

Research Article

Prediction of Information Talent Demand Based on the Grayscale Prediction Model and the BP Neural Network

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With the increasing popularity of the Internet technology, people are now increasingly accustomed to obtaining information or help through the Internet. Meanwhile, the great development of the information service industry has led to the explosive growth of the demand for information service talents. In recent years, many information service talent demand reports have been released in China, and it has an important guiding significance for information service industry planning. However, there are three problems with the information service industry talent demand reports at present. First, the relevance and support of talent demand analysis and forecast to information service industry planning need to be clarified. Second, the coordination and cooperation of information service personnel demand report preparation need to be improved. The third is the wider application of scientific and reasonable information service personnel demand forecasting models. In the future, we need to develop and use more reasonable information service personnel demand forecasting models and improve the quality of information service personnel demand reports. At the same time, the supporting role of the information service industry in scientific planning needs to be strengthened continuously. Therefore, information service industry talent demand forecasting is of great significance. In this paper, a prediction model of information service talent demand is established by using gray system theory. For the deviations of the GM (1, 1) model, a combined GM (1, 1)-BP neural network prediction model is proposed. The simulation results show that the prediction results of the prediction model in this paper are satisfactory. Therefore, the GM (1, 1)-BP model proposed in this paper can be used as a reference for government decision-making and information service personnel training.

1. Introduction

Talent is the primary resource to support China's innovative development [1]. Rational use of talents and accurate prediction of the demand for talents will affect the rapid development of a country. The industrial talent demand forecast is to adapt to the new round of scientific and technological revolution and industrial change trend, to analyze and forecast the number of talents needed for high-quality development of the industry, which is an important basis for scientific development of industrial talent training. With the vigorous development and wide application of new technologies of artificial intelligence, cloud computing, mobile Internet, and big data in Germany, information

technology services have become the strategic engine of comprehensive digitalization, informatization, and intelligence of economic society. Information technology services are becoming a key force for driving technological innovation, economic and social transformation, and upgrading and high-quality development.

All walks of life are vigorously developing and using information industry applications [2]. Some studies show that 33.5% of enterprises have practiced applying information technology in practical work and production processes and have successful products and cases. 32.6% of enterprises are setting up their information service platforms. 25.6% of the companies have conducted sufficient research and are ready for development.

At present, the professional talents related to information technology cannot meet the needs of the rapid growth of enterprises [3]. Statistics show that there are currently only 4.7 million IT professionals in the country. In the next 3–5 years, the gap of big data talents is as high as over 15 million, and the information service industry is bound to face a global shortage of professional talents [4].

At present, information service talents are mainly distributed in mobile Internet [5]. This is followed by O2O, financial Internet, games, social networking, education, enterprise services, and other fields, as shown in Figure 1.

Information service talent demand forecast can provide reliable basis for talent planning in the information service industry and provide real-time data for the compilation of talent demand reports. The extensive application of the information service talent demand model can serve various industries synergistically and make talents to be applied more fully and reasonably. The development of talent demand forecasting can be divided into three stages [6]. A good talent demand forecasting model can not only accurately predict the total amount of talent demand but also predict the future growth trend of talent demand. Accurate prediction results can promote the growth of talents and ensure the full and reasonable use of talents. The initial stage is the manual method, that is, scientific researchers through manual ways to collect talent data. Then, the talent data are estimated based on experience. The calculation is large, the working process is complex, and the prediction result is far from the actual value when errors occur, so the limitation is very obvious. Subsequently, talent demand prediction models based on mathematical statistics theory emerged, such as linear regression and gray model (GM), mainly using some mathematical modeling methods to analyze talent demand prediction [7]. These methods can only describe the linear or upward trend of talent demand. The trend of talent demand is not necessarily a rise or linear trend but also a downward trend and nonlinear change characteristics [8]. The models established by these methods cannot accurately describe the characteristics of talent demand change, and the prediction accuracy is sometimes very low. Modern statistical methods, such as the back propagation neural networks (BPNN), have been applied in talent demand prediction [9]. They have strong nonlinear modeling ability and can be adjusted adaptively, so they become the most commonly used methods of talent demand prediction. Since talent demand prediction is a complex system with many characteristics, a single neural network cannot comprehensively track the characteristics of talent demand change [10].

