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Forecasting of Thai International Imports and Exports Using Holt-Winters' and Autoregressive Integrated Moving Average Models

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ABSTRACT

Imports and exports are two vital issues of the Thai economy, which were ranked as the 23rd largest economy in the world in 2020. Therefore, this research aimed to examine the Thai import and export volume trends (in million Baht) from January, 2010 to December, 2022. To conduct the analysis, the research employed Holt-Winters' additive and multiplicative models, as well as various seasonal ARIMA models. The models were evaluated using different selection measure criteria, and the results indicated that the Holt-Winters' multiplicative forecasting model was optimal for predicting both import and export volumes, as it produced the least mean absolute error (*MAE*) and root mean square error (*RMSE*). Thus, it is recommended for future Thai imports and exports forecasts. However, it is notable that the COVID-19 pandemic had a significant impact on the country′s imports and exports during the 2019-2020 period.

KEYWORDS: Imports, Exports, ARIMA model, Holt-Winters' model, Seasonal, Forecasting

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1. INTRODUCTION

Imports and exports are two crucial issues of the Thai economy. In 2020, Thailand's GDP makes it 23rd largest economy in the world. Thailand was both a major exporter and the 25th largest importer. Its imports and exports constituted more than 130% of its GDP, according to the world bank, 2022 (World Bank, 2022). Thailand′s top 10 exports comprised vehicles (including parts and equipment), precious minerals and gems, and computers (including components), while Thai top 10 imports included crude oil, machinery and components, and electrical machinery and components, among others, as per Thailand trade policy and strategy (Tread Policy and Strategy office, 2022). To stimulate economic growth, the Thai government has actively encouraged exports through various policies and initiatives, including the ″Thailand 4.0″ policy, which seeks to transform the country′s economy from a manufacturing-based to a value-based one by emphasizing innovation, creativity, and technology. As part of this strategy, the government has invested in infrastructure and logistics to enhance the efficiency of imports and exports, according to the OECD (OECD, 2017). Moreover, to promoting exports, the Thai government has also been striving to reduce the country′s reliance on imports, especially for energy, through the development of renewable energy sources such as wind, solar, and biomass, as well as the promotion of energy conservation and efficiency measures, as stated by the Ministry of Energy, 2021 (Ministry of Energy, 2021).

Forecasting is a widely used method for predicting uncertain future events using existing information. The Holt-Winters' method developed by (Winters, 1960) is a seasonal time series model used to study the trend, pattern and forecasting future events from time series data. The model is an automatic forecasting framework based on exponential smoothing where more weight is assigned to recent values. It is either additive or multiplicative based on the pattern shown by the time series plot. Many researchers have used Holt-Winters' method to studied and forecast various events. For example, (Mladenović et al., 2016), analysed the export trends of the Republic of Serbia during the period of 2004 to 2014. Holt-Winters' and ARIMA models were the two models used in the study. The forecast accuracy of the two models were compared for a period of 12 months. In (Nieto et al., 2021), studied the cargo volume trends of the ports of San Pedro Bay, California, United States of America (USA) using data from 2008 to 2016. Multiplicative Holt-Winters' with two other time-series models and one machine-learning model were the models considered in the study. The models forecast cargo through the ports of results show that the multiplicative Holt-Winters' model is the best method to forecast imports and exports of bulk cargo. In (Wongoutong, 2021) studied the effect on forecasting accuracy of multiplicative and additive Holt-Winters' method using ten simulated datasets of different seasonality trends. Five actual datasets, in which it was difficult to distinguish the type of seasonal component, were also considered in the study. The results are in line with the significance of the correct identification of the type of seasonality before applying Holt-Winters' method.

Autoregressive Integrated Moving Average (ARIMA) model, developed by (Box & Jenkins, 1976), is the most commonly used model in statistical analysis for forecasting. The models are especially useful for analyzing non-stationary time series data that can be explained by its past observations or lagged values. It utilizes autoregression (AR), moving average (MA), and seasonal differencing to identify trends and generate forecasts. The model building procedure involves finding the differences in the series by generating changes in the set {p, d, q, P, D, Q} to ensure that stationarity is satisfied. Therefore, it is essential to test the overall stationery to determine the appropriate orders of the AR and MA components. This testing procedure requires a powerful algorithm for iterative estimation to reduce the computation burden. After obtaining the estimated parameters of a tentatively identified ARIMA model, diagnostic checking is necessary to confirm that the model is adequate. To select the optimal model, various statistical criteria such as *MAE*, *MAPE*, *RMSE*, and *MSE* are used. These measures provide information about the accuracy of the forecasts generated by different models. The goal is to choose the set of orders {p, d, q, P, D, Q} that produces the smallest values of *MAE*, *MAPE*, *RMSE*, and *MSE*. This approach is based on the statistical principle of minimizing the error between the actual and forecasted values. It involves identifying, estimating, and diagnosing predictions using lagged moving averages to smooth time series data. (Benvenuto et al., 2021).

