Research Article

Prediction of China’s Housing Price Based on a Novel Grey Seasonal Model

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Abstract

The fluctuation of real estate prices has an important impact on China’s economic development. Accurate prediction of real estate market price changes has become the focus of scholars. The existing prediction methods not only have great limitations on the input variables but also have many deficiencies in the nonlinear prediction. In the process of real estate market price forecasting, the priority of data and the seasonal fluctuation of housing price are important influencing factors, which are not taken into account in the traditional model. In order to overcome these problems, a novel grey seasonal model is proposed to predict housing prices in China. The main method is to introduce seasonal factor decomposition into the new information priority grey prediction model. Two practical examples are used to test the performance of the new information priority grey seasonal model. The results show that compared with the existing prediction models, this method has better applicability and provides more accurate prediction results. Therefore, the proposed model can be a simple and effective tool for housing price prediction. At the same time, according to the prediction results, this paper analyzes the causes of housing price changes and puts forward targeted suggestions.

1. Introduction

As an integral part of the Chinese economy, China’s real estate industry has experienced explosive growth over the last 20 years. The average selling price of commodity housing has increased from ¥ 2,112 per m2 (in 2000) to ¥ 7,892 per m2 (in 2017). The average annual growth rate is at least 8%, which is particularly high in the large- and medium-sized cities of eastern and central China. The rapid development of the real estate industry not only provides powerful financial support for large-scale urban construction in China but also arouses an excessive enthusiasm for real estate investment [1]. Compared with real estate markets of the other countries, China’s real estate markets have unique features. First of all, there is a huge demand for housing market in China because of the large population, rapid economic development, and ongoing urbanization [2]. Secondly, the masses regard housing as a requisite for marriage and children’s education because of the special household registration policy [3]. Thirdly, China’s real estate is closely related to the national macro economy. The development of the real estate industry in a region is beneficial to its economic development, and in turn economic development promotes the prosperity of its real estate industry [4]. In addition, real estate development not only offers a major financial source to local governments but also is an important means of urban planning and construction. Fourthly, the development of the real estate industry is always accompanied by police regulation. China’s real estate markets have obvious regional features. Specifically, the excessively rapid rise of housing prices in a region is fundamentally ascribed to the rapid economic growth and the increasing of the urban population in the region, as well as the optimism of the whole real estate industry [5–7]. To maintain the stability of real estate markets, regional governments have taken various measures (e.g., adjusting bank rates, restricting the purchase quantity of housing, regulating the ratio of down payment, and specifying the local minimum working years for housing purchasers). Facts prove that such measures play an active role in maintaining the stability of real estate...
markets, and China’s real estate markets continue to grow under control.

Many scholars have done a lot of research on the real estate market. Dievweit et al. [8] divided housing prices into land prices and construction prices and verified the linear relationship between the growth rate of construction costs and housing prices. Rapach and Strauss [9] analyzed the differences in housing price growth in the American states and pointed out the links between housing prices and the monetary aspects of these states. Chang et al. [10] summarized the impact of investment in the real estate market on international housing prices. Yang et al. [11] thought housing affordability will affect the well-being of residents living high and used housing price to income ratio as the measurer of housing affordability. Ge et al. [12] found a declining trend of the average housing price from coastal areas to inland areas in China and analyzed the influence of traffic accessibility on housing price.

It has been shown that effective prediction provides useful reference for potential house buyers, thus avoiding blind purchase. Based on the prediction of future housing price fluctuations, policymakers can preadjust real estate policies to reduce the stagnancy of real estate markets and to prevent the occurrence of economic crises. Ge [12] used multiple regression analysis in order to analyze the main determinants of housing prices in the New Zealand market and found that a one-percent increase in migration arrivals is associated with approximately a 10 percent changes in housing prices with a one-year lag. Tech [13] constructed a constant quality price index for urban land transactions to determine the relationship between land price and housing price in the short and long run with the hedonic approach. Wei and Cao [14] introduced a dynamic model averaging method to forecast the growth rate of housing prices in 30 major Chinese cities. Crawford and Fratantoni [15] compared the forecasting performance of three types of university time series models: an autoregressive integrated moving average model (ARIMA), autoregressive conditional heteroskedasticity model, and regime-switching. They found that simple ARIMA models generally perform better in out-of-sample forecasting. Grey model contributes another solution in forecasting housing price. Chen et al. [16] forecasted the future trend of housing price earnings ratio in Wuhan based on a model combined with grey prediction and linear regression. Yan et al. [17] forecasted seasonal housing prices by regression and grey models and integrated via the wavelet neural network approach for error correction. Moreover, the machine learning algorithm also has many applications in housing price forecasting, which has excellent properties with respect to predict time series [18–20].

