Forecasting Models for Thailand's Electrical Appliances Export Values

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Abstract: - This research aimed to study forecasting models for Thailand's electrical appliances export values. Thailand's monthly electrical appliances export values were gathered from the Information Technology and Communication Center, Ministry of Commerce, from January 2006 to November 2022. The data from January 2006 to December 2021 were used to construct and select the forecasting models, and the remaining were used for measuring the model's accuracy. Since the electrical appliances export values showed trends and seasonal variation, the researcher selected the Holt-Winters method with various initial settings, the Box-Jenkins method, and Long Short-Term Memory Neural Networks (LSTM) for constructing models. The forecasting models were chosen by minimum Root Mean Square Error (RMSE) as a criterion. Mean Absolute Percentage Error (MAPE) was employed to measure the accuracy of the forecasting model. The study revealed that the Box-Jenkins model gave the appropriate forecasting model for Thailand's electrical appliances export values and gained a MAPE of 8.0%.

Key-Words: - Forecasting, Electrical Appliances Export Values, Holt-Winters Method, Box-Jenkins Method, Long Short-Term Memory Neural Networks

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1 Introduction

Electrical appliances have become an essential factor that plays an important role in daily life. Electrical appliances help the well-being of the people in the houses, communities, and societies to be more comfortable. Thailand's electrical appliances industry produces electrical appliances for domestic sales and export to foreign countries. Thailand is an important electrical appliance manufacturing base in Asia. As the government has a policy to promote foreign investment in the electrical appliances industry and the development of electrical appliances parts since 1972, it also has a policy to support the production of electrical appliances in Thailand during the year 2016-2020, [1]. According to the Office of Industrial Economics report in 2020, Thailand's electrical appliances exports 65-70% of the total electrical appliances production. The main export products are air conditioners, televisions, radios, refrigerators, washing machines, and compressors. The export value of electrical appliances was 889,541.55 million baht or 11.06% of the total export value of the country, [2]. Since exports drive investment expansion and increase labor demand, it also assists in importing foreign currency and causing efficient use of resources, and creating added value to resources.

Accurate forecasting enables businesses to plan their production and exports better. As a result, the inventory is lower and the production costs and export costs are decreased. It also helps the government formulate trade policies supporting exports to help businesses grow faster.

Currently, the most widely used forecasting method is time series analysis. Time series analysis constructs models or equations to guide future value predictions. The method uses historical data collected in an order of time to study the patterns, and data correlation to build models. This study will construct a model to forecast the export values of electrical appliances in Thailand

The Holt-Winters method is simple and easy to use. They are best suited for time series that tend to be linear and fluctuate seasonally. The different settings of levels, trends, and seasonal variations affect the Holt-Winters forecasting performance, [3]. This has led to extensive studies of different default levels, trends, and seasonal factors. The study of [4], found that significantly MAPE values change resulting from different initial settings. In [5], the author employed Extended Additive Holt-Winters and Holt-Winter methods with four initial settings to construct the forecasting models for Thailand's crude palm oil production and crude palm oil price. The results from both forecasting methods confirmed that different initial settings gave significantly different MAPE values. In [6], the author proposed a new default setting for the multiplicative Holt-Winters model compared to the original Holt-Winters setting and Hansun' s initial settings, [7]. The study showed that the proposed initial settings gave the best result for all ten datasets. Therefore, this research will examine various initiations that are proposed by the different studies.

Box-Jenkins method is reputable for providing high accuracy in short-term prediction. In [8], the author predicted the total imports and exports in Saudi Arabia by employing ANN and ARIMA models. It was found that both methods are appropriate for forecasting the total annual imports and exports of Saudi Arabia kingdom. Box-Jenkins method was applied to forecast the imports and exports of paper products in Turkey, [9]. Autoregressive with seasonal dummies and Box-Jenkins were employed to forecast the imports and exports of Pakistan and it was found that Box-Jenkins provided better accuracy for the exports and autoregressive with seasonal dummies demonstrated more precision for the imports, [10].