The ARIMA can be modified to suit different models based on different time series. Many researchers have used ARIMA to forecast various events. For example, (Benvenuto et al., 2021), studied the dynamics of COVID-19 in India using ARIMA to determine both the prevalence and incidence of the disease. In (Fattah et al., 2018) adopted the ARIMA approach to forecast the demand for finished products in food manufacturing. In (Kamoljitprapa & Sookkhee, 2022), employed an alternative technique, the Box-Jenkins time series procedure, to forecast the total amount of CO_2 emissions in Thailand from 2001 to 2020. In (Kaur & Rakshit, 2019), used suitable ARIMA methods for forecasting the analysis of rainfall. In a context of the exports and imports, ARIMA models are also play a vital role in these area. For example, (Panday & Dhakal, 2020), studied the use of ARIMA models to forecast exports and imports in Nepal's agricultural sector and found that ARIMA models provided more accurate forecasts compared to other techniques. In (Oghenekevwe & Mercy, 2021), used ARIMA models to forecast Nigeria's export and import performance in the agricultural sector and found that ARIMA models could accurately predict export and import trends. Therefore, forecasting techniques such as the ARIMA and Holt-Winters' methods can significantly contribute to a country's economy by providing a roadmap for sustainable trade growth and development. Policymakers and stakeholders can make informed decisions about their imports and exports, which can significantly contribute to a country's economy.

2. MATERIALS AND METHODS

The time series data used in this study was collected by the Information Communication Technology Center, Office of the Permanent Secretary, Ministry of Commerce, spanning from January 2010 to December 2022 (a total of 132 months) (Office of the Permanent Secretary, 2023). The models used 120 months for training data and the last 12 months were used for the test set. The R software was utilized to estimate the model parameters and perform diagnostic tests to validate the models.

2.1 Holt-Winters' Method

The Holt-Winters' method (Winters, 1960), is a seasonal time series model used to study the trend, pattern and forecasting future events from time series data where recent values are assigned more weight (Chatfield & Yar, 2014). The model is either additive or multiplicative based on the pattern shown by the time series plot.

The additive model is generally stated as;

$$J_t = \delta\left(y_t - S_{t-p}\right) + \left(1-\delta\right)\left(J_{t-1} + H_{t-1}\right),$$

$$H_t = \beta\left(J_t - J_{t-1}\right) + \left(1-\beta\right)H_{t-1},$$

$$S_t = \lambda\left(y_t - J_t\right) + \left(1-\lambda\right)S_{t-p}.$$

The multiplicative model is generally stated as;

$$j_t = \delta\frac{y_t}{s_{t-p}} + \left(1-\delta\right)\left(j_{t-1} + h_{t-1}\right),$$

$$h_t = \beta\left(j_t - j_{t-1}\right) + \left(1-\beta\right)h_{t-1},$$

$$s_t = \lambda\frac{y_t}{j_t} + \left(1-\lambda\right)s_{t-p},$$

where $0 \le \delta \le 1$, $0 \le \beta \le 1$, $0 \le \lambda \le 1$: δ , β and λ are the smoothing parameters, J_t is the smoothed level at time t, H_t is the change in the trend at time t, S_t is the seasonal smooth at time t, p is the number of seasons per year. The Holt-Winters' algorithm requires starting value for each of the component values. Most commonly are:

$$j_p = \frac{1}{p}\left(y_1 + y_2 + \ldots + y_p\right),$$

$$h_p = \frac{1}{p}\left[\frac{y_{p+1} - y_1}{p} + \frac{y_{p+2} - y_2}{p} + \ldots + \frac{y_{p+p} - y_p}{p}\right].$$

The formulas for linear and trend component are the same for both additive and multiplicative models as shown:

$$s_1 = Y_1 - j_p, \quad s_2 = Y_2 - j_p, \quad s_p = Y_p - j_p$$

(seasonal component for additive model),

$$s_1 = \frac{Y_1}{j_p}, \; s_2 = \frac{Y_2}{j_p}, \ldots, \; s_p = \frac{Y_p}{j_p}$$

(seasonal component for multiplicative model).

So, the forecast model for time period is shown in Eq. (1),

$$F_{t+p} = J_t + pH_t + S_{t+p-1}. \tag{1}$$

2.2 ARIMA (Box and Jenkins) Model

The model combines the autoregressive (AR) and moving average (MA) concepts and can be denoted by ARIMA (p, d, q), where p represents the order of the AR component, d is the order of differencing, and q represents the order of the MA component. Eq. (2) presents the general form of the ARIMA model:

$$\phi_p\left(B\right)\left(1-B\right)^d x_t = \theta_q\left(B\right)\varepsilon_t, \tag{2}$$

where ϕ_p and θ_q are the AR and MA characteristic operators, and are represented by:

$$\phi_p\left(B\right) = 1 - \sum_{i=1}^{p}\phi_i B^i = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p,$$

$$\theta_q\left(B\right) = 1 - \sum_{i=1}^{p}\theta_i B^i = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q,$$

respectively. Here, B is a backward shift operator that shifts the time series data back by one time period, $B\left(y_t\right) = y_{t-1}$, and ε_t is the forecasting error term.

