Comparison of Population Prediction Accuracy of Different Forecasting Models in the Yangtze River Delta

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***Abstract*—Prediction is an important aspect of modern scientific management. Accurate predictions can help decision-makers make the right decisions and improve the quality of their choices. This article studied the temporal evolution of the population in the Yangtze River Delta from 1990 to 2019 by using three grey models namely GM (1,1) model, GM (2,1) model, and DGM (2,1) model. It evaluated the fitting accuracy of different models for population prediction in the Yangtze River Delta using residual error test and posterior error test. The results showed that GM (1,1) fit well the most since the population growth rate in the Yangtze region is primarily time-homogeneous.**

***Keywords*—China's demographic prediction, forecasting and simulation, models and applications**

I. Introduction

The Yangtze River Delta region is one of the most active, open, and innovative regions in China's economic development, but there is little research on population forecasts of it. China's aging population, negative population growth in 2023, and urgent economic recovery from the impact of the pandemic have made future population predictions for different regions particularly important today. For this, choosing a suitable prediction model is crucial. The purpose of this article is threefold: a general overview of the history of population projections over the past 70 years comparing and evaluating the commonly used models for population projections, and selecting the best-fit model for population predictions in Yangtze River Delta.

The article is organized as follows. In the literature review, we outline the importance of population prediction and population prediction in China, therefore emphasizing the dominant role of the Yangtze River Delta in the economic field in China. Several research achievements related to the population of the Yangtze region are introduced and analyzed. We also list six commonly used models in population prediction, and compare their advantages and limitations. In the Data & Method section, we give the data source of the following experiment and how the data are organized, and we show the Matlab code of three Grey Models. Empirical results are arranged into graphs and displayed in the Result session, which has shown that the GM (1,1) model makes the most accurate projection. In the Discussion part, we point out the limitations that exist in our investigation and extend several improvements in further research.

II. Procedure for Paper Submission

A. Importance of Population Projection

Population projections are attempts to show how human population statistics might change in the future [1]. These projections are an important input to forecasts of the population's impact on this planet and humanity's future well-being [2]. The population prediction provides important information for social and economic development planning, and the prediction results can indicate the problems that may occur in economic development, thereby helping to formulate correct policies. Population prediction began in 1696 when British sociologist G. King used simple mathematical methods to roughly calculate the population development of Britain in the next 600 years [3]. Although this result is far from the actual situation in the future, his ideas are very enlightening to the work of future generations. In the 1950s, Walter Greiling projected that the world population would reach a peak of about nine billion in the 21st century and then stop growing after an improvement in public health in less developed countries [4]. In a 2004 long-term prospective report, the United Nations Population Division projected that the world population would peak at 9.2 billion in 2075 and then stabilize at a value close to 9 billion out to as far as the year 2300 [5]. In 2017, the UN predicted that the global population would reach 11.2 billion by 2100 and still be growing then at the rate of 0.1% per year [6].

With the decline of fertility and the extension of human life expectancy, aging has become a global phenomenon. China has implemented the family planning policy for a long time, and the aging situation is more serious. According to Fig. 1, the birth rate in China, during COVID-19, accelerated its decline.

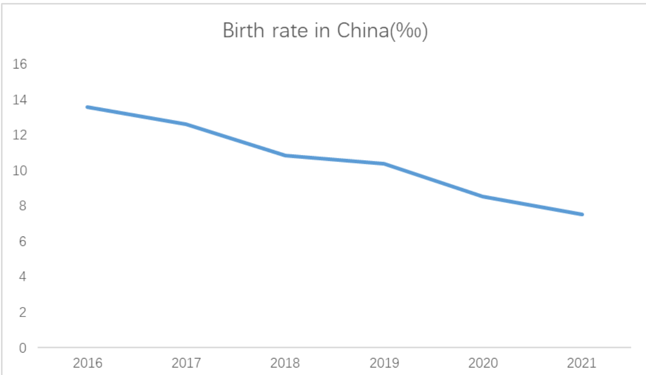


Fig. 1. Birth rate in China from 2016 to 2021.

