Forecasting China's Air Cargo Volume by ARIMA vs Holt-Winters

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Abstract— This study compares the accuracy of ARIMA and Holt-Winters forecasting models in predicting China's air cargo volume for a 5-year ahead horizon. Using time series data from 2000 to 2023. ARIMA model emphasizes autocorrelation within the data, while Holt-Winters model accounts for level and trend components, excluding seasonal effects. Both models are applied using univariate forecasting approaches to evaluate their performance in predicting future air cargo volumes. A comparison of the forecasting models for China's air cargo volume shows that the ARIMA (1,1,0) model outperforms the Holt-Winters non-seasonal smoothing model. ARIMA predicts a steady increase in cargo volume from 6.90 million tons in 2024 to 7.89 million tons in 2028, while Holt-Winters forecasts lower values, from 7.17 million tons in 2024 to 7.44 million tons in 2028. ARIMA performance indicator is also better, with lower RMSE, MAE, and MAPE, indicating more accuracy and reliability of predictions. This study highlights the ARIMA model's advantages in forecasting air cargo volume and provides valuable insights into different univariate forecasting methods.

Keywords: Air Cargo, ARIMA, Holt-Winters, China.

I. INTRODUCTION

Air cargo is vital for global trade, speeding up and improving efficiency. Since 1970, air cargo volumes have doubled about every 10 years. It is a key revenue source for airlines (Feng et al., 2015). Airlines move over 62 million tons of cargo yearly. These goods account for more than 35 per cent of global trade, but less than 1 per cent of global trade volume. It is worth around $8.3 trillion each year, or $22.7 billion per day (IATA, 2024).

In April 2024, data from the International Air Transport Association (IATA) showed a strong increase in air cargo demand. Cargo tonne kilometers (CTK) rose by 11.1% compared to April 2023. International flights saw an 11.6% increase. This was the fifth month in a row with double-digit growth. Regional shares were 33.3% in Asia/Pacific, 21.4% in Europe, 26.9% in North America, 13.5% in the Middle East, 2.8% in Latin America, and 2.0% in Africa.

China's air cargo sector grew rapidly from 2000 to 2023 (see Figure 1). Economic development, rising industrial output and expanding global trade links drove this growth. In 2024, the Civil Aviation News of China reported that China signed air transport agreements with 129 countries and regions. Chinese cargo airlines serve 61 countries and 142 airports outside China, and 42 countries under the "One Belt, One Road" initiative. With new trade patterns, rising cross-border e-commerce, and changing cargo sources, air cargo will keep growing. In 2023, the Civil Aviation Administration of China (CAAC) released guidelines to speed up the development of smart civil aviation. This aims to create a more efficient air logistics system.

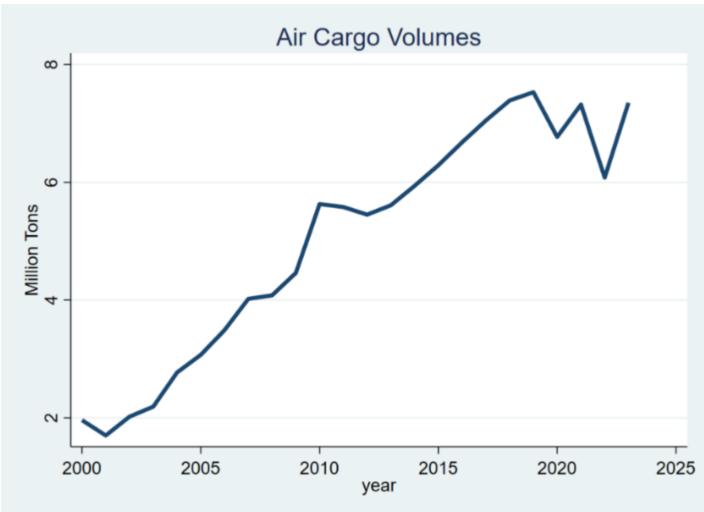


Fig. 1. Air Cargo Volume in China from 2000 to 2023

Accurate forecasting of air cargo volumes is crucial for logistics planning, resource allocation, and decision-making. Although research often focuses on passenger capacity, air cargo forecasting is still limited (Anguita & Olariaga, 2023; Chou et al., 2011). This study uses data on China's air cargo volumes from 2000 to 2023. Applying two simple and widely used time-series forecasting methods, ARIMA and Holt-Winters, to predict future volumes. These models are known for capturing seasonal patterns and trends effectively. This study aims to compare the prediction performance to highlight their strengths and limitations.