For seasonal time series data, a seasonal ARIMA model, denoted by ARIMA (p, d, q) (P, D, Q) is commonly used. Eq. (3) shows the seasonal ARIMA model, which includes the seasonal AR and MA components, as well as the seasonal differencing parameter, D:

$$\phi_p\left(B\right)\omega_P\left(B^s\right)\left(1-B^s\right)^D y_t = \theta_q\left(B\right)\gamma_Q\left(B^s\right)\varepsilon_t \tag{3}$$

where $\omega_p\left(B^s\right)$ and $\gamma_Q\left(B^s\right)$ are the seasonal AR and MA characteristic operators respectively,

$$\omega_P\left(B^l\right)=1-\omega_1 B^s-\omega_2 B^{2s}-\ldots\omega_P B^{Ps},$$

$$\gamma_Q\left(B^l\right)=1-\gamma_1 B^s-\gamma_2 B^{2s}-..\gamma_Q B^{Ps},$$

and l is the sub index that stands for the seasonal period. The orders of the seasonal AR, MA, and differencing components are denoted by P, D and Q, respectively.

In summary, the ARIMA model provides a useful framework for modeling non-stationary time series data, and the inclusion of seasonal components in the model can further improve its accuracy and predictive power.

2.3 Model Evaluation

In the context of forecasting, the occurrence of errors is inevitable. To minimize these errors and ensure a high level of accuracy, several measures, such as the mean absolute error (MAE) and root mean squared error ($RMSE$) are commonly used and are used in this study.

The MAE evaluates the average magnitude of the errors in a set of predictions, without considering their direction. It is calculated as the average of the absolute differences between the predicted values ($\hat{y}_i$) and actual values (y_i) across the number of observed values (n). The weights assigned to each individual difference are equal. The MAE can be calculated as shown in Eq. (4),

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \tag{4}$$

$RMSE$, on the other hand, is a quadratic scoring rule that also assesses the average magnitude of the error. It is computed as the square root of the average of the squared differences between the predicted and actual values. The $RMSE$ can be calculated as shown in Eq. (5),

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{5}$$

3. RESULTS AND DISCUSSION

As depicted in Figure 1 the trend of Thailand's imports and exports over the past 12 years has been characterized by an overall upward trajectory punctuated by fluctuations. Specifically, Thailand's imports exhibited a downward trend from 2012 to 2016, followed by an upward trend from 2016 to 2019. Conversely, Thailand's exports have shown a consistent increase over time, albeit with occasional downturns. It is noteworthy that both imports and exports experienced a sharp increase in value around mid-year 2020. Again, the pandemic had a noticeable effect, with a decline in imports during the 2019-2020 period. Therefore, the graphs of both imports and exports series exhibited the non-stationarity at a level.

Moreover, Figure 2 and Figure 3 show that the magnitude of the seasonal component does not change with time; thus, a multiplicative decomposition is more appropriate. Hence, multiplicative Holt-Winters' model handles the data efficiently. Furthermore, Table 1 shows that the *MAE* and *RMSE* values obtained using this model satisfy the forecasting error criteria outlined in Section 2.

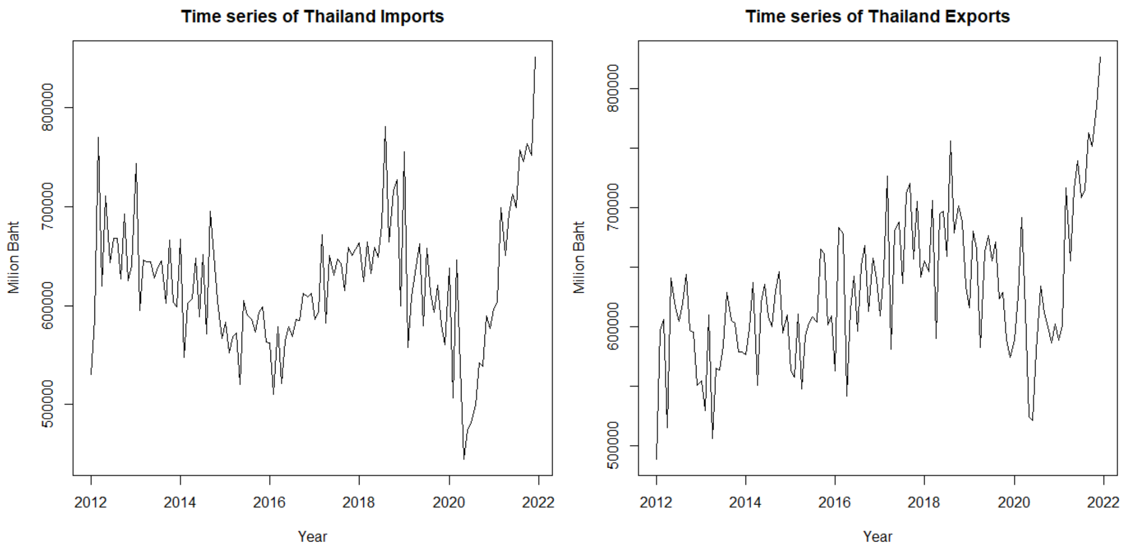
Table 1 The computed forecasting errors for the imports and exports using additive and multiplicative Holt-Winters' models