Previous literatures [21–26] have made important contributions to the relevant influencing factors and prediction methods of housing prices. However, traditional methods require too much variable information and are therefore difficult to use. Seasonal factors and data priority are often ignored. Therefore, how to predict the future housing price with limited information is a very important topic. Based on the principle of new information priority, we propose a combination of seasonal factor decomposition and improved grey model. In this paper, we selected Handan (a small city in northern China) and Kunming (a medium-sized in southern China) as the subject of this study. The two cities are obviously different in terms of economic development levels, living environment quality, regional policy measures, and real estate market situation. The rest of this article is as follows. In the second section, we mainly introduce the grey season model of prior accumulation of new information. In the third section, we used the model and substituted the experimental data to predict China’s housing prices and explained these experimental results. In Section 4, we put forward some suggestions for the improvement of China’s real estate market based on the calculation results of the model in Section 3. The fifth section is the conclusion of the article.

2. The New Information Priority Accumulated Grey Seasonal Model

Grey prediction model is famous for its ability to process poor information and predict accurately, but it cannot be directly applied to seasonal data. In order to overcome this defect, we first analyze the seasonal factors of the sequence and then established NIPGSM (1, 1) model by combining a principle of new information priority [27].

2.1. Seasonal Factor Decomposition. Set the nonnegative sequence as \( y^{(0)} = \{y^{(0)}(1), y^{(0)}(2), \ldots, y^{(0)}(n)\} \) where \( n \) is the number of the data sample. The sequence \( S = \{s_1, s_2, \ldots, s_L\} \) is the fixed seasonal factors of the historical data sequence \( Y^{(0)}, \) where \( L \) is the length of a cycle. There is

\[
m = \text{int}\left(\frac{n}{L}\right),
\]

where \( m \) represents the number of cycles and int indicates that \( m \) is the max integer less than \( n/L. \) The 68 consecutive months of data collected in this article will be cycled every year, and, the value of \( L \) and \( m \) is 12 and 5, respectively [28].

Definition 1. Suppose \( Y^{(1)} = \{y^{(1)}(1), y^{(1)}(2), \ldots, y^{(1)}(L)\} \) is the seasonal mean sequence of \( Y^{(0)}, \) where

\[
y^{(1)}(i) = \frac{y^{(0)}(i) + y^{(0)}(i + L) + y^{(0)}(i + 2L) + \ldots + y^{(0)}(i + (m - 1)L)}{m}, \quad i = 1, 2, 3, \ldots, L.
\]
2.2. The NIPGM (1,1) Model. We put the sequence \( X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(m)\} \) which represents the long-term trend of the series, where \( m \) represents the year and can be obtained by sequence \( Y^{(0)} \) as follows:

\[
x^{(0)}(k) = \sum_{i=1}^{k} y^{(0)}((k-1)L + i).
\]  

(5)

Definition 2 (see [27]). Set the nonnegative sequence as \( X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(m)\} \). The sequence \( X^{(r)} = \{x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(m)\} \) is the new information priority accumulated sequence of \( X^{(0)} \). There is

\[
x^{(1)}(k) = \sum_{i=1}^{k} \lambda^{k-i} x^{(0)}(i), \quad k = 1, 2, \ldots, m.
\]  

(6)

The parameter \( \lambda \) represents the accumulative weight and \( 0 < \lambda < 1 \), which can adjust the predicted results of the model. The \( \lambda \)-order accumulated generating operator (\( \lambda \)-AGO) is the principal process of this method, which can give more weight to new information in the prediction process.

