Study of Several Exponential Smoothing Methods for Forecasting Crude Palm Oil Productions in Thailand

Kittiphoom Suppalakpanya[1], Ruamporn Nikhom[2], Thitima Booranawong[3] and Apidet Booranawong[4*]

[1]Faculty of Agro-Industry, Rajamangala University of Technology Srivijaya, Nakhon Si Thammarat, Thailand
[2]Faculty of Engineering, Thaksin University, Phatthalung Campus, Phatthalung, Thailand
[3]Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, Nakhon Si Thammarat, Thailand
[4]Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla, Thailand

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Abstract

In this paper, a study of several exponential smoothing methods for forecasting crude palm oil productions in Thailand during January 2018 to March 2018 is presented. The exponential smoothing methods include the Double Exponential Smoothing (DES) method, the Multiplicative Holts-Winters (MHW) method, the Additive Holt-Winters (AHW) method, the Improved Additive Holts-Winters (IAHW) method, and the Extended Additive Holts-Winters (EAHW) method. The input data from January 2006 to December 2017 are collected from the database of the Department of Internal Trade, Ministry of Commerce, Thailand. The major contributions of our paper are twofold. First, the well-known exponential smoothing methods (i.e. the DES, the MHW, and the AHW methods) and the recent methods proposed in the literature (i.e. the IAHW and the EAHW methods) are tested and evaluated. Here, the best forecast results by optimal solutions are determined. Second, different sets of input data including 3-year data (2015-2017), 6-year data (2012-2017), 9-year data (2009-2017), and 12-year data (2006-2017) are used as the inputs for all forecasting methods. Here, how the different sets of input data affect forecasting accuracy are revealed. Our study demonstrates that the traditional AHW and the recently proposed EAHW methods provide the smallest forecasting error measured by Mean Absolute Percentage Error (MAPE) in forecasting crude palm oil productions. The study also indicates that both the AHW and the EAHW methods significantly show accurate forecast results when 12-year input data are applied. Forecast results of January 2018 to March 2018 and the trends of the average monthly and yearly palm oil productions are also reported. We believe that the research methodology and results presented in this work can be useful for strategy setting of the Thai agriculturist and government.

Keywords: exponential smoothing methods, forecasting, crude palm oil productions, Thailand
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*Corresponding author: Tel.: 66 74 558831 Fax: 66 74 287276
E-mail: apidet.boo@gmail.com, apidet.b@psu.ac.th

1. Introduction

Oil palm (*Elaeis guineensis*) is the most popular oil crop in tropical rain forest regions. Thailand is the third largest palm oil producers in the world, following Indonesia and Malaysia [1]. Most of the palm oil produced in Thailand is used for domestic consumption in terms of food and an alternative fuel feedstock. During 2012-2016, the volume of crude palm oil consumed for food products and biodiesel was increased by 1.78% and 8.11% per year, respectively [2]. To arrange the food security and economic stability, the Thailand government, by the Department of Energy Business, allocates biodiesel productions with some flexibility blending ratios of B100 (pure biodiesel) and diesel, based on the volume of crude palm oil output situation. The biodiesel blending ratio which commonly used in Thailand is varied from B3 to B7 (or 3%v/v to 7%v/v biodiesel blended with diesel) [3]. As on the 1st quarter of 2017, the volume of crude palm oil obviously increased, thus the Department of Energy Business had an announcement to raise the biodiesel blending ratio from B5 to B7 on 8 May 2017. Hence, the excess volume of crude palm oil supplied from markets was absorbed to prevent the fall in oil price problem. For this reason, an accuracy of forecasting future volume of crude palm oil with appropriate forecasting methods is an implement for the government to make immediate decision and to devise a suitable strategic plan of palm oil management in Thailand.

To forecast time-series data, the well-known traditional exponential smoothing methods are widely used: the Holt's linear exponential smoothing method (or the DES method) and the Holt-Winters methods (the MHW and the AHW methods). They are suitably used for data that trend and seasonality behaviors are present. Although the mentioned methods are not new as presented in the research literature, they are popularly used in practice and various applications as reported by many researchers [4-11]. Here, many studies apply such methods due to their simplicity, robustness, low complexity, and algorithm efficiency [4-11].