In recent years, Long Short-Term Memory Neural Networks (LSTM) gained popularity in time series forecasting. LSTM and ARIMA models were used to forecast Ecuador's imports of household appliances. The results revealed that the LSTM produced a better fit and improved predictions than the ARIMA model, [11]. The LSTM was used to forecast the total trade volume of China Shandong Province's imports and exports. The results revealed that the LSTM outperformed the cubic exponential smoothing method, [12]. In [13], the authors employed ARIMA, ETS, TBATS, SVR, RFR, LASSO, MLP, XGB, and HDL methods to predict the global trade of ten major countries. The results revealed that the Hybrid Deep Learning method provides the best performance. Therefore, this study employs the Holt-Winters Exponential Smoothing method with various initial settings, the Box-Jenkins method, and LSTM in the prediction of the electrical appliance export values of Thailand.

2 Data Collection and Methodology

Thailand's electrical appliances monthly export values are collected from the Information Technology and Communication Center, Ministry of Commerce from January 2006 to November 2022. The data from January 2006 to December 2021 were used to construct and select the forecasting models, and the remaining were used for measuring the model's accuracy. Three forecasting methods which are the Holt-Winters method with various initial settings, the Box-Jenkins method and LSTM are employed to construct the forecasting models.

2.1 Holt-Winters Method

The Holt-Winters exponential smoothing method is an analytical method that is suitable for time series with a linear trend and seasonality. It is often used for short-term forecasting. The Holt-Winter method deals with three smoothing parameters: α, γ, δ tuning levels, trends, and seasonal factors. The tuning parameters must have values between 0 and 1. The Holt-Winters method has two models: the additive model and the multiplicative model. The additive model is suitable for constant seasonal influences and the multiplicative model is fit for seasonal influences which variate to the trend value, [14].

2.1.1 Additive Holt-Winters Model

In the case of time series that has a linear trend, a constant slope (β_1) , and a constant seasonal fluctuation (S_t). Equation (1) is used to describe the time series with an additive model, [15].

$$Y_t = (\beta_0 + \beta_1 t) + S_t + \varepsilon_t \tag{1}$$

For the additive model, T_{t-1} and T_t are the time series level at time t-1 and t. T_{t-1} and T_t are defined as $T_{t-1} = \beta_0 + \beta_1(t-1)$, and $T_t = \beta_0 + \beta_1 t$. β_1 is the slope from time t to time t+1. Y_t, ε_t are the real data and the error at time t. $\hat{T}_t, b_t, \hat{S}_t$ are the estimated level, slope, and seasonality at time t. $\hat{T}_{t-1}, b_{t-1}$ are the estimated level and slope at time t-1. $\hat{S}_{t-L}$ is the estimated seasonality at time t-L and L is the number of seasons in a year. The smoothing equations (2)-(4) are used to update $\hat{T}_t, b_t, \hat{S}_t$ from time t-1 to time t, [13].

$$\hat{T}_t = \hat{T}_{t-1} + b_{t-1} + \alpha e_t \tag{2}$$

$$b_t = b_{t-1} + \alpha\gamma e_t \tag{3}$$

$$\hat{S}_t = \hat{S}_{t-L} + (1-\alpha)\delta e_t \tag{4}$$

2.1.2 Multiplicative Holt-Winters Model

In the case of time series has a linear trend with a constant slope β_1 and a variate seasonal fluctuation. The equation (5) is used to describe the multiplicative model.

$$Y_t = (\beta_0 + \beta_1 t) \times S_t \times \varepsilon_t \quad (5)$$

The smoothing equations (6)-(8) are used to update $\hat{T}_t, b_t, \hat{S}_t$ from time t-1 to time t for the multiplicative model.