The birth rate in 2020 is 8.52‰, which is also the first year below 10‰, hitting a new low point since 1978. The latest population data [7] released by the National Bureau of Statistics shows that the national population at the end of 2022 was 1.411 billion, a decrease of 0.85 million compared to the end of the previous year. Guo and Liu declared in 2023 that the problem of negative population growth faced by China is caused by the long-term accumulation of population reproduction methods [8]. Because of the large population base, China's aging population is unprecedented. Population change is closely related to economic development, and forecasting the pattern of population development has become an important basis for formulating China's social and economic policies. Considering the situation, it is of critical importance to choose the most suitable model for predicting the population of a certain area.

B. Main Methods & Model Evaluation

In this chapter, this paper will briefly introduce several widely used models in population forecast.

GM (1,1) model: In 1982, Professor Deng proposed the GM (1,1) model with a predictive function based on cybernetics [9]. GM (1,1) is a single-variable grey prediction model with a first-order difference equation. GM (1,1) model has only one dependent variable but no independent variable, which is attributed to both the advantages and disadvantages. GM (1,1) model requires a few amounts of data. However, the GM (1,1) model is a simplified model which leaves out the vague part of the grey model theory. Available data are too deficient to construct a convincing projection model. A variety of modifications have been made in previous articles to improve the forecasting accuracy of the GM (1,1) model in particular cases [10–12].

DGM (1,1) model: The Discrete Grey Model (DGM (1,1)) is considered to be superior to the grey model (GM (1,1)) because it can completely simulate the pure exponential sequences. Wang [13] found out that the predictive capabilities of the GM (1,1) and DGM (1,1) for random sequences conforming to normal distribution are nearly equivalent. However, the predictive capabilities of the DGM (1,1) model for the other random sequences are all superior to those of the GM (1,1) model. The parameter change of random sequences with the exponential trend can influence the predictive capability of the GM (1,1) model while having no significant influence on the predictive capability of the DGM (1,1) model.

DGM (2,1) model: The DGM (2,1) model is a second-order linear dynamic model with a single band sequence, which uses differential equations to approximate and fit data with stronger trend development and changes. Therefore, this model can be used for monotonic swing development sequences, but when the swing amplitude is large, there is still considerable error in the swing sequence. Therefore, in practical applications, priority should be given to using the GM model for prediction, and for data with poor performance of the GM model, the DGM (2,1) model should be used for prediction.

Malthus model: Malthusian growth model comes from the Principles of Population published by British economist Thomas Robert Malthus in 1798 [14]. In the book, Malthus pointed out that the population grew in Geometric series, while the living resources could only grow in arithmetic progression. The contradiction between the two led to periodic outbreaks of famine, war, and disease.

Malthus's [14] book – *An Essay on the Principle of Population* has its unavoidable historical limitations. In the era of Malthus, poverty, food and clothing, excessive fertility, and insufficient resources, as well as frequent outbreaks of famine, war, and disease, constantly troubled people. After the industrialization and modernization of human society, with the continuous improvement of per capita GDP, the aging and Sub-replacement fertility trend of the population has become a new problem and challenge for population policymaking. In particular, how the labor force population, industrial population, population education, and other factors affect the scientific and technological progress and Demographic dividend will change the relationship between population, resources, and development, so new theories and improvements are needed.

Cohort Component Method (CCM): CCM [15] was first outlined by Canann, and developed in more detail by Whelpton in 1928 and 1936 [16, 17]. How the population of a country will develop in the future depends on three determinants: (I) fertility, (II) net migration, and (III) mortality [18]. CCM simulates the demographic components of fertility, migration, and mortality separately and then merges these results into a simulation of the future population. Adrian and Hana [19] pointed out that there are issues with the CCM, including that the CCM is a one-sex model, the CCM is deterministic whereas the reality is stochastic, and that fertility and mortality rates vary over time. Adrian and Hana stated that issues such as these motivate statistical demography, which attempts to use modern statistical methods to estimate and forecast population quantities, and to take account of uncertainty about them.

Probabilistic population forecasting: Probabilistic forecasts are now routinely used in several disciplines. These include finance, where risk management is a common use of probabilistic forecasts in financial asset management, and trading decisions that are made based on predictive distributions of assets, often using automated computer trading programs.

