FORECASTING HOUSING PRICES IN URBAN NANNING: AN APPLICATION OF TIME SERIES ANALYSIS*

Huan Yang[1], Napawan Netpradit[2] and Lijun Wang[3]

[1-3]Lampang Rajabhat University, Thailand

Corresponding Author's Email: 66877010202@g.lpru.ac.th

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Abstract

Over the past few decades, Nanning has experienced significant urban development and economic growth, in which the real estate sector has played a vital role. Fluctuations in housing prices have had a profound impact on economic stability and social welfare. This study aims to apply advanced statistical time series methods to analyze the evolution of residential housing prices in Nanning and to forecast future trends based on historical data. A dataset comprising 175 data points of residential housing prices in Nanning over the past 15 years was utilized. Six time series analysis methods were compared to examine the characteristics of trend, cycles, and seasonality in housing prices, leading to the development of predictive models.The findings indicate that the Holt-Winters Method yields the lowest Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD), suggesting it is the most suitable time series forecasting method for predicting housing prices in Nanning. This study offers empirical evidence to support the formulation of urban housing policies by government authorities and provides valuable reference for

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investors and residents regarding future market trends, thereby contributing to sustainable urban development and social equity.

Keywords: Nanning City, Residential Housing, Housing Prices, Forecasting, Time Series Analysis

Introduction

In China, with the advancement of the reform and opening-up policy and the acceleration of urbanization, the real estate industry has experienced explosive growth. The per capita floor area of urban residential housing increased from 6.7 square meters in 1978 to 39.8 square meters in 2019. By 2022, the urbanization rate of the permanent population reached 65.22%, and the built-up urban area expanded to 64,000 square kilometers. The surge in the urban population and the rise in household income have led to a substantial demand for high-quality housing. In 2022, the total output value of China's construction industry reached 31.2 trillion yuan, accounting for 6.9% of the national GDP and employing more than 50 million people. Residential housing assets accounted for 77.7% of total household assets, significantly higher than the 34.6% share in the United States.

Nanning, the capital of Guangxi Zhuang Autonomous Region, serves as the political, economic, and cultural center of the province. The city's rapid development and continuous population growth have brought unprecedented opportunities and challenges to its real estate market. Fluctuations in residential housing prices not only directly affect the well-being of citizens but also serve as an important indicator of the city's economic health and social stability. For homebuyers, understanding housing price trends helps them make more informed purchasing decisions. For real estate developers, forecasting housing prices supports the development of more reasonable pricing strategies and investment plans. Moreover, for the government and regulatory agencies, insights into housing price movements are essential for formulating effective housing and urban development policies.

Objectives

1. Comparative Analysis of Time Series Methods

Through time series analysis, this study aims to uncover the trend, cyclicality, and seasonality characteristics of residential commercial housing price fluctuations in Nanning. It compares the applicability and accuracy of six time series forecasting methods in predicting housing prices in Nanning with particular attention given to the performance of the Holt-Winters Method in terms of Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD).

2. Decision Support

By forecasting future housing price trends, this study aims to provide a scientific basis for government agencies and policymakers to formulate effective real estate policies that promote market stability and healthy economic development. It also offers forward-looking market insights for investors and residents, enabling them to make more informed and rational investment and housing decisions.

3. Academic Contribution

Through empirical analysis, this study enriches the application of time series analysis in the field of real estate market forecasting and provides methodological insights and references for future related research.

Literature Review

In recent years, housing prices have become a key indicator in urban economic research, and many scholars have employed time series methods for empirical research. In the Turkish real estate market, Yilmaz and Kestel (2020) constructed four models-GLM, VAR, ARIMA, and Holt-Winters-to predict the Housing Price Index (HPI). They found that the SARIMA and Holt-Winters models outperformed the classic ARIMA model in terms of R^2, MSE, and RMSE, demonstrating the significant impact of seasonal factors on housing prices. This study limited its variables to macroeconomic indicators (such as gold, exchange rates, and interest rates) and lacked city-level economic and policy variables, limiting the model's broad applicability. Krishna (2021) developed five time series forecasting models, including the SARIMA, in their study of Dubai's real estate portfolio model. The results showed that the RMSE values were all close to zero, and the SARIMA model residuals were nearly normally distributed, indicating its suitability for short-term price trend forecasting. However, this study failed to account for unexpected factors such as policy adjustments and the impact of the epidemic, and did not conduct error analysis to assess the long-term effectiveness of the model. Herath et al. (2023) studied housing price trends in Sydney, Australia, using two methods: exponential smoothing with trend adjustment and multiplicative decomposition, combining both trend and seasonality. The results showed that multiplicative decomposition provided the smallest forecast error across four error parameters: MAD, MSE, MAPE, and RMSE, with the lowest MAPE value of 6.92, outperforming other traditional models. While this study was able to validate the forecast results against actual market data, it was limited by a short data period and the neglect of external environmental shocks.