$$\hat{T}_t = \hat{T}_{t-1} + b_{t-1} + \frac{\alpha e_t}{S_{t-L}} \quad (6)$$

$$b_t = b_{t-1} + \frac{\alpha\gamma e_t}{S_{t-L}} \quad (7)$$

$$\hat{S}_t = \hat{S}_{t-L} + \frac{(1-\alpha)\delta e_t}{T_t} \quad (8)$$

2.1.3 Holt-Winters Model with Different Initial Settings

The different initial settings provide different accuracy of the Holt-Winters model. This research divides the initial settings into two categories. The first category consists of seven different patterns. The seasonal influence patterns 1-6 for the additive model are given by equation (9), and for the multiplicative model are given by equation (10). The seasonal influence patterns 7 are computed by using the ratio to moving average method to decompose the time series and get b_0, b_1 for level, slope, and $\hat{S}_t$ seasonal factor, then using only seasonal factor, [6].

$$\hat{S}_i = Y_i - \hat{T}_L \quad ;i = 1,\ldots L \quad (9)$$

$$\hat{S}_i = \frac{Y_i}{\hat{T}_L} \quad ;i = 1,\ldots L \quad (10)$$

The level component of patterns 1-5 for both the additive model and multiplicative model is given by equation (11).

$$\hat{T}_L = \frac{(Y_1 + Y_2 + \cdots + Y_L)}{L} \quad (11)$$

The level component for patterns 6-7 is defined as equation (12), [6].

$$\hat{T}_L = \frac{LY_L + (L-1)Y_{L-1} + \cdots + (L-m+1)Y_{L-m+1}}{L + (L-1) + \cdots + (L-m+1)} \quad (12)$$

Pattern 1: [16], [17], suggested the growth component as equation (13).

$$b_L = \frac{1}{L}\sum_{i=1}^{L}\left(\frac{Y_{i+L} - Y_i}{L}\right) \quad (13)$$

Pattern 2: [4], [18], advised the growth component as equation (14).

$$b_L = Y_2 - Y_1 \quad (14)$$

Pattern 3: [4], [18], suggested the growth component as equation (15).

$$b_L = \frac{(Y_2 - Y_1) + (Y_3 - Y_2) + (Y_4 - Y_3)}{3} \quad (15)$$

Pattern 4: [4], [18], proposed the growth component as equation (16).

$$b_L = \frac{Y_L - Y_1}{L - 1} \quad (16)$$

Pattern 5: [4], [18], recommended the growth component as equation (17).

$$b_L = 0 \quad (17)$$

Pattern 6-7: [7], suggested the growth component as equation (18).

$$b_L = \frac{1}{L^2}\left(\frac{2LY_{2L} + (2L-1)Y_{2L-1} + \cdots + (L+2)Y_{L+2} + (L+1)Y_{L+1}}{2L + (2L-1) + \cdots + (L+2) + (L+1)} - \frac{LY_L + (L-1)Y_{L-1} + \cdots + 2Y_2 + Y_1}{L + (L-1) + \cdots + 2 + 1}\right) \quad (18)$$

The second category employs the data from the first 2-15 years (K=2,…,15) to calculate label, trend, and seasonal components by using the ratio to moving average method to decompose the time series. Then get b_0, b_1 for level and slope of a linear trend and $\hat{S}_t$ seasonal factor, and calculates $\hat{T}_t$ by applying equation (19)-(20). t denotes the number of data used in calculating initial settings.

$$\hat{T}_t = b_0 + b_1 \times t \quad (19)$$

$$b_L = b_1 \quad (20)$$

This research employed the Solver module in Microsoft Excel to estimate the smoothing parameters: α, γ, δ to obtain the minimum RMSE.

2.2 Box-Jenkins Method

The Box-Jenkins method is widely used in modeling and forecasting. The Box-Jenkins method defines a predictive model by first checking whether it is stationary. Stationary time series have a constant mean and variance. If the time series has a trend, it will be converted to stationary by taking the difference. If the time series has seasonal influences, it is converted to stationary by seasonal difference. In case of time series have an inconstant variance, taking a log is performed to make the time series stationary. Once the stationary time series is established, there are four steps to analyze, [15]:

Step 1. Find models that are expected to be suitable by considering the correlogram of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the time series which are similar to the ACF and PACF of the population.