Model	***MAE*** ($\times 10^4$)	***RMSE*** ($\times 10^4$)
Imports:		
Additive seasonal	3.55	4.71
Multiplicative seasonal	2.65	3.38
Exports:		
Additive seasonal	3.54	4.21
Multiplicative seasonal	2.57	3.33

The comparison of the fitted values using the additive and multiplicative Holt-Winters' models with the actual values are shown in Figure 4 and Figure 5 for imports and exports, respectively. Both graphs satisfy the assumption of constant variance and independence normality, yet it is clear that Holt-Winters' multiplicative model (red line) follows the actual trend more closely than Holt-Winters' additive model (blue line). The analysis also involves looking at the Autocorrelation Function (ACF).

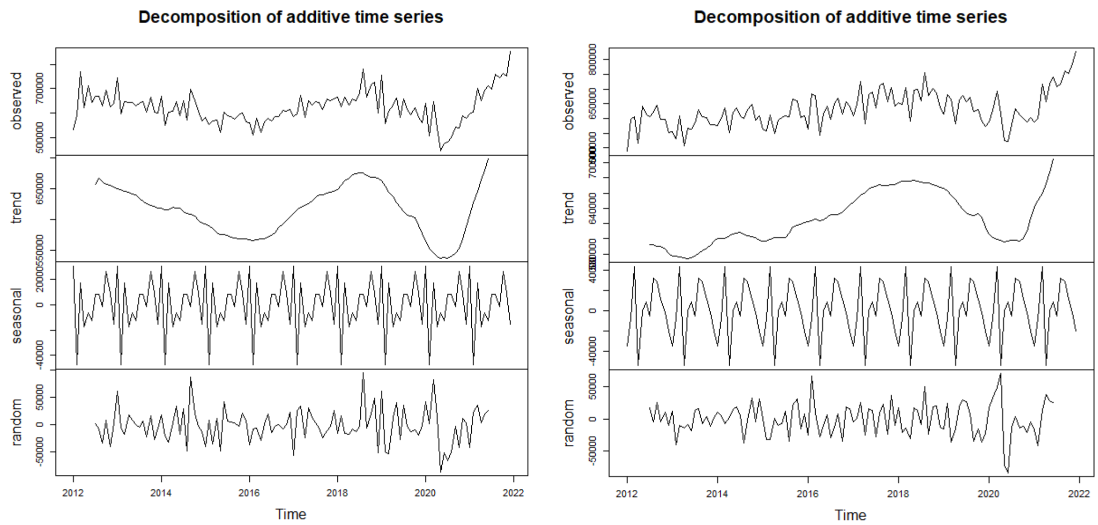
Table 2 The computed of forecasting errors for the imports and exports using ARIMA model

Model	**MAE** ($\times 10^4$)	**RMSE** ($\times 10^4$)
Imports: ARIMA$(3,1,0)(0,0,1)_{12}$	3.58	4.86
Exports: ARIMA$(0,1,1)(0,0,2)_{12}$	3.30	4.23



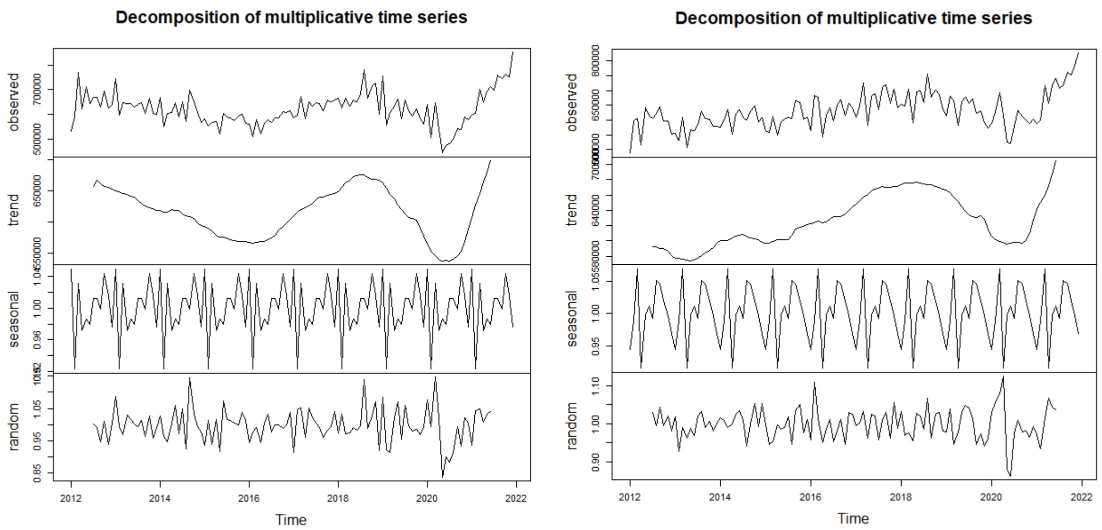
(a) (b)

Figure 1 Trend of Thailand's (a) imports and (b) exports over the years 2012 to 2022



