ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

Analysis of Domestic Population Aging Forecast Based on Combined Forecast Model

Linlin Su[1], Yaxin Zhou[2], Qi Fang[3]

[1]*Mathematical Department, University College School (UCL), London, WC1E 6BT, United Kingdom*
[2]*International School, Huaqiao University, Quanzhou, 362000, China*
[3]*Nanyang Technopreneurship Center, Nanyang Technological University, 637553, Singapore*

Abstract: *It is of practical significance to clarify the influencing factors of population aging to effectively respond to the challenges of aging and promote the development of China's economy and society. This paper takes population aging influencing factors as the research object, and on the basis of reasonable assumptions The three single models of quadratic exponential smoothing prediction, modified gray prediction and BP neural network prediction are constructed, and then the error sum of squares of in-sample prediction is derived separately, and then the weights are determined according to the inverse of the error sum of squares method to construct a combined prediction model of population aging, and the conclusion that the prediction of combined prediction model is more effective regardless of in-sample prediction or out-of-sample prediction is drawn; and then the model is used to predict the prediction results show that the problem of population aging in China will remain increasingly serious in the future.*

Keywords: *Quadratic exponential smoothing prediction; modified gray prediction; BP neural network*

1. Introduction

Due to the one-child policy in the early 1980s, China's population aging problem is more serious than that of other countries. Since the 1990s, the process of population aging has accelerated and the proportion of the elderly population over 65 years old has increased[1]. It rose from 5.57% (63.14 million) in 1990 to 9.4% (127.14 million) in 2012 and is expected to continue rising to exceed 20% by 2040. In addition, China's fertility rate has now fallen below replacement level, and the population life expectancy and mortality rates are approaching those of developed countries. Therefore, in order to effectively respond to the challenges of aging and to investigate the influencing factors of population aging in China, we have selected six important influencing factors: birth rate (X1), population mortality rate (X2), urbanization rate (X3), GDP per capita (X4), number of health care units (X5), and average number of students in high school and above per 100,000 population (X6)[2].

Using the birth rate and mortality rate as benchmarks, we analyzed indirect factors such as urbanization rate through a mathematical model. Considering the large amount of data, it is necessary to first pre-process the data for all data impact factors and save the data needed in the subsequent procedure as other files separately[3]. In order to give full play to the advantages and weaknesses of the single model, we can assign certain weights to each single model by certain criteria, and then construct a combined prediction model, and conclude that the combined prediction model is more effective in both in-sample and out-of-sample prediction. The model is then applied to predict the level of aging in China from 2022 to 2025, and the prediction results show that the problem of population aging in China will become increasingly serious in the future.

2. Principle of prediction method

2.1 Analysis and solution of the problem

According to the report "World Population Prospects: The 2015 Revision" published by the United Nations, the median age of China's population will change from 37 years in 2015 to 49.6 years in 2050, which means that China's population structure is aging rapidly, the "demographic dividend" is gradually fading, and the problem of population aging is becoming more and more prominent. The prediction of the aging level can provide a basis for the formulation of relevant policies and measures, and thus effectively avoid the negative effects of population aging[1].

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

2.2 Model Introduction

2.2.1 Quadratic exponential smoothing forecasting method

Secondary exponential smoothing is a smoothing on top of the primary exponential smoothing value, and its predictions are more accurate because secondary exponential smoothing makes fuller use of the sample data. The quadratic exponential smoothing model can be formulated as,

$$\hat{X}_{t+T} = a_t + b_t T \tag{1}$$

2.2.2 Modified Gray Forecasting Method

The modified gray forecasting method means that the residuals are used to modify the traditional gray forecasting model, and the prediction error becomes significantly smaller after the modification. The modified gray prediction GM(1,1) model is used in this paper, and its modeling steps can be expressed as the following four steps.