II. PREVIOUS STUDIES

Over the past two decades, China's air cargo industry has experienced dramatic transformation, driven by rapid economic growth, expanding international trade, and substantial investments in aviation infrastructure. Sun and Li (2011) established a strong link between the air transportation industry and China's economic growth, highlighting air cargo as a contributing factor. Feller (2006) observed that China presents numerous opportunities, with U.S. and Chinese agreements since 2004 allowing U.S. air carriers to establish cargo hubs in China. Notably, Beijing Capital Airport and Shanghai Pudong Airport are nearing full capacity for take-off and landing flights.
Zhou et al. (2022) conducted a regression analysis on panel data from 91 Chinese cities above the district level between 2006 and 2019. Their study found that the development of air cargo infrastructure promotes the concentration of manufacturing industries and supports overall economic development. This underscores the growth potential within the air cargo sector. Hakim and Merkert (2016) used the Pedroni/Johansen cointegration test and Granger causality tests, confirming a long-run one-way Granger causality from GDP to both air passenger and cargo traffic in South Asia. The rise of cross-border e-commerce has also emerged as a significant growth driver for the air cargo industry, reflecting a global trend in e-commerce development.

Shuying et al. (2020) analyzed the correlation between cross-border e-commerce and air cargo development in China (especially in Zhengzhou City) using a VAR model. They highlighted the need for further research into this relationship. Leung et al. (2000) proposed a network framework extending traditional business-to-business e-commerce to the industry level, identifying both challenges and opportunities that e-commerce presents to the air cargo industry.

Forecasting models have long been a focus in the air transportation sector. Srisaeng et al. (2015) constructed artificial neural network models to forecast domestic air passenger demand and revenue passenger kilometers in Australia. Javanmard and Martínez-Hernández (2024) developed a hybrid framework integrating machine learning algorithms to forecast air passenger and cargo demand in Canada. Nieto and Carmona-Benítez (2018) employed ARIMA, GARCH, and Bootstrap time-series methods to estimate passenger volumes in the U.S., arguing that accurate traffic forecasts are crucial for airline and airport decision-making.

Grosche et al. (2007) utilized gravity models to forecast inter-city air traffic, focusing on economic activity and geographic characteristics. Lim and McAleer (2002) applied the ARIMA method to forecast tourist arrivals in Australia, comparing EMSE and MAPE results for different periods. Chen et al. (2009) used Holt-Winters, SARIMA, and GM (1,1) models to forecast inbound air traffic to Taiwan, evaluating the effectiveness of various forecasting methods. Rodriguez et al. (2020) employed a dynamic linear modeling (DLM) approach to forecast short-term passenger and air cargo demand at Colombia's major airports, assessing the impact of current air transportation policies. Alexander and Merkert (2021) used a gravity modeling approach to predict the value of U.S. air imports, demonstrating the sensitivity of the U.S. to air transportation demand. Liu et al. (2020) tested various forecasting models, including multivariate linear regression (MLR), ARIMA, support vector regression (SVR), neural networks (NN), and gradient boosted regression trees (GBRT), using a year's worth of air cargo volume data. Their findings indicated that ARIMA has notable advantages for short-term prediction of air cargo volume.

The purpose of this study is to verify whether ARIMA or Holt-Winters provide the most accurate forecasts of air cargo volumes. Also, by evaluating these models, an attempt is made to determine which model provides more accurate forecasts and better supports logistics and economic planning.

III. METHODOLOGY

Accurate forecasting of air cargo volumes is crucial for optimizing logistics, managing supply chains, ensuring efficient airport operations, and supporting economic growth. In this study, used univariate forecasting to predict future air cargo volumes. This approach relies only on past values of the series itself, rather than on the relationship between the series and external factors. Univariate forecasting can offer some advantages over more complex multivariate models (Grubb and Mason, 2001).

This study collected data on China's annual air cargo volumes from 2000 to 2023 and applied two well-known time series forecasting models: ARIMA and Holt-Winters. The ARIMA method focuses on the patterns in the data's autocorrelation, giving importance to specific data points. In contrast, the Holt-Winters method uses exponential smoothing and emphasizes the most recent observations (Carmona-Benítez and Nieto, 2017). Compare these models by calculating the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). This comparison helps us evaluate which model provides more accurate predictions.