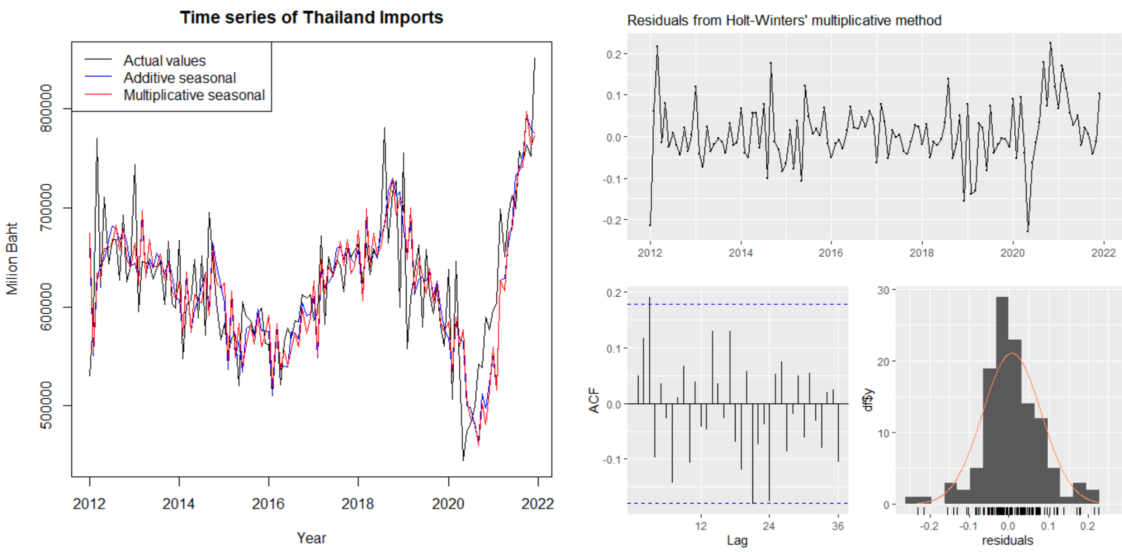
(a) (b)

Figure 2 Additive decomposition plots for Thailand's (a) imports and (b) exports



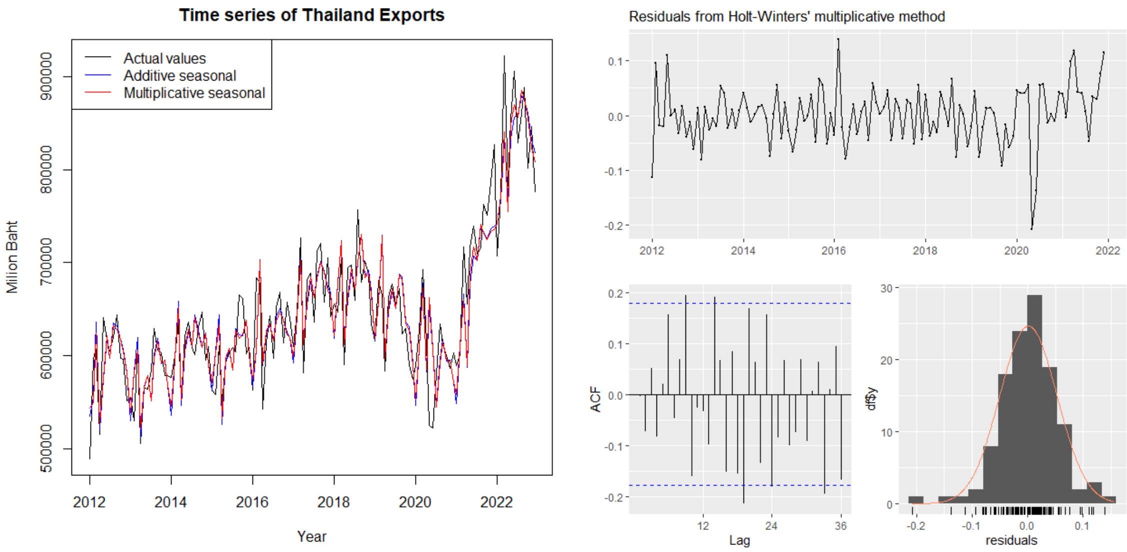
(a) (b)

Figure 3 Multiplicative decomposition plots for Thailand's (a) imports and (b) exports