In the first step, let the original sequence be X(0),and construct a gray prediction GM(1,1) model based on X(0), where k∈[1,n]:

$$X^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] \mathrm{e}^{-ak} + \frac{b}{a} \tag{2}$$

In the second step, the predicted value $\hat{X}(0)$ of X(0) can be obtained by subtracting xx ,once from (1) obtained by equation (2).

$$\hat{X}^{(0)}(k+1) = \left(1 - \mathrm{e}^{a}\right)\left[X^{(0)}(1) - \frac{b}{a}\right] \mathrm{e}^{-ak} \tag{3}$$

In the third step, the difference between X(0) and $\hat{X}^{(0)}$, E(0), is taken as the residual series, and its tail residual subsequence {E(0)(k0),E(0)(k0+1),...,E(0)(n)} is used to construct the gray prediction GM(1,1) model. If the residual subsequences are all positive, they can be constructed directly; if they are all negative, they can be constructed directly as positive numbers, and the negative sign is added after construction; if there are positive and negative numbers, the absolute value of the smallest negative number should be added to transform them into positive numbers for construction, and the absolute value is subtracted after construction. Taking all positive numbers as an example, the gray prediction GM(1,1) model based on the residual subsequence is as follows, when k∈[k0,n]:

$$E^{(1)}(k+1) = \left[\mathrm{E}^{(0)}(1) - \frac{b_E}{a_E}\right] \mathrm{e}^{-a_E k} + \frac{b_E}{a_E} \tag{4}$$

In the fourth step, the second step is repeated for the $\hat{\mathrm{E}}^{(1)}$ obtained in the third step to obtain its predicted value, and then the modified gray prediction GM(1,1) model is obtained.

$$\hat{X}^{(0)}(k+1) = \left(1 - \mathrm{e}^{a}\right)\left[X^{(0)}(1) - \frac{b}{a}\right] \mathrm{e}^{-ak} + \delta\left(k - k_0\right)\left(1 - \mathrm{e}^{a_E}\right)\left[\mathrm{E}^{(0)}(1) - \frac{b_E}{a_E}\right] \mathrm{e}^{-a_E k} \tag{5}$$

Equation (5) is only the case when the residual subsequence is positive. If they are all negative, "+" becomes "-"; if there are positive and negative, "+" remains unchanged and the absolute value of the smallest negative number in the residual subsequence is subtracted at the end of the equation.

2.2.3 BP neural network prediction method

BP neural network is a multilayer forward network with one-way propagation , and a more typical three-layer structure network (including input layer, hidden layer and output layer) is selected for prediction in this paper, and its structure is shown in Figure 1.

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

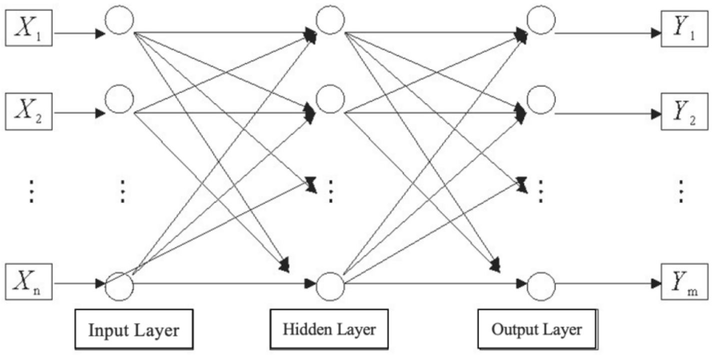

Figure 1: BP neural network structure diagram

The modeling steps can be expressed as the following six steps.

In the first step, the data are dimensionless and normalized so that the input data and target data fall in the interval of [-1,1].

In the second step, the number of neurons in the hidden layer is n=(n0+n1)1/2+a; where n0 and n1 are the number of neurons in the input and output layers, respectively, and a is a constant and a∈[1,10]. Of course, in the actual process, various parameters must be adjusted continuously to strive for the optimal prediction effect.

The third step is to create the network. In this paper, the transfer function of the input layer and the hidden layer is set to tansig, that is, f(x)=(1-e - x)/(1+e-x); the transfer function of the output layer is set to purelin, the training function is set to trainlm, the weight learning function is set to clearngdf; the performance function is set to mse, and the simulation function is set to sim.

The fourth step, set the parameters. In this paper, we set the display amplitude of the training state to 50, the learning rate to 0.1, the momentum coefficient to 0.9, the training times to 1000, and the error accuracy to 0.001.

In the fifth step, during the training process, the threshold and weights are adjusted repeatedly to reduce the value of the performance function mse, and the training is terminated when the predetermined error accuracy is reached.