According to Adrian and Hana [19], Probabilistic population forecasts have four advantages. One is that probabilistic forecasts provide a basis for assessing changes over time. The second is to provide a general assessment of accuracy, which has become a standard expectation in recent decades for estimates and forecasts in many fields. The third is that probabilistic forecasts allow one to assess differences between outcomes and expectations. A fourth reason for producing probabilistic forecasts is that they can be an input to decision-making that attempts to limit the risk of an adverse outcome or to balance these risks against future benefits.

Table 1 shows the features & limitations of different models.

Table 1. Comparison between different models

Models	GM (1,1) model	DGM (1,1) model	DGM (2,1) model	Malthus model	CCM	Probabilistic population forecasting
	Grey Models, single variable, establishing mathematical models to make predictions based on a small amount of incomplete information					
Features & Limitations	Homogeneous exponential sequence	Index sequence	Second-order white differential equation, suitable for irregular sequences of changing trends	Logistic models, historical limitations	Depends on mortality, fertility, and net migration, one-sex model, fixed mortality, and fertility rate	Helpful in decision-making, balancing risks between future benefits

C. *Yangtze River Delta*

Yangtze River Delta region, referred to as the Yangtze River Delta; Includes Shanghai, Jiangsu, Zhejiang, and Anhui, a total of 41 cities; It is located in the lower reaches of the Yangtze River in China, near the Yellow Sea and the East China Sea, at the intersection of rivers and seas, and has many coastal ports along the river. It is an alluvial plain formed before the Yangtze River entered the sea.

By the end of 2019, the Yangtze River Delta had a population of 227 million and a regional area of 358000 square kilometers [20]. In 2022, the GDP of the Yangtze River Delta region reached 29 trillion yuan, and the economic volume of all districts and cities in the Yangtze River Delta region reached over 100 billion yuan; The urbanization rate of the permanent population exceeded 60%, creating nearly a quarter of China's total economic output and a third of China's total import and export volume with less than 4% of its land area [21]. Selecting the best model to predict the population in the Yangtze River Delta region is beneficial to the policy-making of the society and economy in this region.

D. *Current Research*

Zhang [22] selected indicators from three levels of socio-economic, ecological environment, and soil and water resources to estimate and analyze the spatial characteristics of the resource and environmental carrying capacity in the Yangtze River Delta region in 2022. The situation of the resource and environmental carrying capacity in the Yangtze River Delta region is not optimistic, and there are significant differences in the resources and environment within the region. Some regions still face significant pressure on the resource and environmental carrying capacity.

Yan, in 2020, used methods such as kernel density, center of gravity, concentration index, and offset sharing to study the spatiotemporal evolution of population in the Yangtze River Delta from 2000 to 2018 [23]. The results showed that:

1) The population pattern is not balanced, and the population concentration is showing a steady growth trend;
2) The transformation of the population growth pattern is mainly manifested in the accelerated population growth rate in some underdeveloped areas;
3) Economic factors, social development, and fiscal level are the important driving forces for population migration and growth in the Yangtze River Delta.

Sun [24] forecasts the population carrying capacity of urban agglomeration by building a multi-objective evaluation system and scientifically predicts the appropriate population size of urban agglomeration in 2030 based on the estimated population carrying capacity. The results showed that:

1) The population of the urban agglomeration will still be relatively excessive;
2) Resources are a key factor restricting the future population development of urban agglomerations;
3) The appropriate population size of all cities except Zhenjiang is within the maximum population size that can be carried.

III. Data and Method

A. *Data and Source*

Population data of four provinces in the Yangtze River Delta from the latest 30 years are used for my following projections, which is, 1990~2019. First, the National Bureau of Statistics of China (NBSC) [7], the most authoritative census agency in China, has only provided about 30 years of population data in its database. Plus, China has been in a state of stable political power and economic growth in the past three decades, which has reduced the unstable influence on the population forecast. Due to the pandemic, population data after 2022 has not been considered.

