A comparison forecast volume of outbound containers in case of The Bangkok port Between Exponential Smoothing and ARIMA Model

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Abstract: This research aims to compare the forecast of container consumption between Exponential Smoothing and ARIMA methods and make a forecast volume of outbound containers from Bangkok Port. Using time series data of the quantity of containers departing from Bangkok ports from January 2011 to December 2020 from Port authority of Thailand. By using the criterion of the root mean squared error (RMSE), it was found that the ARIMA forecasting method was more suitable for this set of time series data than the Exponential Smoothing method. The ARIMA forecasting method was root mean square error (RMSE) is 3310.72 and the exponential smoothing method was root mean square error (RMSE) is 3381.09 However, both methods could be used combined for forecasting to serve as an appropriate forecast model.

Index Terms: Quantity of containers, ARIMA, Exponential smoothing

1. Introduction

Container shortage is disrupting the supply chain in Thailand over the past 2-1 years (2021-2020), resulting in a shortage of 5.1 million container containers in .2020 As a result, the export of products to foreign countries has a wide impact on the industrial sector in Thailand. In an interview with Miss Ghanyapad Tantipipatpong, chair of the Thai National Shippers' Council (TNSC) said that the problem is that China, the world's largest exporter, has a demand for more than 200 million containers a year and demand for exports of Vietnam, which has experienced a high economic growth, thus make shipping lines opted to provide services to China and Vietnam earlier due to higher freight rates than Thailand [1] [2]. It also said that the impact of the shortage of container trainers for export was another major cause of the Covid-19 virus epidemic, which resulted in huge impact on global supply chains. As a result, the global export of container-packed goods, especially in China, was the most affected and this impact spread throughout the world.

Nevertheless, the growth of ocean freight through container trainers is also becoming increasingly important in shipping and economic development in Asia, whether it is the export of industrial products, agricultural products and food-related goods [3].

Therefore, the planning and management of the container empty container is an important issue for the container port, in order to balance trade and exports to the global freight routes. Container volume allocation planning is a key point of shipping business planning, whether it is container demand planning and managing market condition uncertainty. This can affect third party logistics providers, resulting in increased operating costs and lower incomes if shortage of containers occurs [4]. Thus, of great interest today is the short-term forecast of container consumption for domestic exporters (1 Year), how much the appropriate number should be to prepare and prevent any problems that may arise in the future for third party logistics providers. It is also a guideline for relevant agencies such as the Port Authority of Thailand and the Thai National Shippers' Council (TNSC) to find a way to prevent problems that will affect the economic growth of the country that relies on the export of goods to earn income into the country.

2. Research Objectives

To compare forecasting results of container consumption between Exponential Smoothing Method and ARIMA Method and forecast container consumption for Thai exports from Bangkok Port. (Note: Container counts are compared to 20 ft container sizes and are TEU (Twenty-Equivalent Unit) units) 20 foot container = 1 TEU. 40 foot container = 2 TEU).

3. Lierature Review

The inbound-outbound volume of the container is an indication of how important the port value is in terms of how it operates and drives the nation's economy [5]. In particular, the Maritime operators face great challenges in the Covid-19 Coronavirus (COVID-19) situation. From this situation it has had a chain effect since it caused disruption in the supply chain of the product and the effect spread throughout the world, causing international shipping to have an impact on global supply chains due to the manufacturing sector where consumption for businesses must connect goods and services worldwide through shipping via sea containers [2]. In doing business all over the world that must be connected is an important part of the results that when one country in the world has a problem, it will have an impact on different countries, for example, in the case of China's Covid-19 Coronavirus (COVID-19) crisis, China's economy slows down and production disruptions including China's global supply chain is inevitably affected. When China was unable to produce its products, it resulted in a problem with its shipments to the distributed consumer countries in the world, and ultimately a contraction in global economic activity [6].

When the transport of goods is disrupted, sea freight activities through the container are inevitably affected because if the cargo is not shipped with a container, the quantity of the container will be unbalanced. Global shipping demands empty containers to prepare for export; therefore, the forecasting plan for the container machine is especially important in this critical situation. In previous studies, there were a number of studies using different container machine forecasting schemes, for example, a comparative study of the container forecasting method at Lianyungang Port and Shanghai Port by using Gray forecasting modeling, triple exponential smoothing model, multiple linear regression model, and backpropagation neural network [7]. In the study of fulfillment, it is a shipping agent container service provider in preparing an empty container for pick-up in the container depot in order to improve the service efficiency of the ship line and increase the efficiency of the supply chain in Thailand [8], forecasting of container box against COVID-19 situation impact using Seasonal Autoregressive Integrated Moving Average (SARIMA) technique and the Exponential Smoothing State Space Model (ETS) technique to determine the appropriate method for the situation [2].