In the sixth step, the BP neural network is used to simulate the prediction and simulate the output data.

2.2.4 Combined predictive models

In 1969, Bates (Bates) and Granger (Granger) pioneered the combined forecasting model method[2]. The method is based on certain criteria to give each individual model a certain weight, and then the new model is formed by combining them together according to the weights . The main methods for setting the weights of this model are equal weight method, simple weighted average method, error square and inverse method, etc. Since the first two methods are simpler but have large errors, the error-squared and inverse method is used to set the weights in this paper. Then the weight of the i-th single model can be expressed as.

$$w_i = D_i^{-1} / \sum_{i-1}^{n} D_i^{-1} \tag{6}$$

Where: n is the total number of single models, in this paper n=3,i.e. there are 3 single models; Di denotes the error sum of squares of the prediction within the sample of the ith single model, i.e. there are.

$$D_i = \sum_{i-1}^{T} \left(x_t - \hat{x}_{it} \right)^2 \tag{7}$$

The larger Di is, the larger the prediction error of the i-th individual model and the smaller the corresponding weight, and vice versa.

After finding the weights of each individual model, the combined forecasting model is as follows.

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

$$\hat{x}_t = w_1\hat{x}_{1t} + w_2\hat{x}_{2t} + w_3\hat{x}_{3t} \tag{8}$$

3. Predictive Model Construction and Solving

3.1 Analysis of the validity of combined forecasting model forecasts

3.1.1 Construction of combined prediction models

1) Data source

This paper selects the population aging index data from 1978 to 2021 (in this paper, the aging population refers to the population aged 65 and above in China, and the population aging index data is the ratio of it to the total population in China). In order to study the effectiveness of the combined forecasting model, the population aging data from 1978 to 2010 are taken as in-sample data and the population aging data from 2011 to 2021 are taken as out-of-sample data, so as to analyze the effectiveness of the combined forecasting model and the out-of-sample forecasting of the three individual models.

2) Constructing a single prediction model

In this paper, in order to calculate the weights of each individual model for constructing the combined forecasting model, three individual models were constructed using MATLAB (2016) and the sum of squared errors for in-sample forecasting were derived separately.

(1) Quadratic exponential smoothing prediction

For the quadratic exponential smoothing prediction, the value of α has a certain influence on the prediction accuracy, so that α is 0.1, 0.2,...,0.9, and then the α that minimizes the error sum of squares is selected. for different α, the error sum of squares of in-sample prediction is shown in Table 1.

From Table 1, we can see that when α is 0.5, the sum of squared errors of in-sample prediction is the smallest, so in this paper, if α is 0.5, the sum of squared errors of in-sample prediction is 2.7238.

Table 1: Sum of squared errors of predictions within samples with different α

Takes values	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Error sum of squares	8.72	3.51	2.84	2.77	2.72	2.92	3.28	3.80	4.56

(2) Modified gray forecast

For the modified gray prediction, this paper selects k0=5, at this time, the subsequence of residuals has positive and negative, then the absolute value of the least negative number should be added to transform it into a positive number to construct, and then subtract the absolute value after construction. The constructed model is as follows.

When k<5, $\hat{X}^{(0)}(k+1) = 4.1191e^{0.0238k}$

When k ≥ 5, the $\hat{X}^{(0)}(k+1) = 4.1191\mathrm{e}^{0.0238k} + 0.9030\mathrm{e}^{0.0075k} - 1.0983$. And then it can be found that its in-sample prediction error is 2.5643.

(3) BP neural network prediction

For BP neural network prediction, the input variable is population aging index data. In this paper, if the number of neurons in the input layer is 5 and the number of neurons in the output layer is 1, the number of neurons in the hidden layer is 4 to 12. After training, the error is minimized when the number of neurons in the hidden layer is 9. At this time, the sum of squares of its in-sample prediction error is 1.7641.

