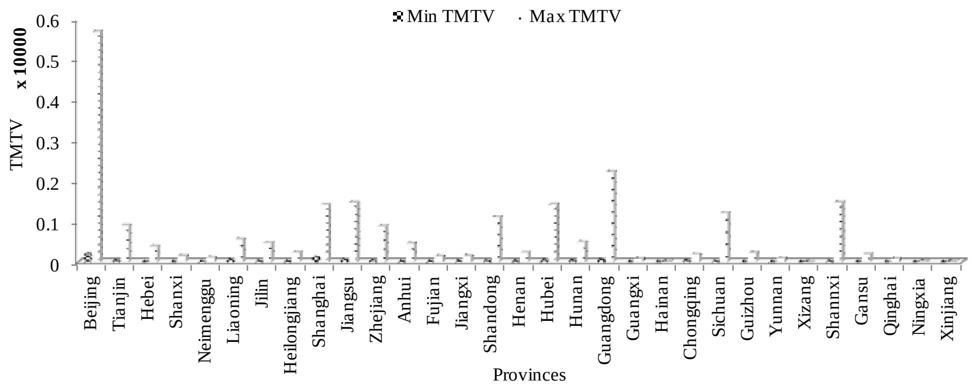

Figure 5. TMTV for 31 Chinese provinces during 2001 - 2019

From Figs. 6 and 7, it can be found that the regional distribution differences of government expenditure on education, science, and technology are basically consistent with the regional distribution of R&D capacity showed in Figs. 2 - 5, that is, the research capacity in the eastern coastal areas are higher than those in the central and western regions. In addition, R&D capability is closely related to the external trading policy environment, the strategic positioning of new products and the international competitive environment. From the perspective of talents training in universities, in order to enhance the competitiveness of R&D talents, it must emphasize the independent practice ability and engineering practice ability of talents training. Around the social needs of various industries and practical activities for information technology talents training, engineering practice projects can be added in the process of education management, and encourage self- learning for the design and program realization of new products. The application investigation of new patents and new products is also carried out in the form of team formation so as to stimulate the independent practice awareness of R&D talents.