With the rise of the information service industry, more and more academic scholars have researched the demand for information service talents [11]. As early as 2005, literature [12] carried out a forecast study on the demand for information service professionals. At present, the research methods and models used in this field are gradually becoming mature. Literature [13] analyzes and predicts the demand for information service talents in China by using the change index of information service talent demand (LPDIC). Literature [14] used the nonlinear regression model to predict the demand for information service talents

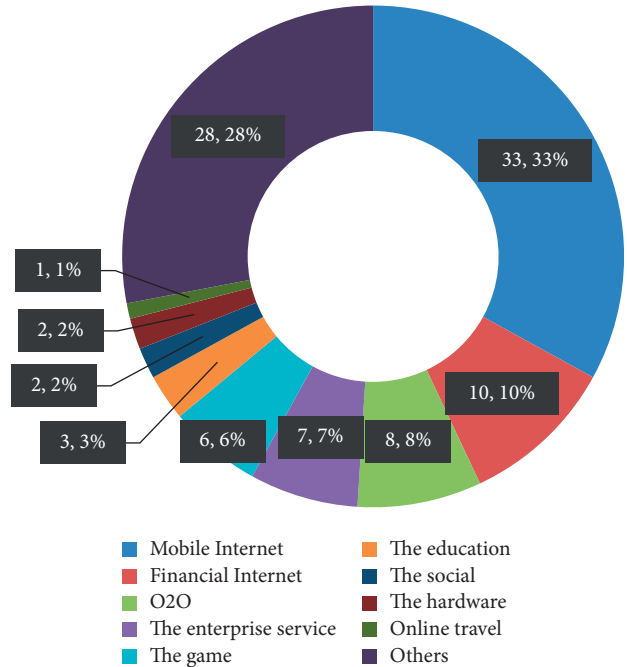


FIGURE 1: Industry distribution of data talent demand.

in the Guangdong province. Literature [15] predicts the total amount of information service talents in the Shandong province using binary linear regression prediction and the gray prediction group method. Literature [16] used the smoothing index and time series prediction methods to forecast the demand for talent in property information service in the Zhejiang province.

It can be seen from the above literature summary that Chinese scholars use diversified model methods to predict the demand for information service talents. There are the exponential change method, the nonlinear regression model, the binary linear regression model, GM (1, 1) model, and the exponential smoothing method [17]. The gray GM (1, 1) forecasting model is a common model among single forecasting methods with good forecasting accuracy, which has been widely used in demand forecasting research in many fields [18]. GM has good periodic and linear modeling capabilities [19]. The BP neural network has a powerful nonlinear modeling ability, but a single method can only describe the piecemeal information of talent demand. Based on combinatorial optimization theory and aiming at the shortcomings of current talent demand forecasting methods, this paper proposes a GM (1,1)-BP neural network model based on GM (1, 1) and BPNN for information service talent demand forecasting.

This paper consists of four main parts: the first part is the introduction, the second part is the methodology of the algorithm, the third part is the result analysis and discussion, and the fourth part is the conclusion.

2. Methodology

Gray theory is a kind of a dynamic fuzzy prediction model. Compared with curve fitting, gray model prediction has the

advantage that it does not need a lot of original data and has no requirement for the distribution of data. The system can be monitored in practical applications by extracting valuable contents from known information. The prediction model adopted in this paper is GM (1, 1).

2.1. Construction of the Gray Prediction Model. Since the GM(1, 1) model requires the monitoring data to have an equal time interval in the modeling process, the information service personnel demand data do not have equal time intervals. Therefore, the data of nonisochronous information service talent demand is isochronized by using the cubic interpolation method to form the data sequence of information service talent demand, as shown in the following formula:

$$I^0 = \{i^0(1), i^0(2), i^0(3), i^0(4), \dots, i^0(t)\} i^0(n) \geq 0, \quad (1)$$

$$n = 0, 1, 2, 3, 4 \dots t.$$

In order to fully reveal the development trend of information service personnel demand data, the data are

accumulated to generate (1-AGO) sequence $S^{(1)}(t)$, as shown in the following formula:

$$I^{(1)} = \{i^{(1)}(1), i^{(1)}(2), i^{(1)}(3), i^{(1)}(4) \dots, i^{(1)}(t)\}, \quad (2)$$

$$I^{(1)}(n) = \sum_{x=1}^n i^{(1)}(x) \quad (x) \geq 0.$$

The compact adjacent value of $x^{(1)}$ generates sequence $J^{(1)}$, as shown in the following formula:

$$J^{(1)} = \{J^{(1)}(1), J^{(1)}(2), J^{(1)}(3), J^{(1)}(4) \dots, J^{(1)}(t)\}, \quad (3)$$

where $J^{(1)} = \{0.5J^{(1)}(t) + 0.5J^{(1)}(t-1)\}$.

Then, the GM (1, 1) model can be expressed as the following formula:

$$i^{(0)}(n) + gJ^{(1)}(n) = h, \quad n = (1, 2, 3, 4 \dots t), \quad (4)$$

where g is the development coefficient, and the effective interval is $(-2, 2)$. h is the gray action. Generate the additive matrix H and the constant vector J .

$$H = \begin{bmatrix} -\frac{1}{2} [I^{(1)}(1) + I^{(1)}(2)] & 1 \\ -\frac{1}{2} [I^{(1)}(2) + I^{(1)}(3)] & \\ -\frac{1}{2} [I^{(1)}(3) + I^{(1)}(4)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2} [I^{(1)}(t-1) + I^{(1)}(t)] & 1 \end{bmatrix}, \quad (5)$$

$$J = \begin{bmatrix} I^{(0)}(2) \\ I^{(0)}(3) \\ I^{(0)}(4) \\ \vdots \\ I^{(0)}(t) \end{bmatrix}.$$

MATLAB is used to solve the least square method, and the gray coefficient is calculated, as shown in the following formula:

$$\hat{g} = (H^N H)^{-1} H^N J_t = \begin{pmatrix} g \\ h \end{pmatrix}. \quad (6)$$

Finally, the parameters g and h to be estimated are obtained.

The information service talent demand prediction model is finally calculated, as shown in the following formula:

$$\hat{j}^{(1)}(n+1) = \left(J^{(0)}(1) - \frac{h}{g} \right) e^{-gn} + \frac{h}{g}, \quad n = (1, 2, 3, 4 \dots t). \quad (7)$$

2.2. Accuracy Test of Calculation Results. The accuracy of the results of modeling calculation is tested to verify whether the model meets the prediction accuracy requirements.

The original information service talent demand sequence is $S^{(0)} = (S^{(0)}(1), S^{(0)}(2), \dots, S^{(0)}(n))$. The simulation sequence of information service talent demand is $\hat{S}^{(0)} = (\hat{S}^{(0)}(1), \hat{S}^{(0)}(2), \dots, \hat{S}^{(0)}(t))$. The residual is shown in the following formula:

$$\Delta^{(0)} = S^{(0)}(x) - \hat{S}^{(0)}(x), \quad x = 1, 2, \dots, t. \quad (8)$$

The mean value of the original information service talent demand sequence is shown in the following formula:

$$\bar{S} = \frac{1}{t} \sum_{x=1}^t S^{(0)}(Z). \quad (9)$$

The serial variance of original information service talent demand is shown in the following formula:

$$S_1^2 = \frac{1}{t} \sum_{x=1}^t (S^{(0)}(Z) - \bar{S})^2. \quad (10)$$

The mean value of the residual order of the original information service talent demand is shown in the following formula:

$$\bar{\Delta} = \frac{1}{t} \sum_{x=1}^t \Delta(z). \quad (11)$$

The residual variance of the original information service talent demand sequence is shown in the following formula:

$$S_2^2 = \frac{1}{t} \sum_{x=1}^t (\Delta(Z) - \bar{\Delta})^2. \quad (12)$$

The mean square error of the original information service talent demand sequence is shown in the following formula:

$$C = \frac{S_2}{S_1}. \quad (13)$$

The small error probability test of the original information service talent demand sequence is shown in the following formula:

$$u = (|\Delta(z) - \bar{\Delta}| < 0.6745S_1), \quad (14)$$

where the smaller the mean square error C , the higher the prediction accuracy. The higher the small error probability p , the higher the prediction accuracy. Specific discrimination criteria are shown in Table 1.