Definition 3. Set \( Z^{(1)} = \{z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(m-1)\} \) as the adjacent mean sequence of \( X^{(1)} \); there is

\[
z^{(1)}(k) = 0.5x^{(1)}(k + 1) + 0.5x^{(1)}(k), \quad k = 1, 2, \ldots, m-1.
\]  

(7)

With the sequences \( X^{(0)} \) and \( Z^{(1)} \) shown in Definitions 2 and 3, the formula

\[
x^{(r)}(k + 1) - x^{(r)}(k) + az^{(r)}(k) = b,
\]  

(8)

which is named the mathematical form of NIPGM (1, 1), and then

\[
dx \frac{dx}{dt} + ax = b,
\]  

(9)

which is named the whitening equation of NIPGM (1,1) where \( a \) and \( b \) are the development coefficient and the grey control coefficient of the model, respectively.

Theorem 1. The parameter vector of estimation formula is \( U = [a \ b]^T \). The least-squares parameter estimate of NIPGM (1, 1) satisfies \( U = (B^T B)^{-1} B^T Y \), where

\[
B = \begin{bmatrix}
l-z^{(1)}(1) & 1 \\
-z^{(1)}(2) & 1 \\
\vdots & \vdots \\
-z^{(1)}(m-1) & 1 \\
\end{bmatrix}
\]  

(10)

\[
Y = \begin{bmatrix}
x^{(1)}(2) - x^{(1)}(1) \\
x^{(1)}(3) - x^{(1)}(2) \\
\vdots \\
x^{(1)}(m) - x^{(1)}(m-1) \\
\end{bmatrix}
\]  

Proof 1. Taking \( k = 2, 3, \ldots, m \) into equation (7), there is

\[
\begin{align*}
x^{(1)}(2) - x^{(1)}(1) &= -az^{(1)}(1) + b \\
x^{(1)}(3) - x^{(1)}(2) &= -az^{(1)}(2) + b \\
\vdots \\
x^{(1)}(m) - x^{(1)}(m-1) &= -az^{(1)}(m-1) + b.
\end{align*}
\]  

(11)

Transforming equation (9) into matrix form, there is

\[
\begin{bmatrix}
-l-z^{(1)}(1) & 1 \\
-z^{(1)}(2) & 1 \\
\vdots & \vdots \\
-z^{(1)}(m-1) & 1
\end{bmatrix}
\begin{bmatrix}
a \\
b
\end{bmatrix}
= \begin{bmatrix}
x^{(1)}(2) - x^{(1)}(1) \\
x^{(1)}(3) - x^{(1)}(2) \\
\vdots \\
x^{(1)}(m) - x^{(1)}(m-1)
\end{bmatrix}.
\]  

(12)

To get the optimal parameters, we bring \( \hat{Y} = BU \) into the following formula. The sum of squares of residuals can be obtained as follows:

\[
S = (Y - \hat{Y})^T (Y - \hat{Y}) = \sum_{k=1}^{m-1} \left( (x^{(1)}(k) - x^{(1)}(k + 1)) - (-a \cdot z^{(1)}(k) + b) \right)^2.
\]  

(13)
To get the minimum of $S$, the parameters $a$ and $b$ should meet the following limitations:

\[
\begin{align*}
\frac{\partial S}{\partial a} &= 2 \sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) + a^* \cdot z^{(1)}(k) - b^* \right) \cdot z^{(1)}(k) = 0, \\
\frac{\partial S}{\partial b} &= -2 \sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) + a^* \cdot z^{(1)}(k) - b^* \right) = 0.
\end{align*}
\]  

\[(14)\]

So, we can have

\[a^* = \frac{(m-1)b^* - \sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) \right) \cdot \sum_{k=1}^{m-1} z^{(1)}(k)}{\sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2},\]

\[b^* = \frac{\sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2 \cdot \sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) \right) - \sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) \right) z^{(1)}(k) \cdot \sum_{k=1}^{m-1} z^{(1)}(k)}{(m-1) \cdot \sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2 - \left( \sum_{k=1}^{m-1} z^{(1)}(k) \right)^2}.\]  

\[(15)\]