Step 2. Estimate parameters of the model from time series data.

Step 3. Check whether the model set in Step 1 is suitable, by performing various tests. If the model fails, then adjust the model and return to Step 2.

Step 4. If the model passes all the tests in Step 3, the model can be used for forecasting, then Equation (21) is used to predict future values.
The Box-Jenkins model is defined as follows, [19]:

$$\phi_a(B)\Phi_A(B^L)Z_t = \theta_0 + \theta_b(B)\Theta_B(B^L)\varepsilon_t \quad (21)$$

when

$$\phi_a(B) = (1-\phi_1 B - \phi_2 B^2 - \ldots - \phi_a B^a)$$
$$\Phi_A(B^L) = (1-\Phi_{1L}B^L - \Phi_{2L}B^{2L} - \ldots - \Phi_{AL}B^{AL})$$
$$\theta_b(B) = (1-\theta_1 B - \theta_2 B^2 - \ldots - \theta_b B^b)$$
$$\Theta_B(B^L) = (1-\Theta_{1L}B^L - \Theta_{2L}B^{2L} - \ldots - \Theta_{BL}B^{BL})$$
$$Z_t = (1-B)^d (1-B^L)^D Y_t$$

The d regular difference and D seasonal difference are taken to make the time series stationary. The real data at time t are defined by Y_t. The constant term is defined by θ_0. The order of the non-seasonal autoregressive model is defined by $\phi_a(B)$. The order A of the seasonal autoregressive model is defined by $\Phi_A(B^L)$. The order b of the non-seasonal moving average model is defined by $\theta_b(B)$. Order B of the seasonal moving average model is defined by $\Theta_B(B^L)$. L is the number of seasons in a year. The error at time t is defined as ε_t which has a normal distribution with zero mean and constant variance and ε_t is statistically independent.
Minitab 21.1.0 was used to analyze the Box-Jenkins model in this research.

2.3 Long Short-Term Memory Networks (LSTM)

Artificial Neural Networks (ANN) are built to imitate the human brain to create the capability of learning patterns, recognition, and the extraction of new knowledge, [20].

Neural Networks are a branch of Artificial Intelligence. Neural Networks use backpropagation algorithms to simulate human-like learning. There are two methods of learning. Supervised learning is the process of training computers to solve problems by providing information and target outcome. Unsupervised learning is the algorithm of training a computer by giving unspecific data and letting the computer learn the relationship between them.

LSTM is a recurrent neural network in which the output layer can be fed back into the network. LSTM introduces a memory cell and three gates: input, output and forget gates. The input gate accepts the new data to enter the cell state. The forget gate determines whether the data that enters the cell state should be kept or discarded. The selected data is evaluated from the input data of that node plus the results of the previous node. The output gate prepares data for output.

The data from January 2006 to December 2021 are separated into 70:30. The electrical appliance export values from January 2006 to February 2017 are employed as the training set used for training LSTM. The electrical appliance export values from March 2017 to December 2021 are employed as the test set. The data from January 2022 to November 2022 are used as the validation set. This research employs Python in modeling LSTM. The number of nodes in the input layer is set to 12, 13, 14, 15, and 16 nodes because this time series has both trends and seasonal influences. This research varies the hidden neurons from 2-15 nodes and varies epochs from 100, 200, 300, 400, and 500 epochs. Adam optimizer is used with a learning rate of 0.001 and a momentum of 0.9.

3 Criterion for Model Selection

The forecasting model with the smallest root mean square error was chosen. Then mean absolute percentage error was used to calculate the model's accuracy.