2.3. Improved GM (1, 1) Model. The BP network model is a kind of a multilayer feedforward network trained by an error backpropagation algorithm. It has the characteristics of self-training and self-adaptation, classification, and multidimensional function mapping. At the same time, the non-linear continuous function can be fitted with high precision. In the process of training, the BP network model constantly adjusts the weights of the connections between nodes (neurons) to achieve the purpose of information processing. The common BP network model includes input, hidden, and output layers. Layers are fully connected with each other, and neurons are not connected between layers. Its structure is shown in Figure 2. In the process of training, input training data samples are mapped to the hidden layer, and the actual output values are calculated and transmitted to the output layer. In this process, the weight of the network is unchanged, and the single layer neurons are affected by the previous layer. Its working principle is shown in Figure 3.

The gray system theory requires equal time interval data in the modeling process. However, in practical practice, information service personnel demand data are often unequal intervals, so it is necessary to interpolate the data. The process of interpolation will affect the prediction accuracy of the model. Therefore, we need to find a way to compensate for the error. The BP network model is a widely used network model, which can train the model by taking the residual of GM (1, 1) fitting data as two training sources. Residual correction is performed using trained models. Then, the gray GM (1, 1)-bp tandem combination model is established. The model construction process is as follows: firstly, the GM (1, 1) gray model is constructed. The demand for information service personnel is predicted with the change of time series, and the predicted value of the GM (1, 1) gray model is $\bar{i} = \{\bar{i}_1, \bar{i}_2, \dots, \bar{i}_t\}$, as well as the prediction residual is $\varepsilon_x = i_x - \bar{i}_x$ ($x = 1, 2, \dots, t$). Then, residual sequence is constructed, the BP network model is created, and residual correction is carried out. Finally, the predicted value of the GM (1, 1) model and the predicted residual value were superimposed to obtain the information service talent demand data revised by the BP network model. The specific process is shown in Figure 4.

2.4. Combination Model. The combined prediction model refers to the combination of different single models with different weights for the same prediction object. By combining the advantages and disadvantages of different prediction models, different weight coefficients are given to the selected curve and gray model. The models are combined to optimize the predicted results, and the specific process is as follows:

- (1) Demand data of n groups of information service talents are denoted as $\{i_n, n = 1, 2, 3, \dots, t\}$. The prediction result of the GM (1, 1) gray model is $\{i'_n, n = 1, 2, 3, \dots, t\}$. The predicted result of the curve model is $\{i''_n, n = 1, 2, 3, \dots, t\}$. The

TABLE 1: Grey model accuracy reference table.

Model accuracy level	Mean relative error β	Correlation γ	Mean square error C	Probability of small error p
Level 1 (high)	≤ 0.01	≥ 0.90	≤ 0.35	≥ 0.95
Level 2 (qualified)	$0.01 \leq \beta \leq 0.05$	$0.80 \leq \gamma \leq 0.90$	$0.35 \leq C \leq 0.50$	$0.80 \leq p \leq 0.95$
Level 3 (barely qualified)	$0.05 \leq \beta \leq 0.10$	$0.60 \leq \gamma \leq 0.80$	$0.50 \leq C \leq 0.65$	$0.60 \leq p \leq 0.70$
Level 4 (failed)	> 0.20	< 0.60	> 0.80	< 0.60

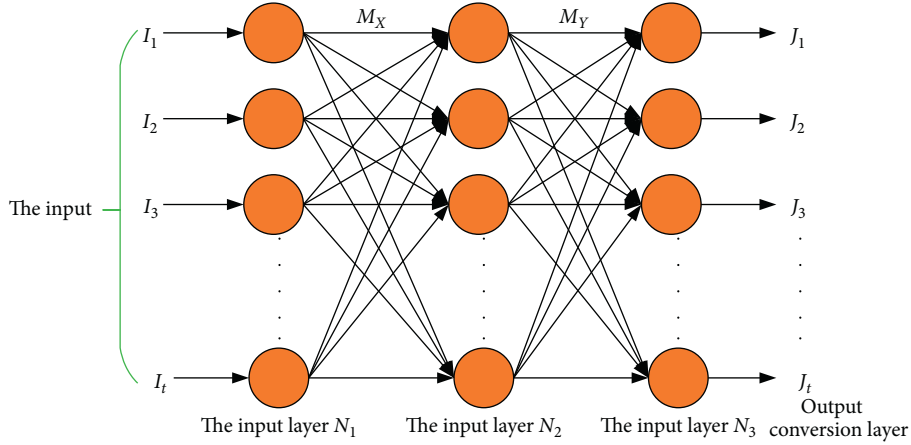


FIGURE 2: BP neural network.