The Yangtze River Delta is composed of four provinces, namely Jiangsu, Zhejiang, Anhui, and Shanghai. The population data of each province over the years are accessible on the official website of the NBSC. Hence, the Yangtze River Delta population is derived by summing the four provinces' population data together. The population data and curve are displayed below in Fig. 2.

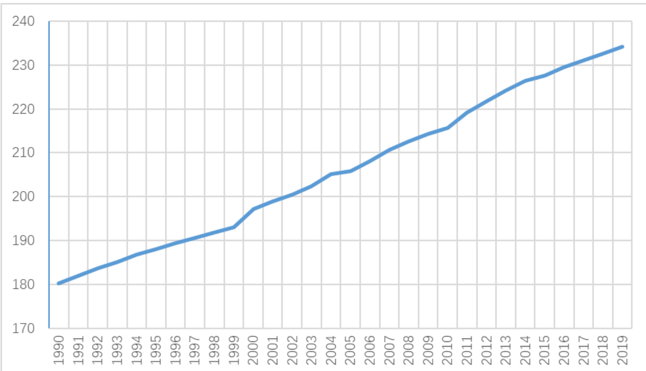


Fig. 2. The population data and curve between 1990 to 2019 (Unit: million people).

B. *Methods*

In my following investigation, I will mainly use three prediction models. They are respectively GM (1,1) model, the GM (2,1) model, and the DGM (2,1) model. I will use two methods to test the fitting degrees of each model. They are respectively Residual error test and the Posterior error ratio test.

Model I: GM (1,1)

Let original series:

$$x^{(0)}(i) = x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)$$

By defining:

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,3, \ldots, n$$

We get a new series $x^{(1)}(k)$: $x^{(1)}(k) = x^{(0)}(1) + x^{(0)}(2) + \cdots + x^{(0)}(n)$. To some processes, $x^{(1)}(k)$ is the solution of the following white-formed ordinary differential equation.

$$\frac{dx^{(0)}}{dt} + ax^{(1)} = u \quad (1)$$

where a and u are gray numbers, that is pendent parameters, which are estimated by the least square method. The equation (1) is called GM (1, 1). The solution of (1) is:

$$x^{(\hat{1})}(k+1) = \left[x^{(0)}(1) - \frac{u}{a}\right] e^{-ak} + \frac{u}{a} \quad (2)$$

The equation (2) is called the time response function. For $k \geq 2$, $x^{(\hat{0})}(k) = x^{(\hat{1})}(k+1) - x^{(\hat{1})}(k)$ is called predicting formula.

Model II: GM (2,1)

Let the original series:

$$x^{(0)}(i) = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)$$

The 1-AGO series:

$$x^{(1)}(i) = x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)$$

and the 1-IAGO series:

$$\alpha^{(1)}x^{(0)}(i) = \alpha^{(1)}x^{(0)}(1), \alpha^{(1)}x^{(0)}(2), \ldots, \alpha^{(1)}x^{(0)}(n)$$

which:

$$\alpha^{(1)}x^{(0)}(k) = x^{(0)}(k) - x^{(0)}(k-1), k = 2,3, \ldots n$$

By taking every two adjacent term's average$x^{(1)}(i)$, we get:

$$Z^{(1)}(i) = Z^{(1)}(2), Z^{(1)}(3), \ldots, Z^{(1)}(n)$$

Then the grey-formed differential equation of GM (2,1) is:

$$\alpha^{(1)}x^{(0)}(i) + a_1 x^{(0)}(i) + a_2 Z^{(1)}(i) = b$$

The white-formed ordinary differential equation is:

$$\frac{d^2x^{(1)}}{dt^2} + a_1 \frac{dx^{(1)}}{dt} + a_2 x^{(1)} = b$$

Let $B = \begin{bmatrix} -x^{(0)}(2) & -Z^{(1)}(2) & 1 \\ \vdots & \vdots & \vdots \\ -x^{(0)}(n) & -Z^{(1)}(n) & 1 \end{bmatrix}$, $Y = \begin{bmatrix} \alpha^{(1)}x^{(0)}(2) \\ \vdots \\ \alpha^{(1)}x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} x^{(0)}(2) - x^{(0)}(1) \\ \vdots \\ x^{(0)}(n) - x^{(0)}(n-1) \end{bmatrix}$.