3) Constructing a portfolio prediction model

From the error sum of squares obtained above, the weights of the three models are 0.2773, 0.2946, and 0.4281, respectively, according to equation (6), then the constructed combined prediction model is as follows.

$$\hat{x}_t = 0.2773\hat{x}_{1t} + 0.2946\hat{x}_{2t} + 0.4281\hat{x}_{3t} \tag{9}$$

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

3.1.2 Analysis of the validity of the forecast

1) Selection of evaluation index of prediction validity

In this paper, the mean square error (MSFE) of prediction is selected as the evaluation index of prediction validity, which is calculated as follows.

$$\mathrm{MSFE}=\frac{1}{T}\sum_{t=1}^{T}\left(x_t-\hat{x}_t\right)^2 \tag{10}$$

In equation (10), T denotes the total number of samples predicted, xt denotes the actual value, and t denotes the predicted value. the smaller the MSFE, the smaller the difference between xt and t, and the more effective the prediction of the model.

2) Analysis of the validity of within-sample predictions

The in-sample projections of the population aging data from 1978 to 2010 were obtained using the three individual models and the combined projection model established to obtain the in-sample projections of the four models from 1978 to 2010, and then the MSFE was calculated from equation (10), respectively, as shown in Table 2.

Table 2: Comparison of MSFE for in-sample prediction of four prediction models

Prediction Method	MSFE	Predictive Validity Ranking
Secondary exponential smoothing forecast	0.0825	4
Modified Gray Forecast	0.0777	3
BP neural network prediction	0.0535	2
Combined predictive models	0.0467	1

As can be seen from Table 2, on the one hand, the combined prediction model constructed based on the three individual models has the smallest MSFE and therefore its in-sample prediction is the most effective; on the other hand, among the three individual models, the BP neural network has the most effective in-sample prediction, followed by the modified gray prediction, and the worst in-sample prediction is the quadratic exponential smoothing prediction.

3) Analysis of the validity of out-of-sample predictions

The in-sample forecasts can hardly reflect the predictive ability of the model for the future, while the out-of-sample forecasts can further analyze the validity of the model forecasts. Although the combined forecasting model has the highest accuracy in the in-sample forecasts, it does not mean that it also has the best predictive ability for the future. Therefore, in order to select the optimal model for more accurate prediction of the future, this paper performs an out-of-sample prediction of the population aging level from 2011 to 2021, and the obtained MSFE values are shown in Table 3.

Table 3: Comparison of MSFE for out-of-sample prediction of four prediction models

Prediction Method	MSFE	Predictive Validity Ranking
Secondary exponential smoothing forecast	0.0884	4
Modified Gray Forecast	0.0752	3
BP neural network prediction	0.0594	2
Combined predictive models	0.0470	1

The following conclusions can be drawn from Tables 2 and 3: first, the MSFE of the combined prediction model is the smallest among the four prediction models for both in-sample and out-of-sample prediction, so the combined prediction model has some validity in predicting population aging; second, among the three individual models, the BP neural network has the highest prediction accuracy for both in-sample and out-of-sample prediction, followed by modified gray prediction, and the worst predictive ability is the quadratic exponential smoothing prediction; third, the study of model predictive validity is mainly to study the predictive ability of the model for the future, and although in-sample and out-of-sample predictive accuracy rank the same in this example, in fact, the model with high in-sample

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

predictive accuracy is uncertain for the out-of-sample predictive accuracy. Therefore, when analyzing the prediction validity, more attention should be paid to the out-of-sample prediction validity under the premise of reasonable in-sample prediction accuracy.

3.2 China's population aging forecast

Based on the empirical analysis of the validity of the combined prediction model, the following conclusions can be drawn: the combined prediction model is valid for both in-sample and out-of-sample predictions, and therefore, the model can be used to predict the level of population aging in China in the coming years. In order to improve the accuracy of the prediction, a single model is constructed using 1978 to 2016 as in-sample data, and then new weights are obtained, which are 0.2952, 0.3239, and 0.3809, respectively, then the combined prediction model is constructed as follows.

$$\hat{x}_t = 0.2952\hat{x}_{1t} + 0.3239\hat{x}_{2t} + 0.3809\hat{x}_{3t} \tag{11}$$

Since China officially entered into an aging country in 2000, although the time of entering is late but the development speed is too fast, so China's aging problem has attracted the attention of many authoritative institutions at home and abroad, and made relevant predictions. The United Nations predicts that the aging level of China's population will be around 11.5% in 2020, and the Development Research Center of the State Council predicts that the aging level of China's population will be around 12% in 2020. As shown in Table 4, China's population aging level in 2022 is predicted to be 11.5485% by the combined prediction model, which is between the predicted values of the United Nations and the National Research Center and is more in line with the reality. Therefore, it is of guiding and practical significance to use the combined forecasting model to forecast the aging level in China.