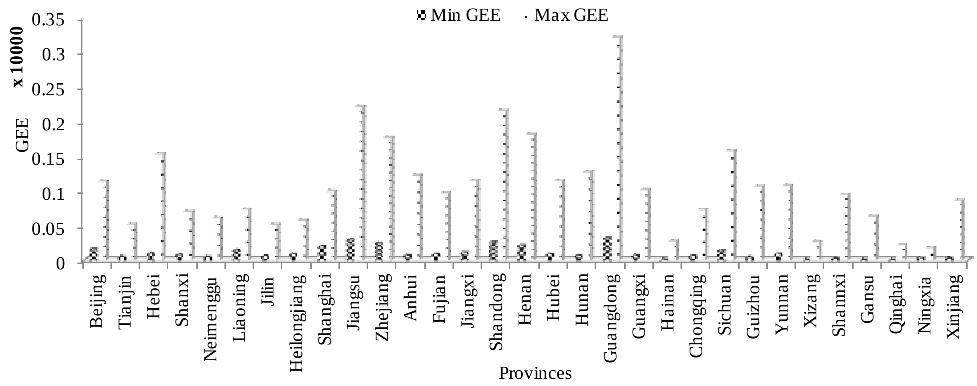

Figure 6. GEE for 31 Chinese provinces during 2001 – 2019

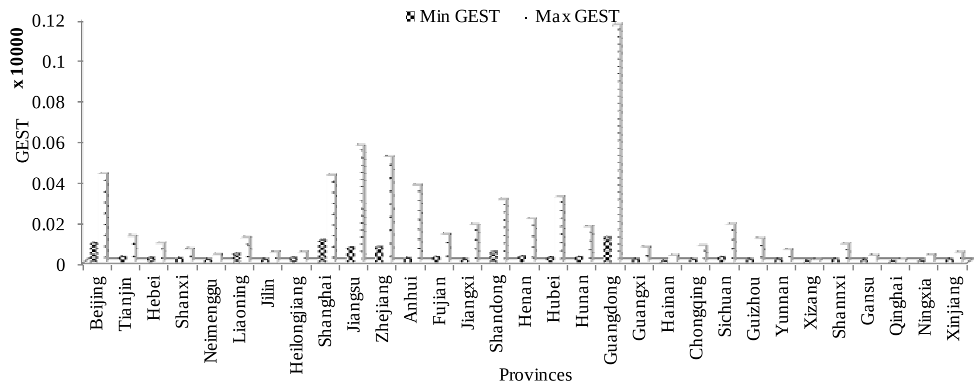

Figure 7. GEST for 31 Chinese provinces during 2001 - 2019

4.3. Verification of BRB expert system for cost prediction

In order to analyze future education management cost planning based on the BRB expert system, this subsection firstly verify the effectiveness of the BRB expert system for education management cost prediction. For this purpose, the data of education management during 2001 to 2018 are used as training data and the data of education management at 2019 as testing data. Based on the BRB expert system detailed in Section 2.2, the results of education management cost prediction are showed in Figs. 8 and 9. The results show that the research on education management cost is closely related to the level of R&D ability, and proves the necessity of research on education management cost prediction, that is the regional distribution differences of education management cost are basically consistent with the regional distribution of R&D capacity showed in Figs. 2 - 7. This also indicates that in order to effectively improve the R&D ability, it is necessary to predict the investment of education management.

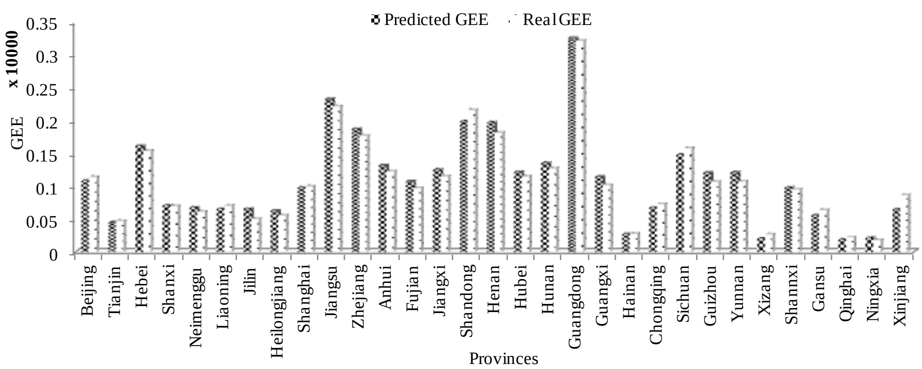

Figure 8. Comparison of predicted GEE and real GEE for 31 Chinese provinces at 2019

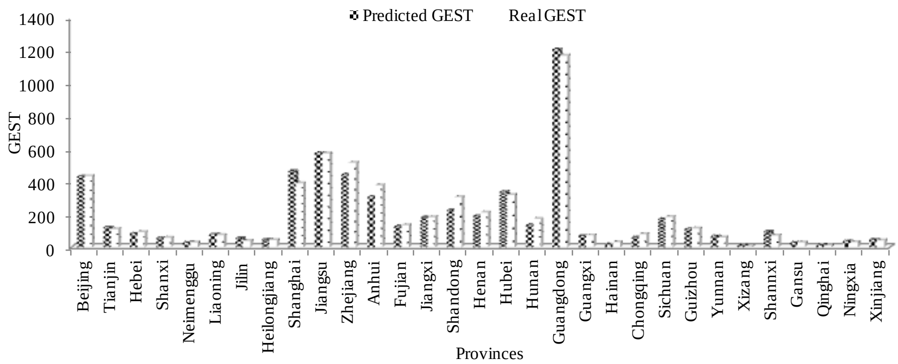

Figure 9. Comparison of predicted GEST and real GEST for 31 Chinese provinces at 2019

From Figs. 8 and 9, they show that the predicted education management costs based on the BRB expert system is highly consistent with the two types of actual education management costs, and the prediction results are applicable to the education management analysis of 31 provinces with high prediction accuracy. Therefore, considering the high fitting degree between the prediction results of BRB expert system and the actual costs, it can be considered that the education management cost prediction based on the BRB expert system has certain reference significance for the future R&D talents training of various provinces.