Then the least squares estimation of parameters in the GM (2,1) model satisfies.

$$\hat{a} = (B^T B)^{-1} B^T Y$$

Model III: DGM (2,1)

Let the original series:

$$x^{(0)}(i) = x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)$$

The 1-AGO series:

$$x^{(1)}(i) = x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)$$

and the 1-IAGO series:

$$\alpha^{(1)}x^{(0)}(i) = \alpha^{(1)}x^{(0)}(1), \alpha^{(1)}x^{(0)}(2), \ldots, \alpha^{(1)}x^{(0)}(n)$$

which:

$$\alpha^{(1)}x^{(0)}(k) = x^{(0)}(k) - x^{(0)}(k-1), k = 2,3, \ldots n$$

The grey-formed differential equation of DGM (2,1) is:

$$\alpha^{(1)}x^{(0)}(i) + ax^{(0)}(i) = b$$

The white-formed ordinary differential equation is:

$$\frac{d^2x^{(1)}}{dt^2} + a\frac{dx^{(1)}}{dt} = b$$

Let $B = \begin{bmatrix} -x^{(0)}(2) & 1 \\ \vdots & \vdots \\ -x^{(0)}(n) & 1 \end{bmatrix}$, $Y = \begin{bmatrix} \alpha^{(1)}x^{(0)}(2) \\ \vdots \\ \alpha^{(1)}x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} x^{(0)}(2) - x^{(0)}(1) \\ \vdots \\ x^{(0)}(n) - x^{(0)}(n-1) \end{bmatrix}$.

Then the least squares estimation of parameters in the GM (2,1) model satisfies.

$$\hat{a} = (B^T B)^{-1} B^T Y$$

The solution of the white-formed differential equation is:

$$x^{(1)}(t) = \left(\frac{b}{a^2} - \frac{x^{(0)}(1)}{a}\right) e^{-at} + \frac{b}{a}t + \frac{1+a}{a}x^{(0)}(1) - \frac{b}{a^2}$$

Evaluation I: Residual error test

R^2 equals to 1-SSE/SST or SSR/SST. The SSE refers to the sum of squares due to error, that is, the sum of squares of each of the residual errors; SST refers to the sum of all squared differences between the mean of a sample and the individual values in that sample.

Evaluation II: Posterior error test

Posterior error ratio (C) is the ratio of residual standard deviation (S_1) and data standard deviation (S_2). If the residual standard deviation is smaller, the prediction accuracy is more excellent. S_1 is the standard deviation of the original data series. S_2 is the standard deviation of the residual of the forecasting data series. C is S_1 divided by S_2. The prediction would be excellent if C is smaller than 0.35. Notably, the posterior error ratio test is often used for grey prediction.

Evaluation III: Small error probability

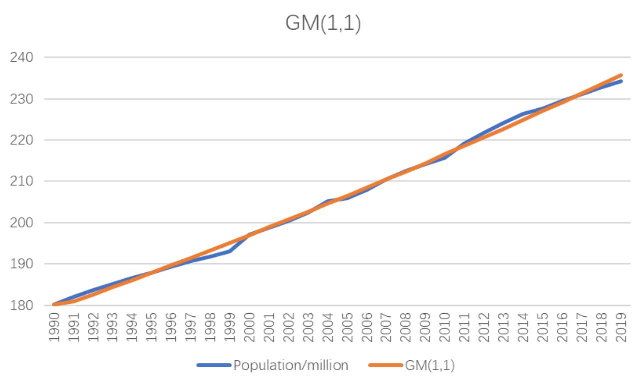
$$P = P\{|e^{(0)}(K) - \bar{e}| < 0.6744 S_2\}$$

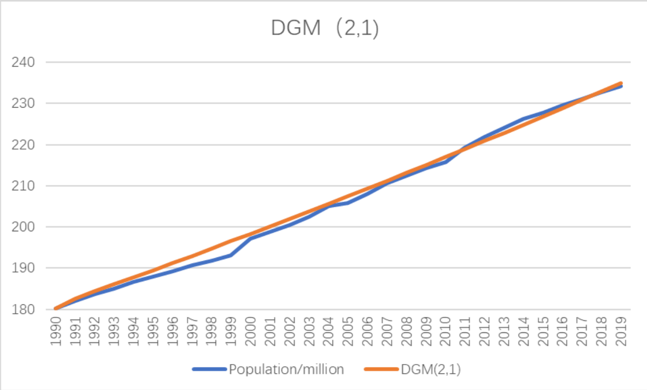
S_2 in the equation is the data standard deviation stated in posterior error test. The prediction would be excellent and precise if P is greater than 0.95.