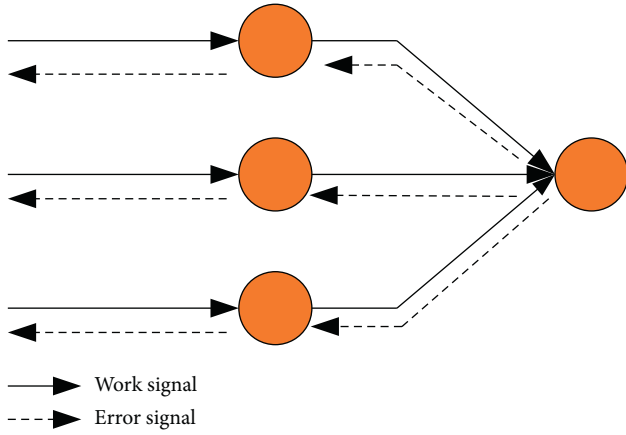


FIGURE 3: BP network signal.

corresponding prediction error of the gray model at phase n is $e'_n = i_n - i'_n$. The prediction error of the curve model is $e''_n = i_n - i''_n$. Assume that the weighted coefficient of the gray model is p_1 and that of the curve model is p_2 , then $p_1 + p_2 = 1$. p_1 and p_2 are optimal solutions that satisfy the prediction model.

- (2) The predicted value of the combined model is $\{\hat{i}_n = p_1 i'_n + p_2 i''_n, n = 1, 2, 3, \dots, t\}$. The prediction error is $e_n = i_n - \hat{i}_n = p_1 e'_n + p_2 e''_n$. J_1 is the sum of squares of prediction errors of two groups of models, as shown in the following formula:

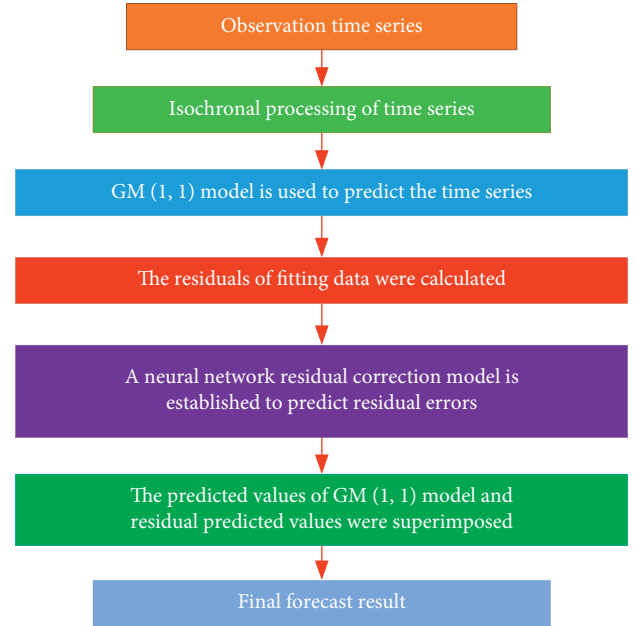


FIGURE 4: Residual correction flow chart of the BP neural network.

$$Y_1 = \sum_{n=1}^t e_n^2 = \sum_{n=1}^t (p_1 e'_n + p_2 e''_n)^2. \quad (15)$$

- (3) To meet the minimum prediction error, we need to meet the following equations:

$$\begin{cases} \min Y_1 = \sum_{n=1}^t (p_1 e'_n + p_2 e''_n)^2, \\ p_1 + p_2 = 1. \end{cases} \quad (16)$$