In summary, while previous studies have achieved some success in using time series to analyze housing prices, covering a variety of countries and model types, most studies have primarily relied on macroeconomic indicators or single data sources, failing to consider factors such as local policies, population, and urban expansion. This limits the applicability of these forecast models in rapidly changing cities. In the context of Nanning, China, the factors affecting the real estate market are very complex. To fill the gap, this study will use six time series analysis methods, combining three factors: trend, cyclicality, and seasonality, to predict and compare housing prices in Nanning, providing a reference for the applicability of the model in similar cities in the future.

Methodology

This study applies advanced statistical time series methods to analyze the evolution of residential housing prices in Nanning. Using a dataset of residential housing prices over the past 15 years, the study compares six time series analysis methods: Trend Analysis, Decomposition, Moving Average, Simple Exponential Smoothing, Double Exponential Smoothing, and the Holt-Winters Method. The Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) are used as evaluation criteria to compare the forecasting performance of each model. The model that produces the lowest MAPE and MAD values is identified as the most suitable time series forecasting method for predicting housing prices in Nanning.

1. Analyzing the Dynamic Characteristics of Time Series

This study analyzes how the time series changes over time by identifying its key components: trend (T), cycles (C), seasonality (S), and irregular fluctuations (I). By examining time series plots in relation to time, appropriate statistical methods are selected for further in-depth analysis.

2. Statistical Data Analysis

This study examines six forecasting methods, including Trend Analysis, Decomposition, Moving Average, Simple Exponential Smoothing, Double Exponential Smoothing, and the Holt-Winters Method. The effectiveness of these methods is evaluated using two key metrics: Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD), which are used to compare the differences and accuracy between the predicted values and the actual values. The details are as follows:

2.1 Trend Analysis

Trend analysis is a commonly used technique in time series analysis. The Linear Trend Model assumes that the long-term changes in the data can be represented by a straight line. This model helps to identify long-term trend patterns and provides a basis for forecasting future values.

$$Y_t = a + b \cdot t$$

- Y_t: The predicted value at time t
- a: The intercept, representing the starting point of the trend line on the vertical axis
- b: The slope, indicating the rate of increase or decrease in the trend over time
- t: Time

2.2 Decomposition

The decomposition method breaks down time series data into four components: trend, seasonality, cyclicality, and randomness. There are two main types of decomposition models: the Additive Model and the Multiplicative Model.

2.2.1 Additive Model

In the Additive Model, a time series is considered to be a simple summation of Trend, Seasonality, Cyclicality, and Irregularity components. This implies that the influence of each component on the time series is independent and additive.

$$Y_t = T_t + C_t + S_t + I_t$$

2.2.2 Multiplicative Model

In the multiplicative model, a time series is considered as the product of four components: trend, seasonality, cyclicality, and randomness. This model is suitable when these components interact with each other and jointly influence the overall fluctuations of the time series.

$$Y_t = T_t \times C_t \times S_t \times I_t$$

- Y_t is the actual observation at time t.
- T_t is the trend component at time t.
- S_t is the seasonal component at time t.
- C_t is the cyclical component at time t.
- I_t is the irregular component or error term at time t.

2.3 Moving Average

The moving average method smooths time series data by calculating the average of a fixed number of consecutive data points and updating this average as the time series progresses.

$$F_{t+1} = \frac{\sum_{i=0}^{n-1} Y_{t-i}}{n}$$

- F_{t+1}: Forecast value for time point $t+1$.
- $\sum_{i=0}^{n-1} Y_{t-i}$: Sum of the last n data points up to time t.
- Y_{t-i}: Actual value at time point $t-i$.
- n is the number of time points used for calculating the average, i.e., the period of the moving average.