In order to validate the effectiveness of the BRB expert system for education management cost prediction, the results of each predicted cost that obtained by different prediction models are measured with accuracy. Tables 3 and 4 shows the comparison of the BRB expert system with other rule-based systems, including fuzzy rule-based system (FRBS) 21 and adaptive neuro fuzzy inference system (ANFIS) [22], and other time series forecasting models, including grey model (GM) [20], auto regressive (AR) model, and moving average (MA) model, in which the comparisons of these models in education management cost prediction are based on MAE and MAPE. From Table 3, the BRB expert system produces satisfactory prediction results for two management costs compared with existing models, and the MAE of the BRB expert system are 82.4 and 18.59, respectively. Comparatively, the MAPE of the BRB expert system are 9.62% and 12.99%, which are better than FRBS and ANFIS. Furthermore, in the comparison of the three time series forecasting models, the BRB expert system also show its better performance in predicting GEE and GEST. Although the AR model has a lower MAE and MAPE in GEE than the BRB expert system, the BRB expert system obtains the second best results in GEE and the best results in GEST. In summary, they reveal that the BRB expert system has a better performance than the other prediction models used in education management cost prediction.

Table 3 Comparison of rule-based systems for education management cost prediction

Predicted	MAE			MAPE		
costs	**BRB**	FRBS	ANFIS	**BRB**	FRBS	ANFIS
GEE	**82.40 (1)**	164.17 (2)	2683.36 (3)	**9.62% (1)**	17.57% (2)	400.76% (3)
GEST	**18.59 (1)**	38.81 (2)	446.91 (3)	**12.99% (1)**	22.74% (2)	245.18% (3)

Table 4 Comparison of time series forecasting models for education management cost prediction

Predicted	MAE				MAPE			
costs	**BRB**	AR	MA	GM	**BRB**	AR	MA	GM
GEE	**82.40(2)**	56.27(1)	384.16(4)	256.94(3)	**9.62%(2)**	4.45%(1)	35.22%(4)	27.43%(3)
GEST	**18.59(1)**	25.27(2)	76.82(4)	54.86(3)	**12.99%(1)**	13.21%(2)	36.92%(4)	23.09%(3)

4.4. Analysis of future education management cost planning

To effectively analyze the change of education management cost planning in the next 6 years, the target input of future education management is obtained by time series forecasting firstly, and then the education management costs of 31 provinces in China in next 6 years are predicted using the BRB expert system. The corresponding results are showed in Fig. 10. It can be clearly found that the government expenditure of two types of education cost planning will show a significant growth trend in the next 6 years, indicating that the training of R&D talents must have time sustainability and it is necessary to continuously invest education funds to support the development of new products and new technologies. This is consistent with China's current development strategy and is also rejuvenating the country through science and education. At the same time, the performance evaluation of the use of education funds should be strengthened when the investment in education funds is increasing. With the increase of the education investment scale, decision makers should have the concept of improving education management efficiency and pay attention to the standardization of education investment management policy and performance accountability system.

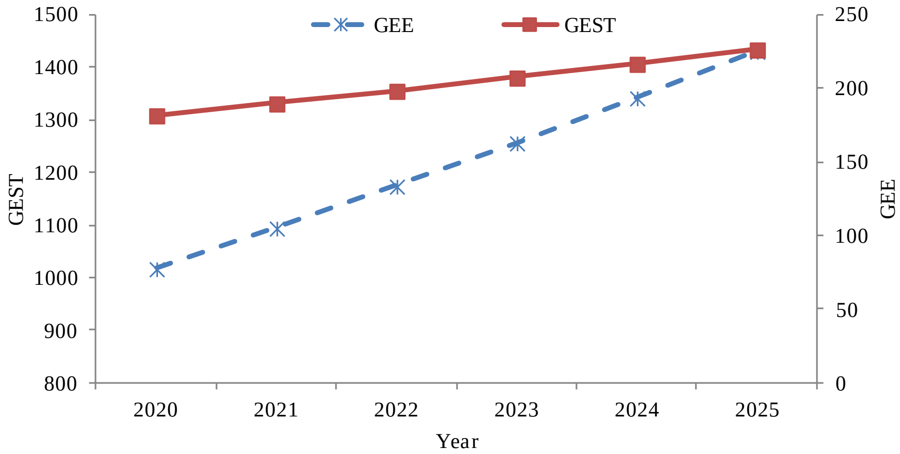

Figure 10. Average predicted GEST and GEE for 31 Chinese provinces in the next 6 years