Let $R = (p_1, p_2)^N T$ be the weight coefficient vector of the combined prediction model, $R = (1, 1)^N$. Calculate the sum of squares of the prediction errors of the gray GM (1, 1) model $E_1 = \sum_1^t (e'_n)^2$. The sum of squares of the prediction error of the curve model is $E_2 = \sum_1^t (e''_n)^2$, whereas the covariance between the prediction error of the gray model, and the curve model is $E_3 = \sum_1^t e'_n e''_n$,

where $E = \begin{bmatrix} E_1 & E_3 \\ E_3 & E_2 \end{bmatrix}$, then formula (16) can be expressed as the following formula:

$$\begin{cases} \min Y_1 = L^N E L, \\ R^N L = 1. \end{cases} \quad (17)$$

3. Result Analysis and Discussion

3.1. Data Sources. This paper mainly predicts the national level's demand scale of information service talents during the 14th five-year plan period. Therefore, the input value is the statistical value of the number of information service talents under the national caliber. As for the sample length, there are two prediction methods involved in the

combinatorial model, which have different requirements for the sample length. The gray model adopts small sample prediction, and data within 10 years are usually used in the literature for prediction. Some studies have shown that good results can be obtained when the sample size of gray prediction is about 8. Therefore, considering the trend of national economic development and referring to similar literature, 8 samples were selected as input values in this paper. This paper selects the data from China Statistical Yearbook (1999–2020) and takes the full-time equivalent number of R&D personnel from 2012 to 2019 as the input value of the gray forecasting model. The data from 1995 to 2019 were used as the input values of the exponential smoothing model. In this way, the combination of long period and short period prediction is realized to ensure prediction accuracy. Due to the policy of relevant statistical scope, the above data do not include data from Hong Kong, Macao, and Taiwan.

3.2. Gray Prediction of Information Service Talent Demand. The full-time equivalent number of information service personnel from 2013 to 2020 is shown in Table 2.

According to the data, the original data sequence is constructed, and the cumulative data sequence $I^{(0)}$, data matrix H , and J_1 are obtained after processing, as shown in the following formula.

$$\begin{aligned} I^{(0)} &= \{3.4271, 3.5334, 3.7106, 3.7584, 3.8786, 4.0332, 4.3818, 4.8015\}, \\ I^{(1)} &= \{3.4271, 6.9605, 10.6707, 14.4291, 18.30757, 2234.09, 26.7227, 31.5242\}, \\ H &= \begin{pmatrix} -5.1933 & 1 \\ -8.8156 & 1 \\ -12.5514 & 1 \\ -16.3683 & 1 \\ -20.3246 & 1 \\ -24.5314 & 1 \\ -29.12.36 & 1 \end{pmatrix}, \\ J_1 &= \begin{pmatrix} 3.5332 \\ 37.107 \\ 37.582 \\ 38.786 \\ 40.332 \\ 43.817 \\ 48.013 \end{pmatrix}. \end{aligned} \quad (18)$$

When the original data sequence level sigma $\sigma^{(0)}(z) = (I_{(z-1)}^{(0)}/I_{(z)}^{(0)})$ falls within the range of capacity $(e^{-(2/t+1)}, e^{(2/t+1)})$, suggests that the original data sequence is a smooth sequence. According to the calculation, the stage

ratios are $\sigma^{(0)}(2) = 0.96, \sigma^{(0)}(3) = 0.93, \sigma^{(0)}(4) = 0.98, \sigma^{(0)}(5) = 0.95, \sigma^{(0)}(6) = 0.97, \sigma^{(0)}(7) = 0.94, \sigma^{(0)}(8) = 0.91$. All fall within the accommodable interval $(e^{-(2/9)}, e^{(2/9)})$, indicating that the original data are a smooth sequence, and

TABLE 2: Full-time equivalent statistics of information service personnel in China from 2013 to 2020.