2.4 Single Exponential Smoothing

The single exponential smoothing method generates forecasts based on the weighted average of past observations, where the most recent data points are assigned the highest weights, and the weights decrease exponentially over time.

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t$$

- F_{t+1} represents the forecast value for time $t+1$.
- Y_t is the actual observed value at time t.
- F_t is the forecast value at time t.
- α is the smoothing constant, with its value range being $0 < \alpha < 1$.

2.5 Double Exponential Smoothing

Double exponential smoothing considers not only the most recent observations but also the trend in the data. It uses two smoothing equations for forecasting: one to update the current level of the time series, and the other to update the trend component.

Level Equation: $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$

Trend Equation: $T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$

Forecast Equation for the next period: $F_{t+1} = L_t + T_t$

- Y_t: The actual value at time t.
- L_t: The level component at time t.
- T_t: The trend component at time t.
- F_{t+1}: The forecast value for time $t+1$.
- α: The level smoothing parameter, controlling the model's emphasis on recent observations, with a value range of $0 < \alpha < 1$.
- γ: The trend smoothing parameter, controlling the model's sensitivity to recent trend changes, with a value range of $0 < \gamma < 1$.

2.6 Holt-Winters Method

The Holt-Winters Method considers not only the level and trend components but also incorporates seasonal adjustments, making it suitable for data with seasonal fluctuations. The Holt-Winters Method is divided into two types: the Additive Model and the Multiplicative Model.

2.6.1 Additive Model

This model is suitable when the magnitude of seasonal variation remains relatively constant and does not change with the level of the time series.

Level Equation: $L_t = \alpha \cdot (Y_t - S_{t-s}) + (1-\alpha) \cdot (L_{t-1} + T_{t-1})$

Trend Equation: $T_t = \gamma \cdot (L_t - L_{t-1}) + (1-\gamma) \cdot T_{t-1}$

Seasonality Equation: $S_t = \delta \cdot (Y_t - L_t) + (1-\delta) \cdot S_{t-s}$

Forecast Equation for the next period: $F_{t+1} = L_t + T_t + S_{t+1-s}$

2.6.2 Multiplicative Model

This model is appropriate when the magnitude of seasonal variations changes in proportion to the level of the time series.

Level Equation: $L_t = \alpha \left(\frac{Y_t}{S_{t-s}} \right) + (1-\alpha)(L_{t-1} + T_{t-1})$

Trend Equation: $T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$

Seasonality Equation: $S_t = \delta \left(\frac{Y_t}{L_t} \right) + (1-\delta)S_{t-s}$

Forecast Equation for the next period: $F_{t+1} = (L_t + T_t) \times S_{t+1-s}$

- Y_t: The actual value at time t.
- L_t: The level component at time t.
- T_t: The trend component at time t.
- S_t: The seasonal component at time t.
- F_{t+1}: The forecast value for time $t+1$.
- α: The level smoothing parameter, controlling the model's emphasis on recent observations, value range $0 < \alpha < 1$.
- γ: The trend smoothing parameter, controlling the model's sensitivity to recent trend changes, value range $0 < \gamma < 1$.
- δ: The seasonal smoothing parameter, controlling the model's adjustment to the seasonal component, value range $0 < \delta < 1$.
- s: The length of the season.

3. Comparison of Forecast Accuracy

This study employs Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) as evaluation criteria. If a forecasting method yields the lowest error in both MAPE and MAD values, it is considered the most suitable predictive model for the given time series data.

3.1 MAPE (Mean Absolute Percentage Error)

MAPE represents the mean percentage error between the predicted values and the actual values. A lower MAPE value indicates higher forecasting accuracy of the model.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|Y_i-\hat{Y}_i|}{|Y_i|}\right)\times 100\%$$

- n is the total number of observations.
- Y_i is the ith actual observation.
- $\hat{Y}_i$ is the ith predicted value.
- $|Y_i - \hat{Y}_i|$ represents the absolute error between the actual and predicted values.
- $|Y_i|$ represents the absolute value of the actual observation.

3.2 MAD (Mean Absolute Deviation)

MAD refers to the mean of the absolute values of forecasting errors. A lower MAD value indicates higher forecasting accuracy of the model.

$$\mathrm{MAD} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

- n is the total number of observations.
- Y_i is the actual observation at the ith position.
- $\hat{Y}_i$ is the fitted value for the ith observation.
- $|Y_i - \hat{Y}_i|$ represents the absolute difference between the actual and fitted values.