To further analyze the future education management cost planning of 31 provinces, the government expenditure on education, science, and technology predicted by the BRB expert system for 31 provinces at 2025 are showed in Fig. 11. The results show that in the future education management cost planning, the government expenditure on education in Henan, Guangdong, Jiangsu, Hebei and Sichuan provinces is significantly higher than other provinces. In addition to Guangdong and Jiangsu provinces, the government expenditure on science and technology in Beijing is higher than other provinces. From the perspective of regional differences of education management cost planning at 2025, except for the situation that the education management costs of Sichuan and Shannxi provinces are significantly higher in the western region, the education management costs of most western regions are still lower than that of the eastern region in China. Similarly, in addition to the high investment in education management costs in Beijing and Hebei provinces, the education management costs in most provinces in northern China are significantly lower than those in southern regions. From the perspective of the relationship between the R&D talents training in China universities and the cost investment of regional education management, effective policies and measures are important to not only make up for the regional differences in R&D talent training and education management, but also weaken the regional differences of China education and talent training.

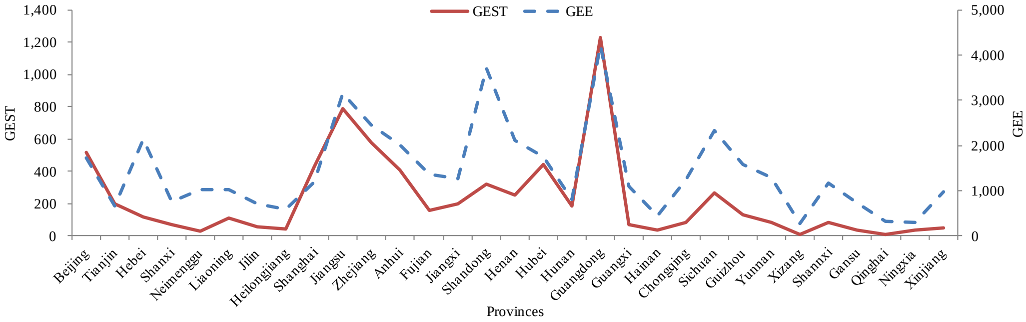

Figure 11. Predicted GEST and GEE for 31 Chinese provinces in 2025

5. Discussions

This study focused on the discussion of R&D talents training in China universities based on education management cost planning. The BRB expert system was proposed with the use of data increment and parameter learning. The results showed that the BRB expert system can be well applied to the prediction of education management cost under high prediction accuracy, which provides a reference for the future planning of education management cost in China universities. As mentioned in most existing studies [23], the results analysis indicated that in the future planning and prediction of education management cost, education management cost shows an increasing trend, but the regional differences of education management cost still exists in China. The regional difference of education management cost exists for a long time. In addition to regional environment, regional policy and regional population, education management cost is closely related to economic development. Education management cost comes from the direct expenditure of government finance in talent training, which is closely related to the financial revenue of local government. This also determines that the cost of education management is closely related to the income of local residents, industrial development and population density. Regional economic factors play a vital role in the development of China's education level [24]. The higher the level of education has positive influence on the higher the regional economic development, therefore, in the long-term development of R&D talents training, the regional differences of education management costs will exist. Furthermore, from the time series change of education management cost, the overall rising trend of education management cost is consistent with China's education policy of paying attention to talent training [25], that is, increasing the investment in education management cost to improve the talent training level of universities and encourage the innovation of R&D talents. This also shows that the investment of education management cost plays a vital role in the process of R&D talent training.

The investment and use of funds is an important basis for the development of higher education, as a non-profit organization, i.e., public knowledge production organization and talent training organization, the development of education needs financial support from all walks of life [26][27]. Some scholars believe that the cost of talents training in Colleges and universities includes direct costs in the process of students cultivating, indirect costs in the process of managing and organizing student training, and all kinds of economic assistance costs. Another group of scholars believe that the training cost of students in Colleges and universities includes direct and indirect resource consumption, which is a combination of multiple meaning costs including school, department, academic and school system cost [28]. This study chooses the direct cost in the process of talents training in universities as the cost prediction objective, and no matter what kind of education management cost accounting method, to a certain extent, it reflects the necessity of effective cost planning and prediction in R&D talents training and education management [6].