There are various forecasting models used, including the Box-Jenkins Method (ARIMA), which is commonly used in time series analysis [9], [10], [11] forecasting models or Exponential Smoothing Methods [9], [12] forecast models that are generalized forecast that are seasonal [11].

4. Research Methods

This research used empirical, social science and quantitative research models using time series data and the number of outbound container uses. In the case of Bangkok Port that serve monthly service from January 2011–December 2020, a total of 120 months has been used statistical data from the Port Authority of Thailand. The model used in forecasting is the exponential smoothing model [13] and ARIMA Model [14]. The program Eviews [15] is used to process and analyze data.

Validity analysis of forecast

In practice, more than one pattern of good time series analysis may be found. Therefore, if it is necessary to select a forecast model that analyzes historical data, which format should be used, it may be determined by the value of the Root Mean Square Error (RMSE) [12], [2], [5].

$$\text{RMSE} = \sqrt{(e^2/n)}$$

where e = Error value

5. Research Results

Exponential Smoothing Forecast is a monthly quantitative analysis of outbound containers in Bangkok Port from January 2011 to December 2020, total of 120 months. When using the data to create a graph, the graph will be formed as shown in Figure 1.

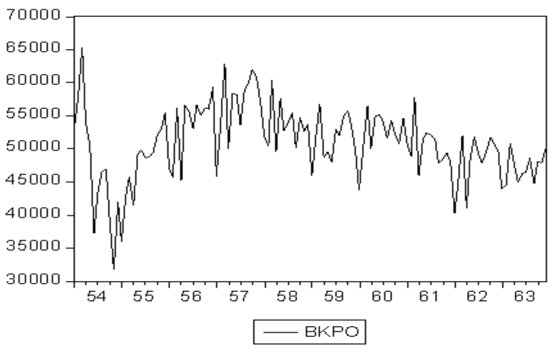


Figure 1 shows a graph of outbound container volumes from Bangkok Port from Jan 2011 to Dec 2020 (Unit: TEU.)

The nature of the data graph shows that the data is both trend and season. For forecasting using the Exponential Smoothing method, Holt-Winters-Additive and Holt-Winters-Multiplicative [16], [12] were used. One of these two methods is considered appropriate for the forecast.

Table1 shows the results of the analysis by Exponential smoothing, Holt-Winters-Additive and Multiplicative.

Model	Parameters			Sum of Squared Residuals	Root Mean Squared Error	End of Period Levels	
	Alpha	Beta	Gamma			Mean	Trend
Holt-Winters-Additive	0.6900	0.0000	0.0000	1,390,000,000	3404.561	48623.19	-2.5949
Holt-Winters-Multiplicative	0.6700	0.0000	0.0000	1,370,000,000	3381.093	48632.50	-2.5949

When comparing Exponential Smoothing in both Holt-Winters-Additive and Holt-Winters-Multiplicative, it was found that Holt-Winters-Multiplicative gave lower statistical measure of Sum of squared Residuals and Root Mean Squared Error. Therefore, the one-year forecast from January 2021 to December 2021 will use the Holt-Winters-Multiplicative method to forecast outbound container volume from Bangkok Port. This can be determined from Figure 2, where the actual data is the BKPO line; the forecast data is the BKPOSM line.