Results

1. F

The data used in this study were obtained from the Wind Information Co., Ltd. database and consist of monthly residential housing prices in Nanning over the past 15 years, covering the period from October 2010 to December 2024, with a total of 175 data points. The price unit is RMB per square meter.Based on this dataset, distribution plots were generated (Figures 1 to 3), and the time series exhibits the following dynamic characteristics: an overall upward trend, a cyclical pattern with repeated fluctuations over longer time spans, relatively small short-term fluctuations within fixed intervals, and only minimal seasonal variation.

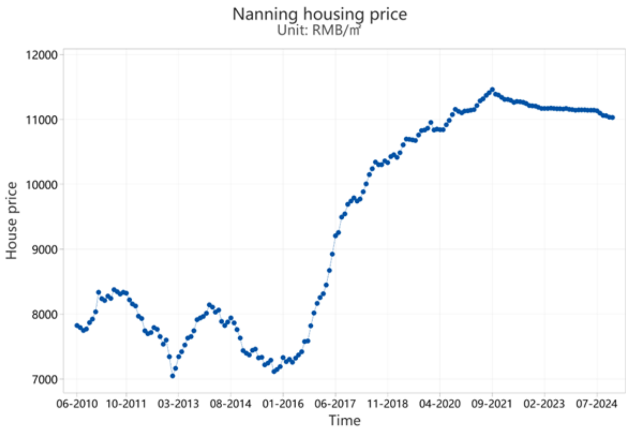

Figure 1: Characteristics of housing price movements in Nanning

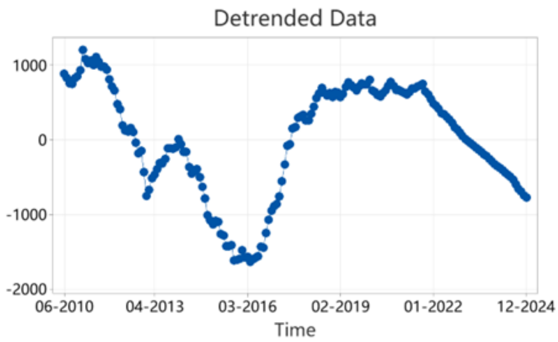

Figure 2: Nanning City's Housing Price Detrended Data

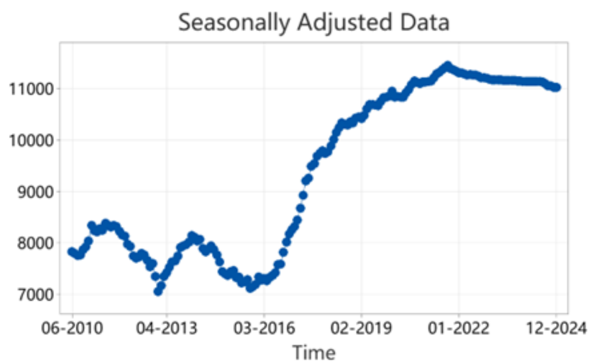

Figure 3: Seasonal adjustment chart of Nanning housing prices

2. Forecasting Results of the Models

2.1 Forecasting Results of the Trend Analysis Method

The forecasting linear equation is: Yt=6914+27.93t, where Yt denotes the forecasted value at time t. The results show MAPE=7, MAD=628, as illustrated in Figure 4.