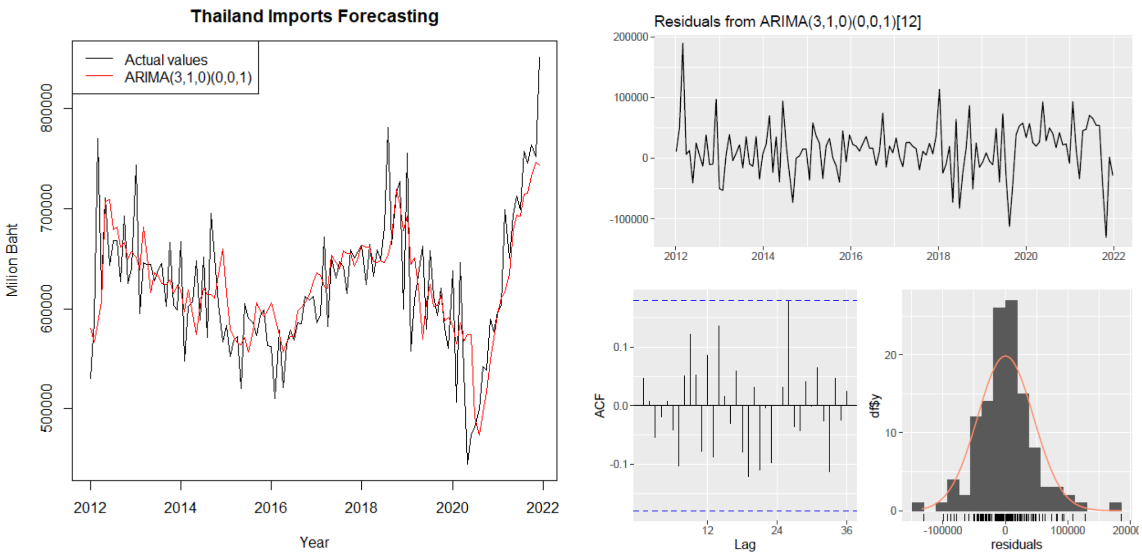
(a) (b)

Figure 4 Comparison of Holt-Winters' additive and multiplicative models for imports (a) and the evaluation of the multiplicative model accuracy (b)



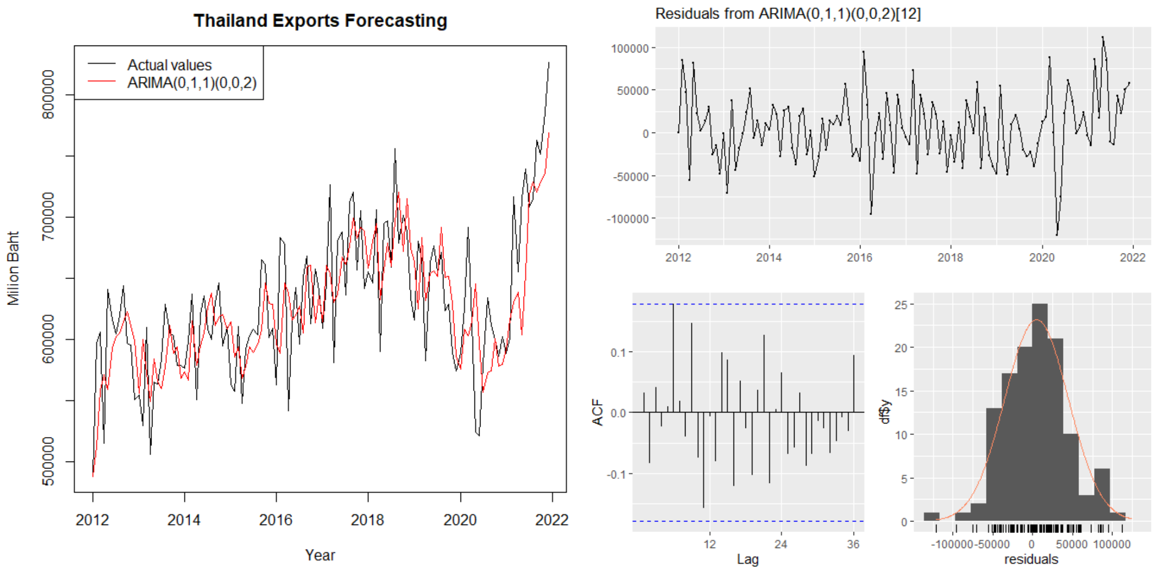
(a) (b)

Figure 5 Comparison of Holt-Winters' additive and multiplicative models for exports (a) and the evaluation of the multiplicative model accuracy (b)



(a) (b)

Figure 6 Actual and predicted values of Thailand's imports using ARIMA(3, 1, 0)(0, 0, 1)$_{12}$ model (a) and the evaluation of the model accuracy (b)



(a) (b)

Figure 7 Actual and predicted values of Thailand's exports using ARIMA(0, 1, 1)(0, 0, 2)$_{12}$ model (a) and the evaluation of the model accuracy (b)

We also applied the ARIMA method by first stationarized the time series data and tested various combinations of the parametric orders {p, d, q, P, D, Q} to determine the best-fitted models. Our findings indicate that the recommended models are ARIMA(3,1,0)(0,0,1)$_{12}$ and ARIMA(0,1,1)(0,0,2)$_{12}$ for imports and exports, respectively. The predicted values align closely with the actual values, as shown in Figure 6 and Figure 7, and the proposed models exhibit small residuals that satisfy the assumptions of independence, normality, and homoscedasticity. However, upon comparing the *MAE* and *RMSE* values presented in Table 2 for the ARIMA models with those obtained from the Holt-Winters' method, we observed that the multiplicative model produced lower error values. Thus, based on our results, the multiplicative Holt-Winters' model is the optimal choice for forecasting Thailand's imports and exports in this study.