In order to avoid the adverse effects of population aging on China's development, policy makers should make reasonable predictions of the aging level, and formulate relevant policies and take relevant measures.

4. Summary and Recommendations

China's population has now entered the elderly type and has a trend of rapidly developing population aging. Population aging is influenced by a combination of factors. The birth rate, death rate, migration rate, and migration rate have a direct driving influence on population aging. On the other hand, economic development, education, and medical conditions have indirect effects on population aging.

In this paper, by constructing three single forecasting models, namely quadratic exponential smoothing forecasting, modified gray forecasting and BP neural network forecasting for population aging, the error sum of squares for in-sample forecasting is derived separately, and then the weights are determined according to the inverse of the error sum of squares method to construct a combined forecasting model for population aging for empirical analysis, and it is concluded that the forecasting of combined forecasting model is more effective regardless of in-sample or out-of-sample forecasting The conclusion is that the combined prediction model is more effective in predicting population aging, whether in-sample or out-of-sample. Since the combined prediction model is a weighted model of several single models, it overcomes the shortcomings of a single model and at the same time combines the advantages of each model, so the model is more effective in predicting the level of population aging in China.

Because of the effectiveness of the combined prediction model in predicting the population aging level, the model is used to predict the aging level in China from 2022 to 2025, and the prediction results show that the population aging problem in China is becoming increasingly serious in the future. Based on this, combined with China's national conditions, this paper puts forward the following four suggestions.

First, since the aging population will lead to the shortage of labor supply, it is necessary to increase the birth rate appropriately. However, it is necessary to grasp the "degree" of this policy to avoid the "baby boom" and labor shortage.

Second, vigorously develop the aging industry. Since most of the aging industry belongs to the tertiary industry, promoting the development of the aging industry can help promote the optimization and upgrading of China's industrial structure, which not only meets the needs of the elderly population, but also reduces the burden of old age on young people and provides employment. This is in line with the

ISSN 2522-3488 Vol. 6, Issue 3: 43-49, DOI: 10.25236/IJNDES.2022.060308

policy of developing the aging industry proposed by the Party Central Committee at the Third Plenary Session of the 18th Central Committee, which can transform the adverse effects of the increasingly prominent population aging problem into a driving force for the optimization and upgrading of industrial structure and economic transformation.

Thirdly, accelerating the development process of urbanization and encouraging the participation of surplus rural laborers in the workforce can not only solve the problem of insufficient labor supply brought about by the increasing level of aging, but also promote the integrated development of urban and rural areas. on April 1, 2017, the country established a new national-level zone, Xiong'an New Area, to lead the future deep urbanization. China should follow the trend of the times and seize the opportunity to properly solve a series of problems caused by the aging population.

Fourth, deepening the reform of the urban and rural pension system is an important part of the overall deepening reform, as well as an important measure to deal with the increasingly serious problem of population aging. Due to the increasing aging of the population and the growing number of elderly people, the protection of the elderly population in urban and rural areas is particularly important. China should improve the efficiency and fairness of the whole society by establishing a pension system covering both urban and rural areas.

Since 2000, when China officially became an aging country, the population structure has been aging rapidly, the "demographic dividend" is gradually fading, and the problem of population aging has become more and more prominent. According to the prediction of this paper, the level of aging will continue to rise in the future, which requires policy makers to formulate corresponding policies and take corresponding measures to effectively avoid the negative impact of aging on China's development.

References

[1] Chen, T. Xu, L., Chen, X.J., Huang, L. S.. Analysis and forecast of population aging in China[C].// Proceedings of the 13th Annual Academic Conference on Management Science in China. [publisher unknown], 2011:717-722.

[2] Zhang Boqin, Gao Xiaocheng, and Mao Huanmin. Analysis and prediction of population aging in China[J]. Journal of Natural Sciences, Harbin Normal University, 2009, 25(03):23-24.

[3] Xu Yi. Analysis on the influencing factors of population aging in China [J]. Contemporary Tourism(Golf Travel), 2018(10):247-248.