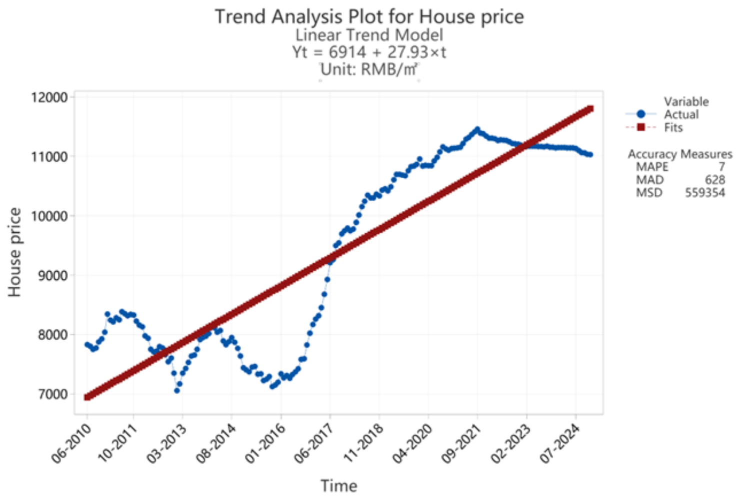

Figure 4: Forecast results using the linear trend model

2.2 Forecasting Results of the Decomposition Method

2.2.1 Additive Decomposition Forecasting Results

Using the additive decomposition model with a seasonal length of 2, the model components are trend plus seasonal. The results show MAPE=7, MAD=628, as illustrated in Figure 5.

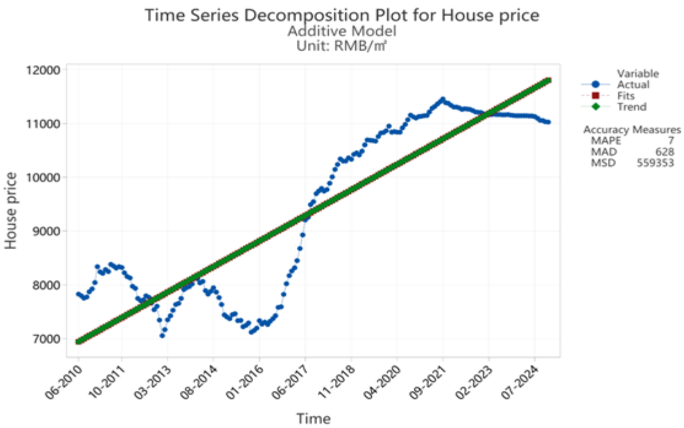

Figure 5: Forecast results using the decomposition-additive model

2.2.2 Multiplicative Decomposition Forecasting Results

Using the multiplicative decomposition model with a seasonal length of 2, the model includes both trend and seasonal components. The results show MAPE=7, MAD=628, as illustrated in Figure 6.

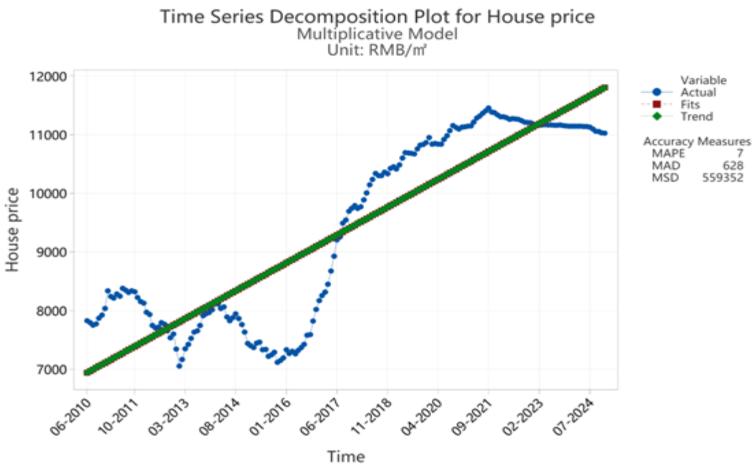

Figure 6: Forecast results using the decomposition-multiplicative model

2.3 Forecasting Results of the Moving Average Method

Using the moving average method with a moving average length of 2, the results show MAPE=1.0, MAD=82.9, as illustrated in Figure 7.

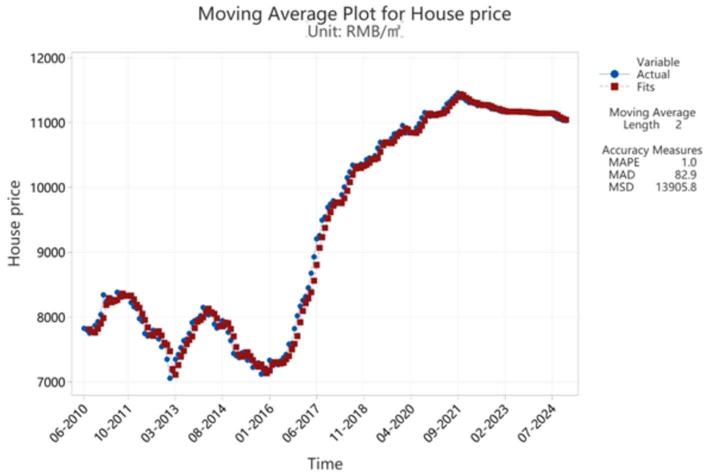

Figure 7: Forecast results using the moving average method

2.4 Forecasting Results of the Single Exponential Smoothing Method

Using the single exponential smoothing method with a smoothing constant of α = 0.9, the results show MAPE=0.79 and MAD=66.90, as illustrated in Figure 8.