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m} e_t^2} \quad (22)$$

$$MAPE = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{e_t}{Y_t}\right| \times 100 \quad (23)$$

4 Results

The Holt-Winters models with different initial settings, Box-Jenkins models, and LSTM models are built for Thailand's electrical appliances export values.

4.1 The Holt-Winters Method

The results from Holt-Winters models with various initial settings were shown in Tables 1 and 2.

Table 1. RMSE of Holt-Winters models with seven different settings

Pattern	Additive model	Multiplicative model
1	3,963.13**	4,103.39**
2	4,098.47**	4,160.79**
3	4,492.53**	4,431.10**
4	4,012.42**	4,113.16**
5	3,972.70**	4,102.35**
6	3,970.68	4,101.46**
7	3,634.90**	3,673.52

** *Residuals have normal distribution at* $a = 0.01$

Table 2. RMSE of Holt-Winters models with different settings from the decomposition method.

Number of years (K)	Additive model	Multiplicative model
2	4,118.17	4,303.69*
3	3,697.96*	3,892.27*
4	3,851.76*	4,672.54*
5	3,716.52	3,811.19
6	3,794.90	3,828.32
7	3,548.65*	3,596.57*
8	3,519.28*	3,647.69*
9	3,717.16*	3,849.71*
10	3,778.39*	3,864.07*
11	3,843.95	3,910.68*
12	4,007.99	4,017.87*
13	4,028.65*	4,033.21*
14	4,007.01	3,993.70*
15	5.623.00*	5,478.79*

**Residuals have normal distribution at* $a = 0.05$

From Table 1, the Holt-Winters models with initial settings pattern 7 obtained the smallest RMSE for both additive and multiplicative models, where the additive model yielded the minimum RMSE of 3,634.90. This result confirmed that the Holt-Winters method with the initial setting proposed by [6], could be a choice to estimate the initial settings for the Holt-Winters method. Residuals from all settings did not have a normal distribution $a = 0.05$, but some had a normal distribution $a = 0.01$.

From Table 2, the additive Holt-Winters with the initial values from the decomposition method, which the initial settings computed from the first eight years of data gained the minimum RMSE of 3,519.28. The initial settings computed from the first seven years of data gave the minimum RMSE for the multiplicative Holt-Winters model. It was found that the residuals from nearly every model had a normal distribution. Therefore, the initial settings from the decomposition method are suitable for the Holt-Winters method.

4.2 Box-Jenkins Method

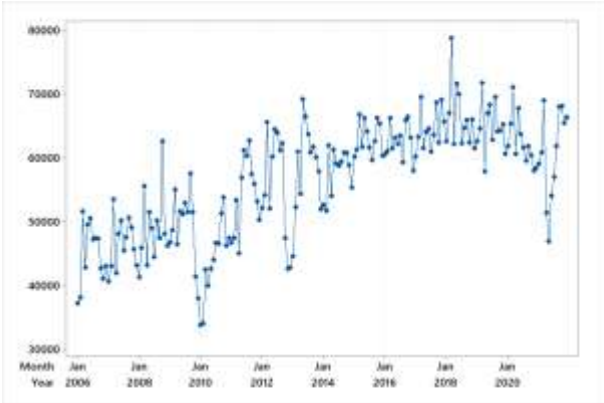

Fig. 1: Thailand's electrical appliances export values from January 2006 to December 2021

From Figure 1, Thailand's electrical appliances export values showed a non-linear trend and seasonal fluctuation. To make the time series stationary, one regular difference (d=1) and one seasonal difference (D=1) were taken. According to Autocorrelation Function (ACF) in Figure 2 and Partial Autocorrelation Function (PACF) in Figure 3, ACF were decreasing after lag 3 and PACF were decreasing after lag 4. Then it was proposed to be a $ARIMA(3,1,4)$ model. In the seasonal part, ACF at lag 12, 24, 36,… were decreasing rapidly and PACF was cut off at lag 48. Then it was suggested to be a seasonal model $SARIMA(4,1,0)_{12}$. Unfortunately, the residuals of the model correlate with each other. The model $ARIMA(3,1,3) \times SARIMA(4,1,0)_{12}$ was suggested.