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE MODEL

The ARIMA (p, d, q) model, which stands for Autoregressive Integrated Moving Average, builds on the ARMA model by including both the autoregressive (AR) and moving average (MA) components (Hu and Yu, 2024). In time series analysis, non-stationary data often need to be adjusted before applying many models. This adjustment process usually involves checking for and removing unit roots. The Dickey-Fuller (ADF) test is usually used to identify the presence of a unit root in a time series, which would make it a non-stationary series. The test involves examining the ADF statistic, p-value, and critical value to decide if a unit root is present (Dickey and Fuller, 1979).

The ARMA model, which integrate autoregressive and moving average components, is denoted as ARMA (p, q), where p and q represent the maximum orders of these components. The general formula for the ARMA model is:

$$y_t = \omega_1 y_{t-1} + \omega_2 y_{t-2} + \cdots + \omega_p y_{t-p} + \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \cdots - \theta_q \mu_{t-q} \quad [1]$$

In contrast, the ARIMA model can handle non-stationary series by differencing them to achieve stationarity. The ARIMA (p, d, q) model is more versatile for this purpose. Its formula is:

$$\Delta^d y_t = \omega_1 y_{t-1} + \omega_2 y_{t-2} + \cdots + \omega_p y_{t-p} + \mu_t - \theta_1 \mu_{t-1} - \theta_2 \mu_{t-2} - \cdots - \theta_q \mu_{t-q} \quad [2]$$

here, $\Delta^d y_t$ denotes he unstable series y_t converted into a stable series by d differences, μ_t denotes the error, ω_m and θ_n denote the coefficients to be determined for the model, and p and q denote the order of the model.

HOLT-WINTERS MODEL

The Holt-Winters model is a time series forecasting method that improves accuracy by using exponentially weighted averaging and considering trend and seasonal components. Winters (1960) introduced this model, which smooths data to better handle patterns in trends and seasonality. In the Holt-Winters seasonal model, it's crucial to estimate the initial values for the level (L), trend (T), and seasonality (S) components. These initial values are the starting points for the model's iterative optimization process. The model uses three main parameters: α for level, β for trend, and γ for seasonal. The expression can be written as,

$$\text{Level}(L): \quad L_t = \alpha \frac{Y_t}{S_{t-m}} + (1-\alpha)(L_{t-1} + T_{t-1}) \quad [3]$$

$$\text{Trend}(T): \quad T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad [4]$$

$$\text{Seasonality}(S): \quad S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-m} \quad [5]$$

$$Predict(\hat{Y}_{t+h}): \quad \hat{Y}_{t+h} = (L_t + hT_t)S_{t+h-m(k+1)} \quad [6]$$

The Holt-Winters non-seasonality model has two main parameters: α for level and β for trend. The expression can be written as,

$$\text{Level}(L): \quad L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \quad [7]$$

$$\text{Trend}(T): \quad T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad [8]$$

$$Predict(\hat{Y}_{t+h}): \quad \hat{Y}_{t+h} = L_t + hT_t \quad [9]$$

VI. FORECASTING RESULTS

The results reveal how effectively different forecasting models predict China's air cargo volume from 2024 to 2028. Table 1 shows that the ARIMA model with parameters (1,1,0) has the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. This indicates that ARIMA (1,1,0) is the most suitable model among those tested for forecasting air cargo volumes. Table 2 shows the forecasts for air cargo volumes. The ARIMA (1,1,0) model predicts a steady increase, starting at 6.90 million tons in 2024 and reaching 7.89 million tons by 2028. In contrast, the Holt-Winters non-seasonal smoothing model forecasts slightly lower values, beginning at 7.17 million tons in 2024 and growing to 7.44 million tons by 2028.

Table 1. ARIMA models selection for used data

Models	AIC	BIC
ARIMA (1,1,0)	36.52	39.93
ARIMA (0,1,0)	38.62	40.89
ARIMA (0,1,1)	37.75	41.15
ARIMA (1,1,1)	37.25	41.79
ARIMA (2,1,0)	37.14	41.68
ARIMA (0,1,2)	38.52	43.06
ARIMA (1,1,2)	38.98	44.66
ARIMA (0,1,3)	39.49	45.17
ARIMA (3,1,0)	38.97	44.64

Note: Low AIC and BIC indicate most appropraite model for predicting air cargo volume.