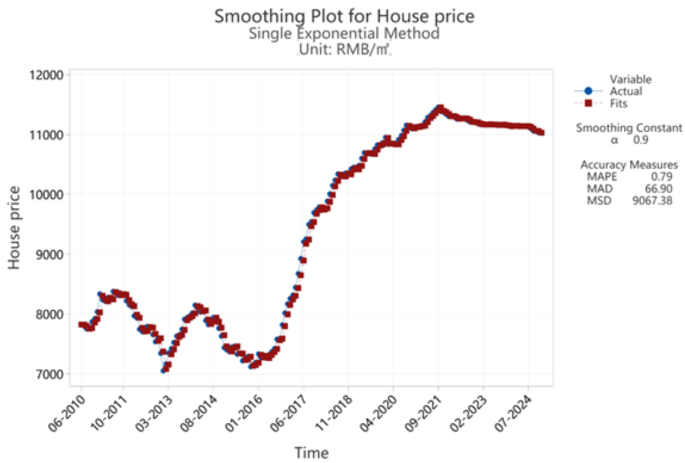

Figure 8: Forecast results using single exponential smoothing method

2.5 Forecasting Results of the Double Exponential Smoothing Method

Using the double exponential smoothing method with smoothing constants α (level) =0.9 and γ (trend)=0.2, the results show MAPE=0.8 and MAD=67.7, as illustrated in Figure 9.

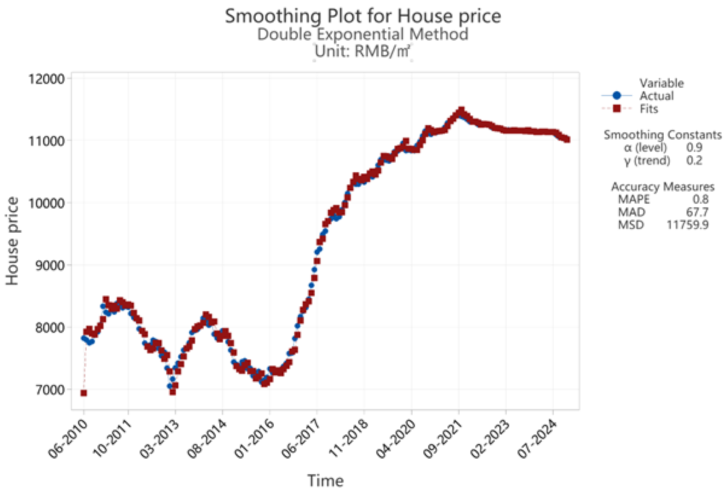

Figure 9: Forecast results using double exponential smoothing method

2.6 Forecasting Results of the Holt-Winters Method

2.6.1 Holt-Winters Additive Forecasting Results

Using the Holt-Winters Additive Method with a seasonal length of 2 and smoothing constants α (level)=0.9, γ (trend)=0.3, and δ (seasonal)=0.1, the model yielded MAPE=0.73 and MAD=60.92, as shown in Figure 10.

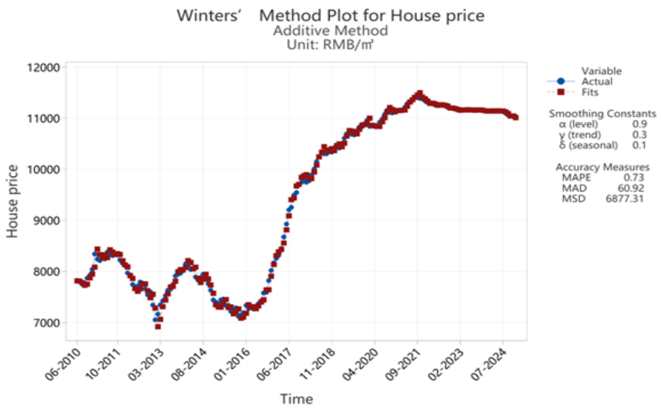

Figure 10: Forecast results using Holt-Winters Method additive model

2.6.2 Holt-Winters Multiplicative Forecasting Results

Using the Holt-Winters Method with the multiplicative model and a seasonal length of 2, the smoothing constants are α (level)=0.9, γ (trend)=0.3, and δ (seasonal)=0.1. The results show MAPE=0.73 and MAD=60.95, as illustrated in Figure 11.