The formula $Y = BU$ can be converted to $U = (B^TB)^{-1}B^TY$, where

\[
B^TB = \begin{bmatrix}
\sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2 - \sum_{k=1}^{m-1} z^{(1)}(k) \\
- \sum_{k=1}^{m-1} z^{(1)}(k) & m-1
\end{bmatrix},
\]

\[
(B^TB)^{-1} = \frac{1}{(m-1)\sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2 - \left( \sum_{k=1}^{m-1} z^{(1)}(k) \right)^2} \begin{bmatrix}
m-1 & \sum_{k=1}^{m-1} z^{(1)}(k) \\
\sum_{k=1}^{m-1} z^{(1)}(k) & m-1 \sum_{k=1}^{m-1} \left( z^{(1)}(k) \right)^2
\end{bmatrix},
\]

\[(16)\]

\[
B^TY = \begin{bmatrix}
- \sum_{k=1}^{m-1} z^{(1)}(k) \left( x^{(1)}(k+1) - x^{(1)}(k) \right) \\
\sum_{k=1}^{m-1} \left( x^{(1)}(k+1) - x^{(1)}(k) \right)
\end{bmatrix}.
\]
Therefore, we can have

\[
U = (B^T B)^{-1} B^T Y
\]

\[
= \left[ a \ast \right.
\left. b \ast \right]
\]

**Theorem 2.** Suppose \( U \) is described in Theorem 1, the prediction sequence of \( H^{(0)} \) can be calculated as follows:

\[
\hat{x}^{(0)}(k) = e^{-a(k-1)}(e^{-a} - \lambda) \left( x^{(0)}(1) - \frac{b}{a} \right) + \frac{b}{a} (1 - \lambda).
\]  

(18)

**Proof 2.** The general solution of equation (8) is

\[
\hat{x}^{(1)}(k + 1) = C e^{-ak} + \frac{b}{a}
\]  

(19)

Suppose \( \hat{x}^{(0)}(1) = x^{(0)}(1) \), the parameter \( C \) of equation (18) can be calculated as

\[
C = x^{(0)}(1) - \frac{b}{a}
\]  

(20)

The reduced form of \( \hat{x}^{(1)} \) is reverse of equation (5), and then

\[
\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \lambda \hat{x}^{(1)}(k - 1)
\]

\[
= e^{-a(k-2)}(e^{-a} - \lambda) \left( x^{(0)}(1) - \frac{b}{a} \right) + \frac{b}{a} (1 - \lambda).
\]  

(21)

2.3. The NIPGSM (1, 1) Model. As stating in equation (1), a forecasting model should take into account seasonal changes and overall trend changes in the observation. The seasonal decomposition was combined with the NIPGM (1, 1) model to construct a new model named the NIPGSM (1, 1) model. Then, the grey prediction model is used to analyze the long-term trend. The steps involved in the modeling process can be illustrated by a flow chart in Figure 1.

With the results of equations (4) and (13), we can obtain the sequence \( \hat{Y}^{(0)} \), which is the prediction sequence of \( \hat{Y}^{(0)} \). The formula is given as follows:

\[
\hat{y}^{(0)}(i + kL) = \hat{x}^{(0)}(k + 1)z_i,
\]  

(22)

where \( i = 1, 2, \ldots, L, k = 0, 1, 2, \ldots, m - 1, m, m + 1, \ldots \).

2.4. Error Test and the Selection of Optimal Parameter. The validation of the model is the guarantee for the model to obtain reliable results. The average absolute percentage error is an important index reflecting reliability. At the same time, we should also note that the performance of the NIPGSM (1, 1) model is closely related to the parameter \( r \). Therefore, we establish the optimization problem solving parameters based on the minimum simulation error as follows:

\[
\min \text{MAPE} = \frac{1}{m - 1} \sum_{k=1}^{m} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right|.
\]  

(23)

The purpose of optimizing the model is to minimize the mean absolute percentage error (MAPE) between the fitted value calculated by the model and the actual value. There are many ways to improve the prediction accuracy by improving the linear fitting effect. For example, we can use the method of approximation that is constantly trying to select the best parameter by increasing the value of \( r \) from –1 to 5 and comparing the value of MAPE. However, this method of constantly approaching attempts requires a lot of time and effort. However, there are also some methods that provide improved methods for improving the accuracy of linear fitting, such as heuristic algorithms and so on. However, this paper proposes particle swarm optimization (PSO) to optimize the parameter \( r \) of the ANDGM model, and the specific process is shown in Figure 2; given the objective function and constraint conditions, the PSO algorithm can quickly find the optimal solution.