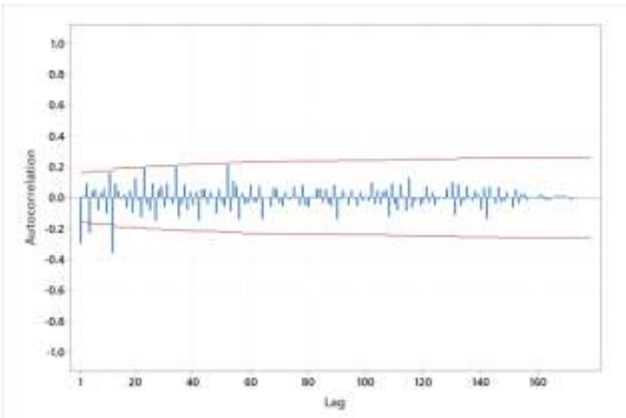

Fig. 2: ACF of Thailand's electrical appliances export values with d=1 and D=1

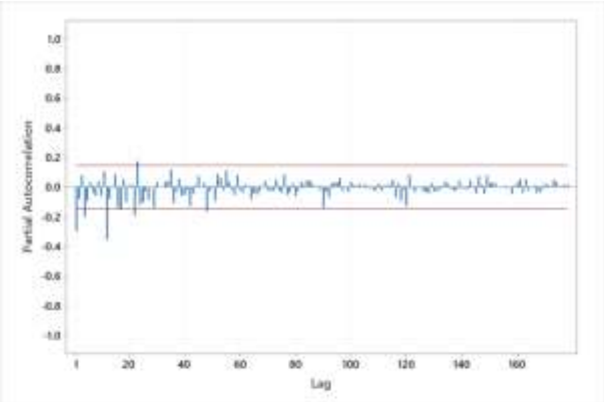

Fig. 3: PACF of Thailand's electrical appliances export values with d=1 and D=1

Table 3 showed all parameters of the model $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$ were statistically significant from zero (p-value was less than 0.05). From the Box-Ljung test, the residuals of the model for all lags were statistically independent (the p-value was larger than 0.05). Therefore, the $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$ model passed the diagnostic check. In addition, the residuals of Box-Jenkins models needed to have a normal distribution. The Anderson-Darling test was employed to test the normality of residuals. Figure 4, showed residuals of the model $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$ had a normal distribution because the p-value was greater than 0.05 (p-value = 0.162). Some other models passed the diagnostic checking but the residuals did not have a normal distribution. Therefore, the model $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$ was the only model that fitted Thailand's electrical appliances export values.

Table 3. Minitab output of the model $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$

Type	Coef.	SE. Coef.	t-value	p-value
ϕ_1	0.8198	0.0868	9.44	0.000
ϕ_2	-0.7280	0.1280	-5.67	0.000
ϕ_3	0.4840	0.1090	4.44	0.000
Φ_{12}	-0.6652	0.0773	-8.61	0.000
Φ_{24}	-0.5773	0.0878	-6.57	0.000
Φ_{36}	-0.5555	0.0868	-6.40	0.000
Φ_{48}	-0.5518	0.0778	-7.09	0.000
θ_1	1.1032	0.0458	24.09	0.000
θ_2	-1.0167	0.0886	-11.47	0.000
θ_3	0.8907	0.0711	12.53	0.000
Modified Box-Pierce(Box-Ljung) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	5.71	13.23	32.08	48.07
DF	2	14	26	38
p-value	0.079	0.595	0.173	0.129