According to the studies in the literature, the works related to forecasting using exponential smoothing methods were described here. We note that we concentrate on forecasting of palm oil productions/or prices which directly relates to this work. In Siregar *et al.* [12], a comparative study of exponential smoothing methods for forecasting palm oil productions in Indonesia was introduced. The input data from 2010 to 2014 (5-year data) were tested with the DES, the MHW, and the AHW methods. The authors concluded that the AHW method showed better performance than the DES and the MHW methods. In Wan Ahmad and Ahmad [13] exponential smoothing methods were applied to forecast crude palm oil prices in Malaysia in 2013. Forecasting accuracy of the exponential smoothing methods was reported, and the authors summarized that such methods could be efficiently applied for the considered application. Finally, forecasting oil prices using time-series methods was presented in Tularam and Saeed [14, 15]. The authors showed that the Holts-Winters methods with the input data from October 2011 to March 2016 collected from the United States Energy Information Administration, gave the better results in forecasting crude oil prices.

According to the efficacy of the exponential smoothing methods in practice as introduced above, in this paper we apply them to forecast crude palm oil productions in Thailand. Several exponential smoothing methods including the DES, the MHW, the AHW, the IAHW, and the EAHW methods are selected and tested. The input data from January 2006 to December 2017 are gathered from the database of the Department of Internal Trade, Ministry of Commerce, Thailand. The contributions of our study are twofold. First, three traditional forecasting methods (i.e. the DES, the MHW, and the AHW methods) and two recent methods proposed in the literature (i.e. the IAHW and the EAHW methods) are tested. Thus, forecast results determined by optimal methods are provided. Second, four sets of input data (i.e. 3-year data (2015-2017), 6-year data (2012-2017), 9-year data (2009-2017), and 12-year data (2006-2017)) are inserted as the input data. Thus, how the different sets of the input data affect forecasting accuracy of the selected methods is studied. Our study shows that the AHW and the EAHW methods give the smallest forecasting error measured by the MAPE, in forecasting crude palm oil productions. In addition, the study reveals that, using more input data, like 12-year data, the AHW and the EAHW methods significantly provide more accurate results. Forecast results of January 2018 to March 2018 by the optimal methods and average monthly and yearly crude palm oil productions are also reported in this paper.

2. Materials and Methods

2.1 Input data

Monthly crude palm oil productions from January 2006 to December 2017 (12 years) as the input data are collected from the database of the Department of Internal Trade, Ministry of Commerce, Thailand [16]. They are illustrated in Table 1.

2.2 Forecasting methods

The DES, MHW, AHW, IAHW, and EAHW methods are described here**.** They are also summarized in Table 2. We note that, as mentioned in the introduction section, such forecasting methods as the different methods of the exponential smoothing family are selected for the test because they are widely used in practice and several applications as reported in [4-11], and many studies apply them due to their simplicity, robustness, low complexity, and algorithm efficiency [4-11]. In addition, we found that how well they perform in the case of the crude palm oil productions with the different sets of input data as proposed in this work was not yet investigated.

The DES method: The DES method is suitably used to forecast data which shows a trend [9, 10, 17]. It includes a trend factor to the equation**.** Three equations are incorporated in this method as shown in equations (1) to (3), where L_i is the estimate of the level of the data series at the sample number i, X_i is the input value (the crude palm oil production provided in Figure 1), b_i is the estimate of the trend of the data series, α and β are the weighting factors with values between 0 and 1, and Y_{i+m} is the forecast value (the forecast crude palm oil production) for the period $i+m$, where m is the number of forecast periods ahead.

$$L_i = \alpha\left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{1}$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \tag{2}$$

$$Y_{i+m} = L_i + mb_i \tag{3}$$

Table 1. Monthly crude palm oil productions (metric ton) from January 2006 to December 2017