The information difference between data is the foundation of grey model modeling. This section describes in detail through the flow chart the thought and process of modeling conditions of adjacent accumulation method as shown in Figure 2.
3. Experiment and Discussion

3.1. Data Sources. The housing price data used in this paper were cited from the website (https://www.creprice.cn/). To stabilize housing prices and prevent an excessively rapid rise, China’s central government has carried out a succession of regulatory policies (e.g., the Five Policy Measures for Strengthening Real Estate Market Regulation) since 2013. Meanwhile, the People’s Government of Hebei Province has adjusted the tax rates on real estate enterprises. Therefore, the housing price data from January 2014 to December 2018 will be used as an observation, and the 8 data from January to August in 2019 were used as a test.

To test the performance of NIPGSM (1, 1) in predicting the housing price, Holt–Winters model and GM (1, 1) model are used for comparison. For the Holt–Winters model, the number of seasons in a year is set at 12. Because the traditional GM (1, 1) model is suitable for small sample, the

![Figure 1: The steps involved in the prediction process of NIPGSM (1, 1).](image1)

![Figure 2: The flowchart of searching for optimum λ by the PSO algorithm.](image2)
observed data of this model are the price data for the 12 months of 2018. Meanwhile, root mean square error (RMSE) and mean absolute percentage error (MAPE) are adopted to evaluate the performance of three models as follows:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2},
\]

\[
MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|.
\]

When MAPE ≤ 10%, the model is highly accurate. Meanwhile, the better performance of the models can be judged by the smaller RMSE.

3.2. Seasonal Analysis of Housing Prices in China. The existing housing price research mainly focuses on the overall change characteristics of price, and there are small short-term monthly or quarterly price change models. China’s real estate market is influenced by its unique environment and has an inherent seasonal pattern. Paper [29] analyzes the differences between the real estate market in the United States, Japan, and the United Kingdom and that of China. It has been pointed out that the starting area and sales area of new houses in the real estate market of China are significantly higher in December, and the rental price of houses is higher in summer and winter, which is different from the economic phenomenon of other countries. To discuss the seasonality of housing price, we also cited data about the selling price index for newly built commodity housing over 35 months (from June 2016 to April 2019). These data can reflect the seasonal features of fluctuations and changes in China’s housing prices and are from the website (https://data.stats.gov.cn/). The data were available from the statistical data about housing sales prices in China’s 70 large- and medium-sized cities, as shown in Figure 3, where the selling price index = (selling price in the reporting period)/(selling price in the base period).

As shown by the variation curve, the selling price index of commodity housing in China’s large- and medium-sized cities varies from season to season. Specifically, the selling price index rises in some months but is very low in others. The selling price index of newly built commodity housing declines in February and rises less rapidly in June every year. However, it has a short-term increase in December. This is due to China’s unique cultural tradition and national condition. Due to the influence of traditional Chinese festivals, during February, the number of consumers buying houses decreased, and the supply of commercial houses was sufficient. Around December, the masses have sufficiently funded, so they have a strong willingness to purchase housing. Meanwhile, real estate developers take incentive measures to attract purchasers. Thus, sales will go up.

The price of commercial housing is affected by various market factors showing seasonal pattern. Firstly, commodity housing prices are influenced by the construction cost of housing. For example, the changes in market prices (e.g., labor cost, material cost, and land price) are cyclical. Secondly, real estate markets involve busy seasons and slack seasons caused by the changes in the supply-demand relationship. Real estate developers mostly increase the supply of commodity housing in March and promote sales after October to recoup funds. Thirdly, under the influence of related policies and economic environments, real estate policies are intensively promulgated in April. Then, such real estate policies will have a far-reaching effect on the marketing strategy of commodity housing in the two subsequent seasons.