Year	Full-time equivalent number (millions of people/year)
2013	3.4271
2014	3.5334
2015	3.7102
2016	3.7584
2017	3.8786
2018	4.0332
2019	4.3818
2020	4.8015

GM (1, 1) prediction can be made. You get $g = -0.0495, h = 318.9304$. The gray differential equation is calculated as the following formula:

$$\frac{dI}{dn} - 0.0495 = 318.9309. \quad (19)$$

On further solving, the prediction model is obtained.

$$I_{(n+1)}^{(1)} = 6803.0793e^{0.0495n} - 6460.3796. \quad (20)$$

In order to analyze the prediction accuracy of the model, the demand of information service personnel from 2013 to 2020 was estimated by the prediction model and compared with the actual value. The predicted results are shown in Table 3. 2013 is the base period, and the predicted value is the same as the actual value. By calculating the correlation model index, the mean relative error $\bar{v} = 2.15\%$, the correlation degree $\gamma = 0.63$, and the posteriori error ratio $C = 0.12$ were obtained. From $|\varepsilon_{n_s}^{(0)} - \bar{\varepsilon}| = \{8.73, 0.32, 0.67, 4.51, 2.74, 7.33, 6.19, 8.45\}$ and $0.67456 = 30.87$, the small error probability $u = 1$ was obtained. The evaluation results of the model are shown in Table 4.

The evaluation results show that the gray prediction model has passed three kinds of tests and performs well in the posterior difference test, which proves that the model has good prediction accuracy. The calculated value is less than the critical value, indicating that the model can be used for medium and long-term prediction. This model is used to predict the demand scale of scientific and technological talents in China during the 14th five-year plan period, and the predicted results are shown in Table 5.

3.3. Time Series Prediction of Information Service Talent Demand. The time series model is a general name for a series of models, among which the most commonly used models are the regression moving average model and the exponential smoothing model. The former is generally used to predict stationary data, while the latter can deal with nonstationary data. In this paper, three common models are used for prediction, and the model with the minimum root mean square error (RMSE) is selected as the time series model. Figure 5 shows the scatter chart of full-time equivalent data of national information service personnel from 1995 to 2019. According to the scatter chart, it can be observed that the change of the number of information service personnel has an overall upward trend. The autocorrelation analysis of the data shows that not all data series

TABLE 3: Comparison between the actual value and the predicted value unit: ten thousand people (year).

Year	The actual value	Observations	Residual ε	The relative error q (%)
2013	3.4271	3.4271	0	0.00
2014	3.5334	3.4427	0.0907	2.57
2015	3.7102	3.6172	0.093	2.51
2016	3.7584	3.8002	0.0418	1.11
2017	3.8786	3.9926	0.114	2.94
2018	4.0332	4.1941	0.1609	3.99
2019	4.3818	4.4062	0.0244	0.56
2020	4.8015	4.6296	0.1719	3.58

TABLE 4: Model evaluation results.

The evaluation index	Model index value	The critical value	Precision grade
Mean relative error β	2.15%	<5%	Level 2
Correlation γ	0.62	>0.6	Level 4
Probability of small error p	1	>0.95	Level 3
Posterior error ratio C	0.07	<0.35	Level 1

are white noise and have time correlation, so the time series model is suitable for analysis.

In addition, by fitting each point in Figure 5, it was found that F value was the largest when the exponential distribution curve was used for fitting, indicating that this group of data presented exponential distribution and was suitable for the exponential smoothing method for prediction. In time series analysis, seasonality is generally considered. Since the data obtained in this paper are annual and do not have seasonal periodicity, only nonseasonal analysis is made. According to the four common models, SPSS software was used to predict and analyze the full-time equivalent number of information service personnel from 1995 to 2019, and the corresponding root mean square error (RMSE) value was obtained as shown in Table 6. Through analysis and comparison, it is found that the Brown linear trend model in the exponential smoothing method has the best prediction effect, and then the model is used to predict the total amount of information service talents from 2021 to 2025. The results are shown in Table 7.

3.4. Combination Forecast of Information Service Talent Demand. The results of the GM (1, 1) prediction model and the BP neural network prediction model are weighted

TABLE 5: GM (1, 1) forecast of demand for information service talents in China during the 14th five-year plan period.