Table 2. China's Air Cargo prediction results from ARIMA and Holt-Winters Models

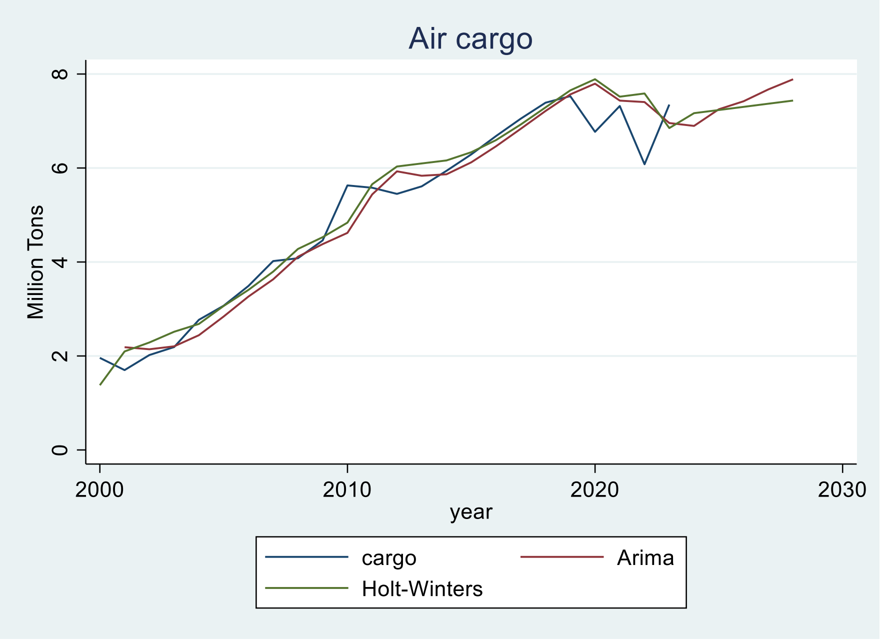
Models/Forecasts	2024	2025	2026	2027	2028
ARIMA(1,1,0)	6.895875	7.250673	7.420894	7.672957	7.888731
Holt-Winters nonseasonal smoothing	7.167315	7.234387	7.30146	7.368533	7.435606

Table 3 evaluates the models using three accuracy metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The ARIMA model has lower RMSE (0.4697) and MAE (0.3265) values, as well as a lower MAPE (7.1169%) compared to the Holt-Winters model. This demonstrates that ARIMA (1,1,0) provides more precise forecasts with fewer errors. Figure 2 visually compares the forecasting results from both models. Overall, the study finds that the ARIMA (1,1,0) model is more effective for predicting air cargo volumes in China. It delivers more accurate forecasts and shows better performance than the Holt-Winters model.

Table 3. Model Comparision

Models	RMSE	MAE	MAPE
ARIMA(1,1,0)	0.4697	0.3265	7.1169
Holt-Winters nonseasonal smoothing	0.4961	0.3418	8.1272

Fig. 2. Forecasting Models Comparison (ARIMA and Holt-Winters)



V. CONCLUSION AND GUIDANCE FOR FUTURE STUDY

This study has evaluated the forecasting accuracy of two models—ARIMA and Holt-Winters—regarding China's air cargo volume. The results show that the ARIMA model with parameters (1,1,0) outperforms the Holt-Winters non-seasonal smoothing model in terms of forecast accuracy. The ARIMA model provided lower values for Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), indicating that it is better suited for predicting future air cargo volumes. The ARIMA model predicts a steady increase in cargo volume over the next five years, while the Holt-Winters model forecasts slightly lower growth.

There are some limitations to this study. The ARIMA and Holt-Winters models used here are relatively simple and may not capture all underlying patterns in the data. The absence of seasonal effects in the Holt-Winters model may have impacted its performance, especially if there are significant seasonal variations in air cargo volume. Furthermore, the study relies on historical data up to 2023, and future changes in economic conditions or trade practices could affect the forecasts.

For future studies, several areas can be explored to enhance forecasting accuracy. First, incorporating additional variables, such as economic indicators or trade policies, might improve predictions. Exploring more complex models or hybrid approaches that combine ARIMA with exogeneous variables. Additionally, applying these models to different regions or comparing them across various industries may provide unique results.

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