3.3. Prediction of Housing Price in Handan City. As a third-tier city in China, Handan can be analyzed as a representative of such cities in China. In recent years, the urban development of Handan city is speeding up, and the housing price is gradually rising. The future housing price changes in such cities have been extensively debated. Many scholars believe that the development potential of small cities is insufficient, and there is no investment value and appreciation potential. However, there are still many capital parties and the masses full of passion about the value of housing. In this paper, we will make a short-term forecast of housing prices and analyze the reasons for the growth of housing prices.

Taking the monthly data over the past five years as an observation, the seasonal factors of Handan’s housing prices are shown in Table 1. It can be observed that the housing prices in this city keep rising. Annual monthly statistics of every year are summative. The original data and the sums are substituted into NIPGM (1, 1). Then, fitting value and forecast value can be obtained. As described in Table 2, the fitting MAPE of NIPGM (1, 1) is 3.82%. It shows that the predicted results are highly accurate. Therefore, we can proceed to the next prediction and analysis.

With seasonal factors and fitted values, future housing prices of the coming three years can be predicted (as described in Table 3). To better reflect the prediction accuracy
of NIPGSM (1, 1), we specially cited actual data about housing prices in the first eight months of 2019 and compared with the GM (1, 1) and Holt–Winters models. Table 4 lists the prediction results of the three models.

Compared with the GM (1, 1) and Holt–Winters models, NIPGSM (1, 1) has the smallest predicted error. Different from the GM (1, 1) model, NIPGSM (1, 1) overcomes the shortcomings that the grey model is only suitable for small-sample prediction. NIPGSM (1, 1) summates the statistics of different years to convert large-sample data into small-sample data and introduces seasonal factors for prediction.

According to the prediction chart on the rising trend of Handan’s housing prices (Figure 4), the housing price maintained an overall upward trend in the last five years and began to rise more rapidly in 2017. The growth of housing prices is mainly due to the following factors:

(i) Firstly, economic development has stimulated the rise of housing prices. In recent years, Handan’s urban economic growth has sped up, and the average annual GDP growth rate is at least 6%. Meanwhile, Handan’s economic restructuring has greatly improved. In particular, the average annual growth rate of the tertiary industry is about 10%.

(ii) Secondly, urbanization has sped up and the population has continued to increase. With the advance of urbanization, there is an increasing demand for infrastructure and community services, as well as housing. The inflow of population (particularly hi-tech and skilled personnel) has stimulated a sharp rise in housing prices.

(iii) Thirdly, regulatory policies have been implemented in the real estate industry. The real estate markets in China’s large- and medium-sized cities have tended to stable, whereas the policies in China’s small cities are relatively loose. In addition, green construction is advocated. The construction cost of housing has increased because of the rise of material prices and labor cost.

(iv) Fourthly, air quality, an integral part of the living environment, has clearly improved. Living environment and infrastructure are important factors for housing purchasers to consider when taking

Table 1: Seasonal factors of housing price in Handan.

| Month | Seasonal factor |
|-------|----------------|
| 1     | 0.078          |
| 2     | 0.079          |
| 3     | 0.08           |
| 4     | 0.081          |
| 5     | 0.082          |
| 6     | 0.083          |
| 7     | 0.085          |
| 8     | 0.086          |
| 9     | 0.086          |
| 10    | 0.087          |
| 11    | 0.088          |

Table 2: Fitting and forecasting of accumulated data of housing price in Handan (¥/㎡).

| Year | Actual value | NIPGM (1, 1) |
|------|--------------|--------------|
| 2014 | 57773        | 57773        |
| 2015 | 62791        | 59296.05     |
| 2016 | 64840        | 67907.49     |
| 2017 | 75900        | 77769.53     |
| 2018 | 91349        | 89063.81     |

Table 3: Forecasting value of housing price in Handan (¥/㎡).