Year	Forecasting talent demand (millions of people/year)
2021	5.1106
2022	5.3683
2023	5.6407
2024	5.9253
2025	6.2258

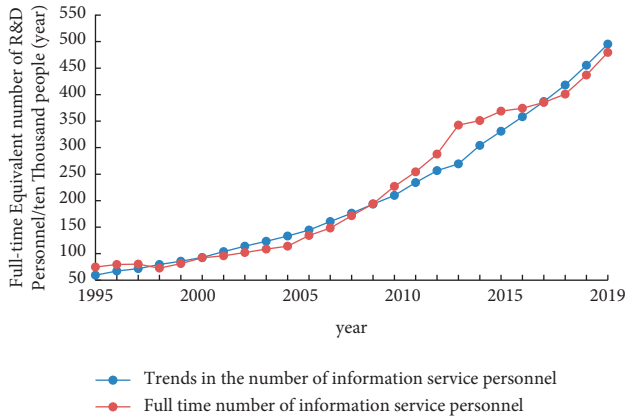


FIGURE 5: Full-time equivalent number of national information service personnel from 1995 to 2019.

TABLE 6: Comparison of RMSE values of all models.

Model	RMSE
Literature [20]	12.32
Literature [21]	12.05
Literature [22]	12.56

TABLE 7: Predicted value of the China information service talent demand index smoothing method during the 14th five-year plan period.

Year	Forecasting talent demand (millions of people/year)
2021	5.6006
2022	5.9924
2023	6.3727
2024	6.7403
2025	7.0965

average using the optimal weighted grouping method. The prediction result of the combined model is obtained according to the weighted average of this weight. To compare the validity of the models, the forecast results of the three models on the demand for information service talents from 2013 to 2020 are shown in Figure 6. Among the three prediction models, the MAE and MAPE of the combined model are 7.15 and 1.77%, respectively, both of which are lower than those of the single model, proving that the combined model has smaller error and better prediction effect.

This model is used to predict the demand for information service talents in China during the 14th five-year plan period, and the predicted results are shown in Table 8.

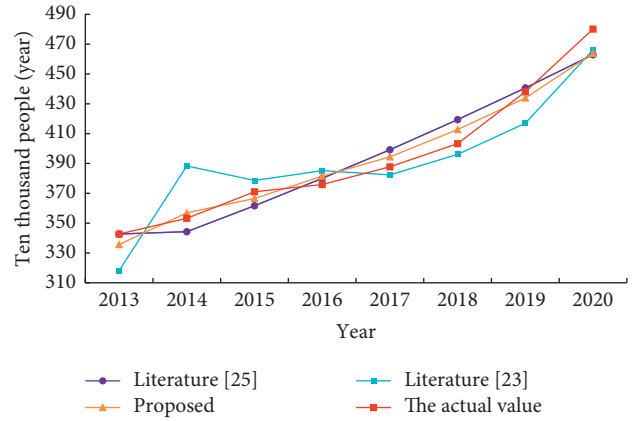


FIGURE 6: Comparison between the predicted value and the actual value of information service talent demand in China from 2013 to 2020.

TABLE 8: Forecast value of national information service talent demand combination during the “14th Five-year Plan” period.

Year	Forecasting talent demand (millions of people/year)
2021	5.2506
2022	5.5474
2023	5.8493
2024	6.1581
2025	6.4749

4. Conclusion

Demand forecasting of information service personnel is of great significance for scientific planning. The curve fitting obtained by calculating the raw statistics can predict the information service talent demand data better, and its effect is good. The algorithm of information service industry talent prediction based on the GM(1, 1) gray model requires less sample data and has high prediction accuracy. However, for data with complex features, the prediction results are not satisfactory, and the prediction curve gradually deviates from the measured curve as the prediction period increases. Therefore, the BP network model can be used to update and optimize the GM(1, 1) model to improve the prediction accuracy. By constructing a combined forecasting model, the advantages of both models are combined to improve the forecasting effect. When analyzing and processing a large amount of discrete and stochastic data, multiple models need to be selected for prediction comparison. In the case of high prediction accuracy, the selection of models should follow the principle of minimizing the average relative error of residuals. The experimental results show that the prediction algorithm in this paper achieves the best results. The combined prediction model formed by assigning unequal weight coefficients improves the prediction accuracy but still inherits the characteristics of the gray model with a large prediction error at the later stage. In the later period, the combined prediction model can be trained by the neural network after wavelet denoising to improve the prediction accuracy.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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