In the existing research of education management cost, most of the studies focused on the concept introduction [29], accounting methods [30][31] and theoretical analysis of education management cost [32], and ignores the consideration of education management cost planning and prediction. In the application of the existing prediction model [21] [22], few scholars consider applying the expert system to the planning of education management cost and accurately predict the future trend of education management cost. In the present study, the cost of education management was predicted based on the BRB expert system and it created the application of the BRB expert system in the field of education management, and further improves the performance of BRB expert system in the prediction of education management cost by proposing incremental prediction and parameter optimization methods, which provides a reference direction for the planning and prediction of education management cost in the future studies.

6. Conclusions

In the present study, the R&D talents training in China universities was studied based on the consideration of education management cost planning. The purpose of the present study is due to the dilemma that the R&D investment intensity of China is higher than most countries, but the quantity of R&D talents per 10,000 employees in China is still lower than some developed countries. Therefore, the study of making an effective education management cost planning is a critical challenge and necessary research objectives for China R&D talents training in new period.

Within the background of considering education management cost planning to improve R&D talents trainings in China universities, the existing China education management cost investments during 2001 to 2019 were discussed firstly to show the past development of universities' R&D talents training and government expenditures. Furthermore, an explainable and advanced rule-based system, called the BRB expert system, was applied to construct a novel education management cost prediction model, so that the future government expenditures on education, science and technology are foreseeable for education managers and they could make visionary planning in future R&D talents training at China universities [33][34].

6.1. Theoretical implications

The BRB expert system-based education management cost prediction model proposed in this study has theoretical implications for future research.

(1) Due to the problem of sparse data in the field of education management cost prediction, the system modeling has to suffer from the over fitting problem. The data increment of education management input and output indicators were used to enrich data for modeling expert system, the resulting BRB expert system is able to overcome the over fitting problem.

(2) To overcome the subjectivity of parameters given by experts, the global parameter learning model was introduced to enhance the BRB expert system construction, so that the parameter values of the BRB expert system can be optimized according to the historical education management input and output data.

(3) The results of comparative studies demonstrated that the data increment and parameter learning could effectively improve the performance of the BRB expert system. The government expenditures on education, science and technology predicted by the BRB expert system were much lower than the other prediction models.

6.2. Policy suggestions

From the present study on R&D talents training in China universities with the consideration of education management cost planning, the following policy suggestions could be summarized for future research:

(1) To optimize the setting of professional knowledge learning in universities based on the demand of economic market and social development, that is the course learning in universities for R&D talents should be improved and designed according to the current

market environment and industry demand, so that they can better understand the market demand and master relevant professional technology through school-enterprise cooperation and exchange, so as to make up for the shortage of professional technicians in relevant fields in the market.

(2) To advocate expanding teaching and cultivate R&D talents' basic quality and professional skills for social practice by relying on the practice carrier outside the universities professional classroom, so they can train professional skills and improve practical ability in expanding teaching.

(3) To establish a diversified training mode for R&D talents, and adopt a variety of talent training methods to improve the innovation of scientific and technological capability is an important strategy for R&D talents training in China universities. Decision makers of education management should also pay attention to improve the professional and technical level of R&D talents so as to ensure that the talents trained in universities can be truly applicable to new products and technologies innovation of actual economic activities.

6.3. Limitations and future researches

The present study has several limitations. The first limitation is related to the modeling process where the four representative indicators were selected based on expert experiment and literature review. More indicators and data-driven indicator selection methods should be used in the modeling process. The second limitation is related to the rule scales of the BRB expert system whose number of rules will increase exponentially with increasing the number of indicators, so the BRB expert system usually have to face the combinatorial explosion issue when considering a large number of indicators.

Despite the limitations outlined above, the results of the present study are meaningful in that we confirm the BRB expert system to predict education management costs. For the future researches, owing to the different characteristics of education management in different provinces and universities, the influences of regional education policies and economic development differences on education management investments should be analyzed and discussed. Furthermore, because of the combinatorial explosion issue, this study only considered four representative indicators in education management cost prediction. Hence, in the future research, more abundant indicators could be involved for education management cost prediction and some extensions of the BRB expert system could be also introduced to model a novel cost prediction method when education manage involves these indicators.

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