| Month | 2019 | 2020 | 2021 |
|-------|------|------|------|
| 1     | 7926.10 | 9077.18 | 10395.44 |
| 2     | 8023.86 | 9189.14 | 10523.65 |
| 3     | 8125.67 | 9305.74 | 10657.18 |
| 4     | 8220.82 | 9414.71 | 10781.98 |
| 5     | 8344.33 | 9556.15 | 10943.96 |
| 6     | 8495.88 | 9729.72 | 11142.74 |
| 7     | 8625.17 | 9877.78 | 11312.30 |
| 8     | 8791.48 | 10068.24 | 11530.42 |
| 9     | 8774.99 | 10049.36 | 11508.80 |
| 10    | 8806.52 | 10085.46 | 11550.15 |
| 11    | 8905.14 | 10198.42 | 11679.50 |
| 12    | 8958.36 | 10259.36 | 11749.30 |

Table 4: The predicted results of three models.

| Month | Actual value in 2019 | NIPGSM (1, 1) | GM (1, 1) | Holt–Winters |
|-------|---------------------|--------------|-----------|--------------|
| 1     | 8220               | 7926.10      | 8431.03   | 7579.50      |
| 2     | 8261               | 8023.86      | 8564.26   | 7502.06      |
| 3     | 8335               | 8125.67      | 8699.59   | 7663.82      |
| 4     | 8293               | 8220.82      | 8837.07   | 7820.92      |
| 5     | 8407               | 8344.33      | 8976.72   | 8006.78      |
| 6     | 8459               | 8495.88      | 9118.57   | 8221.81      |
| 7     | 8421               | 8625.17      | 9262.67   | 8417.59      |
| 8     | 8476               | 8791.48      | 9409.04   | 8651.93      |

| MAPE  | 2.14%               | 6.12%        | 5.05%      |
| RMSE  | 205.59              | 602.50       | 488.23     |
decisions. Handan began to strengthen the harnessing of atmospheric environment since 2014. In 2014, there were 88 days during which the air quality of Handan reached Grade II (AQI $\leq 100$), and Handan ranked the second in Hebei Province in terms of the severity of air pollution. Handan’s poor air quality will improve in 2016. Specifically, there were 189 days during which it reached Grade II. In subsequent years, the Handan municipal government has promulgated a succession of environmental protection regulations and taken appropriate measures, for example, relocating high-pollution factories, imposing traffic restrictions on automobiles within urban areas, and performing real-time monitoring on exhaust emissions of factories. The improvement in Handan’s living environment has a definite positive effect on the increase in its housing prices.

3.4. Prediction of Housing Price in Kunming City. Kunming is a representative of China’s medium-sized cities. It is also among the several cities with the best living environment in China. Therefore, we specially selected Kunming’s housing price data from 2014 to 2018 as a practical example. We compared the housing price of Kunming with that of Handan, explored the changes in seasonal factors in the different cities, and discussed the effect of urban size and living environment on housing prices.

The seasonal factors of Kunming are calculated and shown in Table 5. Through comparative analysis of Handan’s and Kunming’s seasonal factors, the following conclusions can be drawn. Firstly, housing prices of Chinese cities will continue to rise. Specifically, housing prices have relatively slow growth in January annually. After September, real estate markets enter an annual peak season, the willingness to purchase housing begins to increase, and housing prices are relatively high. Secondly, housing prices of small cities very obviously from season to the housing prices of medium-sized cities are relatively stable and rise slowly.

Figure 5 shows the prediction of housing prices of Kunming in the coming three years. According to the trend chart of Kunming’s housing prices, the price will continue to rise in the coming three years. Kunming is among the most livable cities of China, so its housing prices have great potential.

Based on the housing prices of Kunming in 2019, we use the NIPGSM (1, 1) model to predict the housing prices of Kunming in different seasons in the next three years, as shown in Table 5. In order to better reflect the prediction accuracy of NIPGSM (1, 1), we used the prediction results of GM (1, 1) and Holt–Winters to compare the models. The prediction results of these three models are compared with the actual data in 2019, and the prediction errors are shown in Table 6.

From the results obtained in Table 7, it can be seen that all three models can predict Kunming’s housing prices of 2019 accurately. However, the MAPE of NIPGSM (1, 1) is approximately 2.14% and the RMSE also shows that NIPGSM (1, 1) has the better performance than other models.