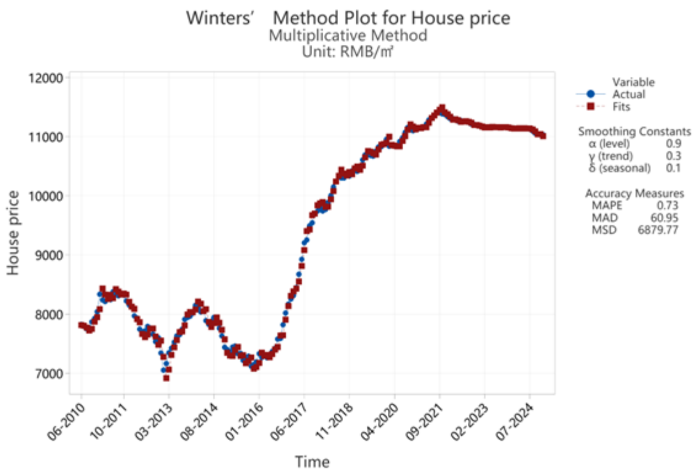

Figure 11: Forecast results using Holt-Winters Method multiplicative model

3. Comparison of Model Accuracy

The forecasting results of the six time-series analysis methods are presented in Table 1. Upon comparison, the Holt-Winters additive model produced the lowest MAPE and MAD values (MAPE=0.73, MAD=60.92), indicating the highest forecasting accuracy among the models evaluated.

	Method		MAPE	MAD
1	Trend Analysis	Linear Trend Model	7	628
2	Decomposition	Additive Model	7	628
		Multiplicative Model	7	628
3	Moving Average		1.0	82.9
4	Simple Exp Smoothing		0.79	66.9
5	Double Exp Smoothing		0.8	67.7
6	Holtwinter's method	Additive Model	0.73	60.92
		Multiplicative Model	0.73	60.95

Table1: Model accuracy comparison table

The Holt-Winters additive model is identified as the most suitable method for forecasting residential housing prices in Nanning, as shown in Table 2 and Figure 12.

Unit: RMB/㎡

Time	Actual value	Forecasted value		
		Holtwinter's Additive Model	Simple Exp Smoothing Method	Moving Average Method
		MAPE=0.081	MAPE=0.091	MAPE=0.114
01-2024	11,144.00	11,139.30	11,142.90	11,146.50
02-2024	11,145.00	11,138.60	11,143.90	11,143.00
03-2024	11,143.00	11,144.30	11,144.90	11,144.50
04-2024	11,142.00	11,139.60	11,143.20	11,144.00
05-2024	11,141.00	11,141.90	11,142.10	11,142.50
06-2024	11,139.00	11,138.00	11,141.10	11,141.50
07-2024	11,130.00	11,139.10	11,139.20	11,140.00
08-2024	11,097.00	11,125.60	11,130.90	11,134.50
09-2024	11,061.00	11,089.80	11,100.40	11,113.50
10-2024	11,055.00	11,042.90	11,064.90	11,079.00
11-2024	11,031.00	11,039.20	11,056.00	11,058.00
12-2024	11,029.00	11,012.30	11,033.50	11,043.00