Regarding the discussion, the optimal model selected, the multiplicative Holt-Winters' model, was used to predict monthly imports and exports values for the year 2022 and compare them with the actual values, which are presented in Table 3. Again, the overall predicted values by the models are consistent with the actual values. The models confirm their accurate prediction and successfully captures the changing trend of imports and exports. Additionally, Table 4 and Figure 8 display the forecasting values (blue line) for 12 periods of the year 2023. The forecasts show rapid fluctuations, with both decreasing and increasing trends. While the point forecasts indicate a downward trend, the prediction intervals allow for potential downward movement in the data during the forecast period for both imports and exports. Also shown in Figure 8, the shade represents the 80% confidence interval (dark grey) and the 95% confidence interval (light grey).

4. CONCLUSION

In conclusion, based on the analysis and visual plots, multiplicative Holt-Winters' forecasting model exhibits the least *MAE* and *RMSE* for both Thailand's imports (2.65×10^4 and 3.38×10^4) and exports (2.57×10^4 and 3.33×10^4) datasets from January, 2010 to December, 2022, compared to additive Holt-Winters' model and seasonal ARIMA model. This model considers not only the dependence on the time series but also the interference of seasonal component, resulting in a relatively high prediction accuracy of long-term trends, which is often used in the field of economic forecasting (Hyndman & Athanasopoulos, 2021). Therefore, the model is recommended for future Thai import and export forecasts.

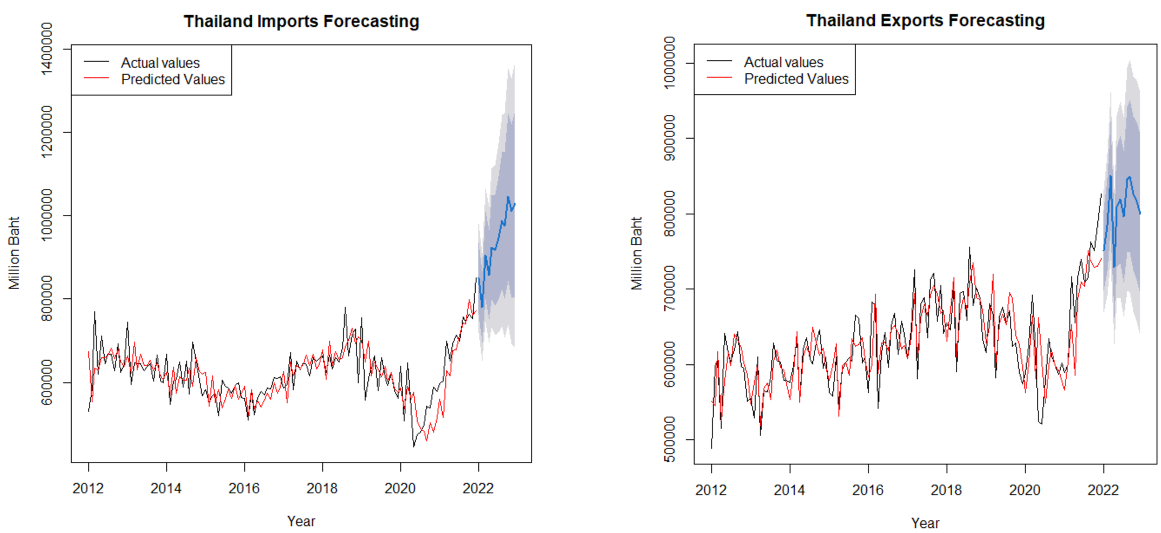
Table 3 Comparison of actual and predicted import and export values (in Million Bath) using optimal model, multiplicative Holt-Winters' model, for the year 2022

Month	Imports			Exports		
	Actual value	Predictive value	Residuals	Actual value	Predictive value	Residuals
January	796,295.6	851,788.8	-0.0651	706,715.7	741,745.4	-0.0472
February	772,456.5	763,243.3	0.0121	771,032.5	770,822.2	0.0003
March	869,554.1	890,302.4	-0.0233	922,277.2	840,113.8	0.0978
April	842,640.8	837,099.4	0.0066	781,925.0	754,351.1	0.0366
May	919,987.4	894,090.4	0.0290	854,264.7	848,356.8	0.0070
June	957,595.3	907,489.6	0.0552	905,744.9	869,202.1	0.0420
July	968,939.5	963,008.0	0.0062	829,028.8	855,766.2	-0.0312
August	1,026,653.5	1,012,311.9	0.0142	861,169.2	885,671.2	-0.0277
September	929,731.9	1,003,353.6	-0.0734	888,371.1	876,639.3	0.0134
October	832,874.8	989,734.3	-0.1585	801,273.4	856,394.9	-0.0644
November	907,142.7	926,844.8	-0.0213	846,190.5	823,913.6	0.0270
December	823,081.5	892,417.6	-0.0777	776,323.6	808,601.7	-0.0400

Table 4 Forecasting import and export values (in Million Bath) using optimal model, multiplicative Holt-Winters' model, for the year 2023