4. Suggestions on China’s Real Estate Market

The calculation results of NIPGSM (1, 1) in this paper show that the housing prices in Xuzhou City, Jiangsu Province, Handan City, Hebei Province, and Kunming City, Yunnan Province, have typical seasonal fluctuation characteristics. Among them, the fluctuation range of house prices in the large city Kunming and the medium-sized city Xuzhou is smaller than that in the small city Handan. However, affected by various factors (such as urbanization, environmental improvement, and policy changes), housing prices in small cities in China (such as Handan) fluctuate greatly, and the growth rate of housing prices has obvious seasonal characteristics. Through the research of this article, it is found that the fluctuation of the housing price is easily affected by the external environment. For example, housing prices in Chinese cities and the level of urban economic development, urban social and social living conditions (distribution of medical resources and education resources), the Chinese government’s macrocontrol of housing prices, the real estate policies of local provincial capitals, and population mobility are related to various factors. At the same time, changes in housing prices have a negative impact on the development of China’s urban economy and the improvement of the quality of life of urban residents. Therefore, in order to maintain the stability of housing price growth and prevent real estate bubbles from adversely affecting regional economic development, this article puts forward the following suggestions:

(i) First of all, it is necessary to gradually and orderly advance the process of urbanization in China and to control the scale of population flow during the development of large and medium cities. With the continuous development of the urban economy, when the urban wage income is much higher than the agricultural production remuneration, the rural population starts to move to the city. Under the conditions of imbalance between supply and demand, the purchase of municipal housing has become a rigid demand. In addition, China’s population ageing trend is becoming increasingly severe, and the influx of highly skilled population has stimulated the demand for commercial housing, so housing prices will rise sharply. In order to balance the upward pressure on housing prices in the context of rigid housing demand in the process of urbanization and to achieve coordinated development between urban development and housing prices, local governments must take measures such as providing more housing for talents, low-rent housing, and security and measures such as sexual housing to alleviate the pressure on housing demand.
Secondly, it is necessary to narrow the gap in resident income and improve people's livelihood. The gap in resident income has a strong effect on urban housing prices. In the process of industrial restructuring, governments should take measures to enlarge employment and increase people's income. In addition, it is necessary to optimize the allocation of urban resources, improve the quality of community services, and develop an all-round housing guarantee system to increase housing affordability for urban residents. Facts prove that favorable living conditions (e.g., good air quality and urban greening) have a significant effect on housing prices acceptable to purchasers.

(iii) Thirdly, it is necessary to carry out national credit and tax policies. Strict policies should be carried out to curb behaviors that disrupt the normal order of real estate markets (e.g., housing speculation). Appropriate tax or credit measures can be taken to prevent the occurrence of the "empty city" phenomenon to a certain extent. For example, people who possess multiple pieces of real estate in a city are taxed in a certain proportion, and differentiated credit services are provided to housing purchasers.

(iv) Fourthly, it is necessary to exert effective land control and create favorable living conditions. Considering that China has a large population but insufficient utilisable land, land should be utilized intensively. Many scholars have studied the actual effect of land prices on housing prices. When governments set land prices, those prices must satisfy the needs of sustainable development. In addition, land resources must be utilized in an optimal manner. In particular, land resources in urban centers can be utilized optimally by relocating old factories and reconstructing old urban areas. The aim is to improve urban ecological environments and urban layout, which are benefit to create favorable living environments.

5. Conclusions

Both the long-term trend and short-term fluctuation of China's housing prices are influenced by policy factors and regional economic development levels. Real estate policies should be suited to local conditions so as not to disrupt the existing market.

NIPGSM (1, 1) provides a new approach to predict China's housing prices. Based on the analysis of past observations, the seasonal factors of future years can be estimated. It has good adaptability to seasonal data. Compared with other models, NIPGSM (1, 1) can simplify the calculation process and obtain better fitting value. Accordingly,
NIPGSM (1, 1) enables us to analyze recent data in a complex and ever-changing social environment and make short-term prediction accurately. This model is expected to make contributions to the studies of China’s housing prices and provide a useful tool for China’s housing purchasers and policymakers. However, the proposed method is not suitable for a large sample. In the future, we will continue to improve the predictive ability of the grey seasonal model with better grey generating operators.

Data Availability

The data used to support the findings of this study are openly available at https://www.creprice.cn/.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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