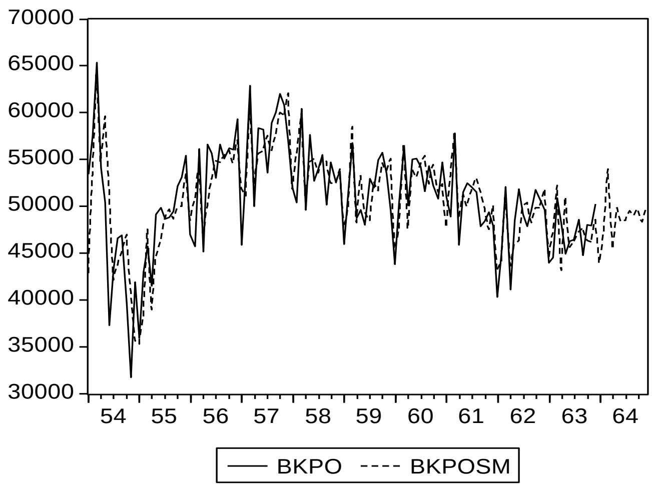


Figure 2 shows the forecast numbers for outbound containers from Bangkok Port in 2021

Table 2 shows the forecast numbers for outbound containers from Bangkok Port in 2021

Month	Number of containers, units as TEU
February 2021	46,976
March 2021	54,014
April 2021	45,456
May 2021	49,836
June 2021	48,435
July 2021	48,504
August 2021	49,487
September 2021	49,011
October 2021	49,705
November 2021	48,336
December 2021	49,643

Forecasting by ARIMA method

Since it was initially known that the nature of the analyzed data tended to be seasonal (and the variance was not constant). ARIMA computation is only necessary to stabilize the data, so it is necessary to make the time series data stationary by calculating normal difference, season difference and take log to reduce the variance, that is, Z = d (log (BKPO), 1,12), when modified, the stationary properties can be examined by considering both the graph and the Unit Root test.

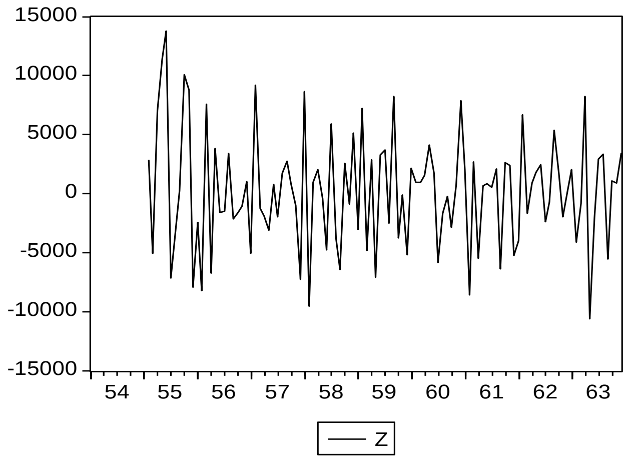


Figure 3 shows the transformation curve by finding normal and season differences in the 1st order

From observing the graph, series z has no constant (θ_0) and yet there is no trend and season, which shows that series z is already stationary. Also, when the unit root of series z is obtained, it is found that it is stationary.

Table 3 shows Augmented Dickey – Fuller Unit Root test on z

Null Hypothesis: Z has a unit root
Exogenous: None
Lag Length: 12 (Automatic based on SIC, MAXLAG=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.633956	0.0004
Test critical values:	1% level	-2.589795	
	5% level	-1.944286	
	10% level	-1.614487	

*MacKinnon (1996) one-sided p-values.

The ARIMA configuration from the correlogram of series z above will be taken into account of the autocorrelation (ACF) correlogram and partial autocorrelation (PACF) to define Autoregressive: AR (p) and Moving Average: MA (q). The results are as shown in Table 4 below.

Table4 shows the correlogram of z data when transforming with normal and season variance in the 1st order