All the models are implemented in Matlab.

IV. Result

The results of forecasting population data by each model are listed below (see Fig. 3):





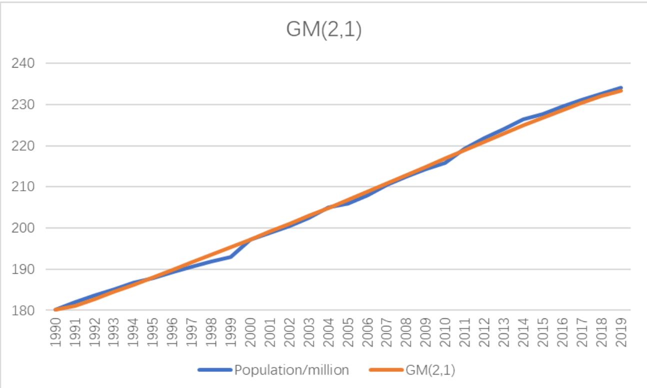


Fig. 3. The results of forecasting population data by each model.

All the models overall accurately fit the original data series quite well.

By comparison, both GM models have achieved good forecasts, while the DGM (2,1) prediction curve seems to deviate slightly from the original population line.

The modeling results are evaluated by residual error test and posterior error test.

Table 2. Evaluation 1 residual error test (The R-square test)

	GM(1,1)	GM(2,1)	DGM(2,1)
SSE	22.0049	23.93176	57.36008
SST	8475.862	8172.07	7851.111
R^2	0.997404	0.997072	0.992694

From Table 2, we find that both GM (1,1) and GM (2,1) perform well in forecasts and GM (1,1) did a little bit better than GM (2,1).

Table 3. Evaluation 2 posterior error test

	GM(1,1)	GM(2,1)	DGM(2,1)
s1	8494.3926	8494.3926	8494.3926
s2	22.0045	23.9318	39.5836
Posterior error ratio	0.0025905	0.002817364	0.004659968

From the result of the second test (see Table 3), we reached the same conclusion as the first one.

Overall, combined with the tests of residual error test and posterior error test, the model GM (1,1) performs better in the population prediction in the Yangtze region.

V. Conclusion

We have reviewed the importance of population forecasts, including providing important information for social and economic development planning and helping to formulate correct policies. We are aware of the severe situation faced by the Chinese government on account of the negative population growth in 2023 in China caused by population aging. Distinctiveness and research importance of the Yangtze River Delta are outlined, and we've studied three current researches related to the population in the Yangtze region, which have referential value to this paper.

Brief information about various common population forecasting models is given, including the GM (1,1) model, DGM (1,1) model, DGM (2,1) model, Malthus model, CMP method, and Probabilistic forecasting method. The first three models are GM models which require only one independent variable, which is the population by year. The result of the investigation shows that the GM (1,1) model projects population trends most accurately.

All of the models I have used in this paper require only one dependent variable, which is not enough for a huge population prediction system. On my further investigation, several extensions are planning to apply:

1. I'm planning to use the probabilistic forecasting method in population prediction. I will search not only for population data with year but also information on mortality rate, fertility rate, and net migration in a small area, which are necessary for a probabilistic population forecast.
2. I'm going to expand my research area from the Yangtze River Delta to the Chinese Mainland, since compared to predicting a small-scale population, predicting the population of the entire country is certainly more helpful for national financial planning.
3. The last idea is the modification of a certain model to make it fit more accurately when forecasting a specific situation.

Conflict of Interest

The author declares no conflict of interest.

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