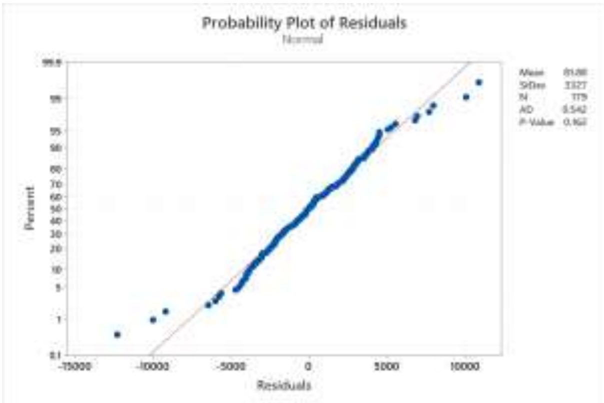

Fig. 4: Anderson-Darling normality test for residuals of the $ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$ model

4.3 Long Short-Term Memory Networks (LSTM)

Increasing the input nodes, the RMSE of the training set was decreasing significantly. On the contrary, the RMSE of the testing set was increasing. To avoid overfitting, the selected model should have the RMSE of the training set and testing set, which have similar values with minimal RMSE. The optimal model of LSTM was 14-5-1 with 300 iterations. The RMSE of the model was shown in Table 4.

Table 4. The RMSE of the training set, test set, and validation set

Model	RMSE		
	Training set	Test set	Validation set
14-5-1	3,566.07	3,545.14	3,570.35

Table 5. The RMSE from three predicting methods

Forecasting model	RMSE
The additive Holt-Winters model with initial setting 7	3,634.90
The additive Holt-Winters model with the initial setting from the decomposition method (The initial settings computed from the first eight years of data)	3,519.28
$ARIMA(3,1,3)\times SARIMA(4,1,0)_{12}$	3,415.49
LSTM	3,545.14

4.4 Model Selection and Performance Measure

From Table 5, the Box-Jenkins model obtained the smallest RMSE. The additive Holt-Winters method with initial settings from the decomposition method, which have the initial settings computed from the first eight years of data, gave the minimum RMSE for the Holt-Winters method. Therefore, the Box-Jenkins method was the most appropriate forecasting method for Thailand's electrical appliance export values and obtained a MAPE of 8.0%. The actual, fits and forecasts from the Box Jenkins method are presented in Figure 5.

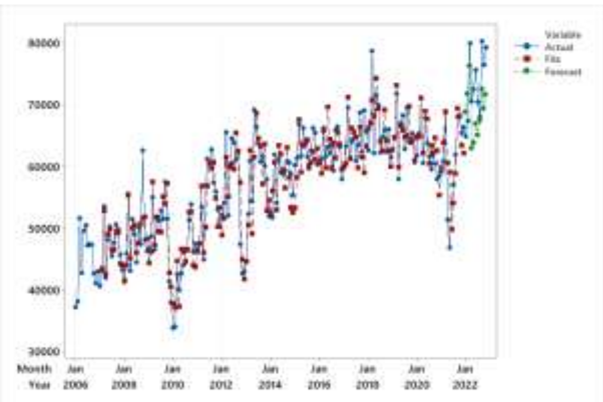

Fig. 5: Actual, fits and forecasts from Box-Jenkins method

5 Conclusion and Discussion

This research presents three different forecasting methods: the Holt-Winters method with different initial settings, the Box-Jenkins method, and LSTM to model Thailand's electrical appliance export values. The results revealed that the Box-Jenkins method gives the best forecasting model for Thailand's electrical appliance export values and yields a MAPE of 8.0%. Therefore, the model should be used to predict Thailand's electrical appliance export values.

The study confirms that Box-Jenkins is a powerful method for time series forecasting. LSTM usually gives the best result. However, this research LSTM does not give the best result since the training data may need to be larger. LSTM requires many data for training and much time for tuning the hyper-parameter of the networks to get a good result. In case of time and data are limited, the Holt-Winters method with initial settings from the decomposition method and the Box-Jenkins method are good choices for time series forecasting.

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Contribution of Individual Authors to the Creation of a Scientific Article

Somsri Banditvilai and Yuwadee Klomwises equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

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