Date: 02/03/21 Time: 10:50
Sample: 2554:01 2564:01
Included observations: 107

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>**|. |</td><td>**|. |</td><td>1</td><td>-0.240</td><td>-0.240</td><td>6.3155</td><td>0.012</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>2</td><td>-0.060</td><td>-0.124</td><td>6.7113</td><td>0.035</td></tr>
<tr><td>.*|. |</td><td>**|. |</td><td>3</td><td>-0.156</td><td>-0.217</td><td>9.4276</td><td>0.024</td></tr>
<tr><td>. |* |</td><td>. |. |</td><td>4</td><td>0.116</td><td>0.008</td><td>10.952</td><td>0.027</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>5</td><td>-0.035</td><td>-0.045</td><td>11.088</td><td>0.050</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>6</td><td>0.038</td><td>0.005</td><td>11.254</td><td>0.081</td></tr>
<tr><td>. |* |</td><td>. |** |</td><td>7</td><td>0.189</td><td>0.246</td><td>15.399</td><td>0.031</td></tr>
<tr><td>**|. |</td><td>.*|. |</td><td>8</td><td>-0.223</td><td>-0.133</td><td>21.274</td><td>0.006</td></tr>
<tr><td>. |* |</td><td>. |* |</td><td>9</td><td>0.125</td><td>0.123</td><td>23.128</td><td>0.006</td></tr>
<tr><td>.*|. |</td><td>.*|. |</td><td>10</td><td>-0.148</td><td>-0.090</td><td>25.767</td><td>0.004</td></tr>
<tr><td>. |** |</td><td>. |* |</td><td>11</td><td>0.245</td><td>0.155</td><td>33.055</td><td>0.001</td></tr>
<tr><td>***|. |</td><td>**|. |</td><td>12</td><td>-0.370</td><td>-0.309</td><td>49.840</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>.*|. |</td><td>13</td><td>0.049</td><td>-0.150</td><td>50.142</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>14</td><td>0.053</td><td>-0.009</td><td>50.497</td><td>0.000</td></tr>
<tr><td>. |* |</td><td>. |. |</td><td>15</td><td>0.069</td><td>-0.014</td><td>51.109</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |. |</td><td>16</td><td>-0.033</td><td>-0.007</td><td>51.249</td><td>0.000</td></tr>
<tr><td>. |* |</td><td>. |** |</td><td>17</td><td>0.094</td><td>0.229</td><td>52.391</td><td>0.000</td></tr>
<tr><td>. |. |</td><td>. |* |</td><td>18</td><td>0.047</td><td>0.084</td><td>52.674</td><td>0.000</td></tr>
</table>

From the correlogram, possible predictors must be determined from the constant ACF and PACF curves of time series to select the most suitable model based on Akaike info criterion and Schwarz criterion, it was found that the most suitable model of series z or d (log (BKPO), 1,12) was AR(1) $SMA(1)_{12}$ model, no fixed term.

Table5 shows the results of the models used in the ARIMA forecast

Dependent Variable: D(LOG(BKPO),1,12)
Method: Least Squares
Date: 02/03/21 Time: 15:19
Sample(adjusted): 2555:03 2562:12
Included observations: 94 after adjusting endpoints
Convergence achieved after 9 iterations
Backcast: 2554:03 2555:02

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR (1)	-0.400124	0.094769	-4.222077	0.0001
MA (12)	-0.945468	0.011727	-80.62242	0.0000
R-squared	0.744032	Mean dependent var		0.003473
Adjusted R-squared	0.741250	S.D. dependent var		0.100303
S.E. of regression	0.051022	Akaike info criterion		-3.092089
Sum squared resid	0.239495	Schwarz criterion		-3.037976
Log likelihood	147.3282	Durbin-Watson stat		2.140440
Inverted AR Roots	-.40			
Inverted MA Roots	1.00	.86 -.50i	.86+.50i	.50+.86i
	.50 -.86i	.00+1.00i	-.00 -1.00i	-.50+.86i
	-.50 -.86i	-.86+.50i	-.86 -.50i	-1.00

From Table 5, when examining statistical significance, it was found that it was statistically significant at a 99% confidence level. In this model, the error value is prop <0.05, so the error value of the model has no Unit Root.

Table6 shows the Augmented Dickey - Fuller Unit Root test for the error model

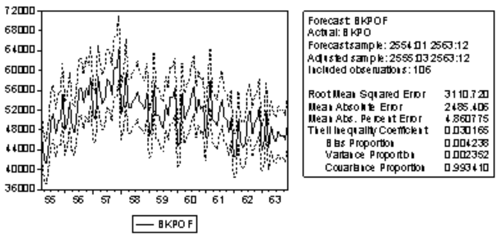
Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic based on SIC, MAXLAG=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.926011	0.0000
Test critical values:	1% level	-3.494378	
	5% level	-2.889474	
	10% level	-2.581741	

*MacKinnon (1996) one-sided p-values.

Therefore, it can be said that the AR (1) SMA (1) 12 model is an efficient and suitable forecasting model to be used for further forecasting. The following graphs of estimates and model scorecards are obtained.

Figure 4 shows the model's estimate curves and scorecards.



Note that the root means square error of the forecasting method ARIMA (3,110.72) is lower than the same value of the Holt-Winters-Multiplicative Exponential Smoothing Forecast (3,381.09).