Table 2: Nanning City Residential Commercial Housing Price Forecast Table

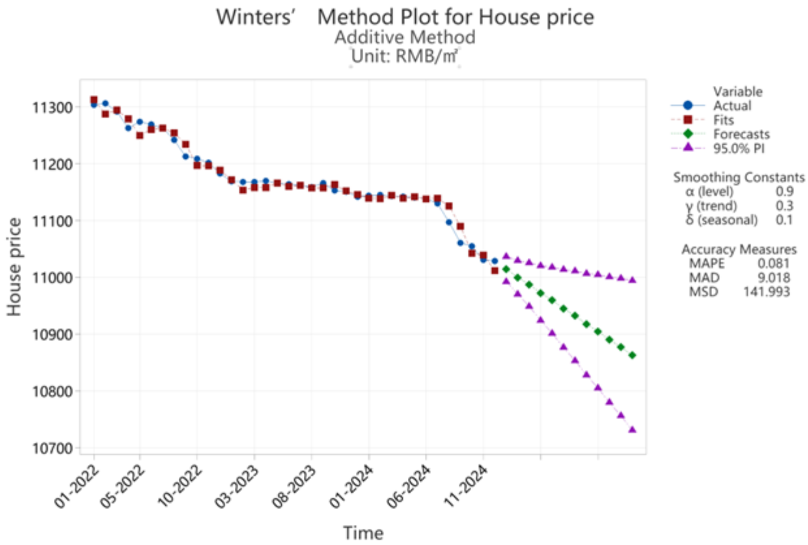

Figure 12: Forecast house prices using Holt-Winters Method additive model

Discussion

This study used a large amount of monthly average data to analyze real estate price fluctuations in Nanning over the past 15 years. Six time-series forecasting methods were compared to determine the most suitable model. The results showed that the Holt-Winters method outperformed the other methods in terms of forecast accuracy, achieving the lowest MAPE and MAD values, with a MAPE value of 0.73.

Trend analysis only considers long-term trends in data and ignores seasonal fluctuations. This can lead to large prediction errors for data with seasonal cyclical characteristics, such as housing prices (such as the annual trading peak and price fluctuations after the Spring Festival). Decomposition models have a static structure and cannot adjust parameters over time. This makes them unresponsive to complex and changing external environments (such as regulatory policy changes and the COVID-19 pandemic), resulting in large prediction errors. The Holt-Winters method dynamically adjusts predictions using three parameters (level, trend, and season). It can simultaneously capture rising and falling price trends (such as urban expansion) and cyclical fluctuations (such as the annual trading peak season), and its prediction accuracy is often superior to models using single features.

During the research process, it was observed that prediction errors were relatively large for certain months, particularly during periods of frequent policy adjustments. This may be attributed to sudden regulatory changes (such as purchase or loan restrictions), which exerted short-term shocks on the market, and traditional time series techniques were insufficient to fully capture such abrupt fluctuations.

In addition, significant volatility in the real estate market was noted in certain years, which could be associated with economic downturns or shifts in housing policy. This finding suggests that future research should incorporate broader macroeconomic variables to enhance the adaptability and robustness of forecasting models.

Recommendation

This study compared the accuracy of six mainstream forecasting models based on long-term time series data of housing prices in Nanning. The results show that the Holt-Winters model performs best in capturing both the trend and seasonality of housing prices, with the lowest forecast error.

This result contrasts empirically with Yilmaz and Kestel's (2020) study on the Turkish housing market. Their study found that the Holt-Winters model provided more accurate forecasts than the traditional ARIMA model, which aligns with the findings of this study. This result also aligns with the findings of Krishna's (2021) study on the Dubai real estate market, where both SARIMA and Holt-Winters methods performed best in a dataset with seasonal patterns, demonstrating the broad applicability and stability of this type of model across diverse global market environments.

1. Practical Implications of the Research Findings

In terms of practical applications, the results of this study can provide empirical evidence for government urban housing policymaking. By identifying cyclical and long-term trends in the real estate market and employing high-precision time series forecasting models such as the Holt-Winters model, scientific decisions can be made in advance regarding land supply, housing planning, and market regulation. The forecasting method proposed in this study is highly replicable and can be applied to rapidly developing, densely populated regional cities.

Furthermore, accurate housing price forecasts can help homebuyers make more informed investment decisions and mitigate risk.

2. Recommendations for Further Research

Future research could incorporate additional macroeconomic indicators that influence the real estate market, such as the Consumer Price Index (CPI), GDP growth rate, market interest rates, inflation rate, and credit policies, in order to develop a more comprehensive housing market forecasting model.

This study primarily relies on traditional time series analysis methods. Future studies may consider introducing nonlinear time series modeling techniques, such as hybrid models (e.g., ARIMA-LSTM) or Structural Equation Modeling (SEM), to enhance the adaptability and accuracy of forecasting models. Such improvements could generate more practically valuable results and offer more precise market insights for government agencies, real estate enterprises, and homebuyers.

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