Month	Imports		Exports	
	Forecasting	95% CI.	Forecasting	95% CI.
January	904,933.5	766,776.5, 1,043,090.5	753,002.3	672,088.5, 833,916.1
February	821,210.0	680,902.6, 961,517.3	801,268.8	705,144.8, 897,392.8
March	936,871.4	757,884.9, 1,115,857.9	873,162.0	758,532.1, 987,791.9
April	876,538.5	689,815.0, 1,063,262.0	747,752.5	641,802.7, 853,702.3
May	919,255.8	701,763.6, 1,136,748.1	825,971.6	700,935.3, 951,007.9
June	906,163.3	669,103.0, 1,143,223.6	843,371.4	70,8026.0, 978,716.9
July	921,168.7	655,931.2, 1,186,406.1	813,393.4	675,858.4, 950,928.5
August	947,892.7	648,857.6, 1,246,927.8	855,085.5	703,502.5, 1,006,668.5
September	916,201.6	600,902.9, 1,231,500.4	858,153.2	699,317.0, 1,016,989.4
October	920,504.1	576,369.0, 1,264,639.2	832,814.5	672424.7, 993,204.3
November	921,810.5	548,874.8, 1,294,746.1	827,651.2	662286.9, 993,015.4
December	891,906.9	502,832.3, 1,280,981.6	801,518.3	635799.8, 967,236.9

Notably, the COVID-19 pandemic had a significant impact on the country's imports and exports, resulting in a modest decline in the years 2019 to 2020 and a subsequent sharp increase in 2021. While Thailand's trade patterns have been generally favorable over the past decade, the COVID-19 pandemic has posed significant challenges to the country's import and export industries, as evidenced by the fluctuations in the data.



(a) (b)

Figure 8 Forecasting values for Thailand's (a) imports and (b) exports using optimal model, multiplicative Holts-Winters' model, for the year 2023

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REFERENCES

Benvenuto, D., Giovanetti, M., Vassallo, L., Angeletti, S., & Ciccozzi, M. (2020). Application of the ARIMA model on the COVID-2019 epidemic dataset. *Data in Brief*, *29*, 105340.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: forecasting and control*. San Francisco, CA: Holden-Day.

Chatfield, C., & Yar, M. (2014). Holt-Winters forecasting: some practical issues. *Journal of the Royal Statistical Society: Series D (The Statistician)*, *34*(2-3), 215-225.

Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., & Lachhab, A. (2018). Forecasting of demand using ARIMA model. *International Journal of Engineering Business Management*, *10*, 1–9. https://doi.org/10.1177/1847979018808673

Hyndman, R. J., & Athanasopoulos G. (2021). *Forecasting: Principles and Practice* (3rd ed.). https:// otexts.com/fpp3/decomposition.html

Kamoljitprapa, P., & Sookkhee, S. (2022). Forecasting Models for Carbon Dioxide Emissions in Major Economic Sectors of Thailand. *Journal of Physics: Conference Series 2346*, 012001.

Kaur, P., & Rakshit, M. (2019). Seasonal and Periodic Autoregressive Time Series Models Used for Forecasting Analysis of Rainfall Data. *International Journal of Advanced Research in Engineering and Technology*, *10*(1), 230-242.

Ministry of Energy. (2021). *Thailand's energy situation*. https://www.energy.go.th /en/energy-situation/energy-situation-in- thailand/

Mladenović, J., Lepojević, V., & Janković-Milić V. (2016). Modelling and Prognosis of the Export of The Republic of Serbia by using Seasonal Holt-Winters and ARIMA Method. *Economic Themes*, *54*(2), 233-260.

Nieto, M. R., Carmona-Benitez, R. B., & Martinez, J. N. (2021) Comparing models to forecast cargo volume at port terminals. *Journal of Applied Research and Technology*, *19*(3), 238-249.

OECD. (2017). *Economic survey of Thailand 2017*. https://www.oecd.org/economy/ surveys/economic-survey-thailand.htm

Office of the Permanent Secretary. (2023). *Ministry of Commerce.* https:// tradereport.moc.go.th /Report/ReportEng.aspx?Report=TradeEnBalanceYearly

Oghenekevwe, O. A., & Mercy, O. O. (2021). Forecasting Export and Import Performance in the Agricultural Sector of Nigeria Using ARIMA Models. *International Journal of Agricultural and Biological Engineering*, *14*(4), 145-152.

Panday, P. K., & Dhakal, R. (2020). Forecasting Exports and Imports of Nepal's Agricultural Sector: A Comparison of ARIMA, ANN and ETS Models. *International Journal of Applied Sciences and Biotechnology*, *8*(1), 15-20.

Trade Policy and Strategy office. (2022). *Ministry of Commerce*. https://www.tpso.moc.go.th /th/node/12413

Winters, P. R. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, *6*(3), 324-342.

Wongoutong, C. (2021). The Effect of Forecasting Accuracy of the Holt-Winter Method When Using the Incorrect Model on a Non-Stationary Time Series. *Thailand Statistician*, *19*(3), 565-582.

World, Bank. (2022). *World development indicators*. https://databank.worldbank.org /source/world-development-indicators