When using the ARIMA to forecast outbound container volumes from Bangkok Port from January 2021 to December 2021, the following data were obtained:

Table7 shows the forecast numbers for outbound containers from Bangkok Port in 2021using the ARIMA method.

Month	Forecast Value Number of containers, units as TEU
January 2021	43,178
February 2021	45,521
March 2021	52,178
April 2021	45,656
May 2021	47,551
June 2021	47,082
July 2021	47,257
August 2021	48,596
September 2021	46,963
October 2021	48,482
November 2021	47,409
December 2021	49,154

As a result of both forecasting methods, the ARIMA forecast method yields the root mean square error: RMSE lower than the Holt-Winters-Multiplicative Exponential Smoothing forecast. It can be seen that the ARIMA forecasting method is more appropriate because it correlates with the actual data higher than that of the Holt-Winters-Multiplicative Exponential Smoothing method. However, the forecast values of both methods are considered reliable because they significantly correlate with the actual data.

Combining forecast

As there is no technique that can forecast accurately in every situation and every forecast period, several forecasting techniques were incorporated [17], [18] to represent forecast including a combination of forecasting techniques by weighting, measuring the accuracy of Average Absolute Forecast Error (AFE), data utilization of forecasting using the Holt-Winters-Multiplicative method of exponential smoothing and ARIMA method from January 2021 to December 2021, then used to create the combined forecast equation.

where $F_{et} = W_1F_{1t} + W_2F_{2t}$

F_{et} = Forecast value in the case of combined forecast

F_{1t} = Forecasting value in technique 2(exponential smoothing – Multiplicative)

F_{2t} = Forecasting value in technique 2(ARIMA)

W_1, W_2 = Weighted value by AFE method

Where $W_1 = \Sigma|e_{F1t}|/|e_{F1t} + e_{F2t}|$

$W_2 = \Sigma|e_{F2t}|/|e_{F1t} + e_{F2t}|$

The combined forecast equation will be obtained as follows:

$$F_{et} = 0.44F_{1t} + 0.56F_{2t}$$

Table8 summarizes the forecast of outbound containers from Bangkok Port (TEU.)

Installment	Forecasting by exponential smoothing - Multiplicative	Forecast value by ARIMA method	Combined forecast
January 2021	43,982	43,178	43,619
February 2021	46,976	45,521	46,832
March 2021	54,014	52,178	53,124
April 2021	45,456	45,656	43,564
May 2021	49,836	47,551	50,483
June 2021	48,435	47,082	48,157
July 2021	48,504	47,257	47,892
August 2021	49,487	48,596	48,440
September 2021	49,011	46,963	48,934
October 2021	49,705	48,482	48,913
November 2021	48,336	47,409	47,979
December 2021	49,643	49,154	49,332

6. Discussions

This research would like to propose the construction and selection method appropriate for the time series of outbound container volumes from Bangkok Port using monthly data from January 2011 to December 2020, total of 120. There are two methods of statistical forecasting, exponential smoothing and ARIMA, using the square root criterion of the mean squared error (RMSE). It was found that ARIMA was more suitable for this set of time series than Exponential Smoothing (Holt-Winters-Multiplicative) method. It could be said that both methods have one part in common that is past valuesand error term. Both methods differ in the process of assigning weight to past lag values and determination of the weight of the discrepancy. In many studies, ARIMA forecast is generally better than exponential smoothing. This is consistent with the work of [19], [12], [9] in which the forecasting method was compared between ARIMA and exponential smoothing, indicating that the ARIMA model was able to produce better long-term forecasts in the event of limited data sources, but failed to produce better forecasts for time series with a narrow range from point to point. On the other hand, the Exponential Smoothing Method can create a better forecast for data with a narrow range from point to point, such as information about exchange rates. But it is not possible to forecast for time series data with longer forecast intervals.

In addition, the ARIMA model forecasting method is suitable and efficient in the context of supply chain and seasonal data [10], at the same time, in order to achieve more accurate forecasting, [5] it was suggested that the combination forecast method should be used.

7. Conclusion

This research seeks to explain that the use of a time-series forecasting tool may be appropriate to select different forecasting methods. However, for forecasts that are likely to increase reliability, other relevant factors should be taken into account, such as the value of merchandise exports.

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