Monthly crude palm oil productions of the years 2006 to 2017												
Month	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
1	37,235.8	75,633.1	86,608.3	83,585.0	89,568.0	49,965.8	130,127.1	190,823.7	110,592.2	60,449.7	85,652.2	96,750.7
2	68,668.1	73,969.1	115,134.3	84,333.1	114,489.7	71,223.3	123,789.3	157,840.0	131,987.8	93,956.9	109,332.7	110,879.5
3	113,396.9	86,889.5	148,951.3	118,579.1	140,780.3	119,903.5	136,420.3	162,546.9	204,559.9	169,545.7	166,879.1	180,740.8
4	128,698.6	77,806.1	133,871.3	122,636.5	124,297.8	136,278.8	127,853.4	151,158.1	199,945.7	209,645.9	170,696.2	217,009.7
5	122,438.9	80,216.8	168,465.4	116,402.9	130,425.2	165,055.8	133,911.1	173,196.9	237,217.6	239,227.0	148,475.5	224,189.5
6	91,600.1	73,414.6	143,853.7	102,521.2	119,990.6	171,253.8	117,452.5	162,095.4	198,461.7	195,580.7	130,196.3	169,887.0
7	85,809.1	78,821.0	141,235.1	108,375.9	118,336.7	170,619.2	134,117.8	176,227.3	174,780.5	160,435.9	127,011.5	159,035.2
8	97,282.3	94,843.8	129,386.2	117,770.0	106,585.9	165,445.9	168,176.0	186,602.8	142,937.7	152,098.0	144,704.7	186,413.0
9	102,093.5	99,581.6	130,114.4	128,550.3	95,806.4	158,593.3	184,083.2	162,276.6	129,878.1	154,470.7	148,685.9	206,238.5
10	110,888.5	105,753.8	115,786.0	123,265.8	79,920.0	192,014.4	183,739.6	166,583.9	127,726.0	160,573.2	133,706.2	243,361.2
11	93,603.3	97,369.2	86,881.2	87,626.9	57,898.4	180,255.7	178,281.2	138,454.7	90,218.7	132,042.0	131,053.4	253,231.2
12	76,644.5	75,152.1	75,189.8	68,836.7	44,531.5	150,102.3	165,537.8	113,775.4	62,830.2	104,853.8	118,331.0	233,256.7

As recommended by researchers [9, 10, 17- 19], the initial values for L_i and b_i are set using equations (4) and (5), where n is the number of months in a year. In addition, optimal values of α and β are also automatically determined. They are selected when the forecasting error (MAPE) is minimized [19]. In this work, the minimization problem is solved using the Solver function in Microsoft Excel. More details and examples can be found in Tratar and Srmcnik [19]. We note that a brief description of the implementation of the DES method and the Solver function in Microsoft Excel are illustrated as an example in an Appendix.

$$L_1 = X_1 \tag{4}$$

$$b_1 = \frac{X_n - X_1}{n-1} \tag{5}$$

Table 2. Summary of the DES, the MHW, the AHW, the IAHW and the EAHW methods

Methods	Level, trend, and seasonal components	Initial values	Forecast value
DES	$L_i = \alpha X_i + (1-\alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1}$	$L_1 = X_1$ $b_1 = \frac{X_n - X_1}{n-1}$	$Y_{i+m} = L_i + mb_i$
MHW	$L_i = \alpha\left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1}$ $S_i = \gamma\left(\frac{X_i}{L_i}\right) + (1-\gamma)S_{i-n}$	$L_n = \frac{X_1 + X_2 + ... + X_n}{n}$ $b_1 = \frac{X_n - X_1}{n-1}$ $S_i = \frac{X_i}{L_n}$	$Y_{i+m} = (L_i + mb_i)S_{i-n+m}$
AHW	$L_i = \alpha(X_i - S_{i-m}) + (1-\alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1}$ $S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n}$	$L_n = \frac{X_1 + X_2 + ... + X_n}{n}$ $b_1 = \frac{X_n - X_1}{n-1}$ $S_i = X_i - L_n$	$Y_{i+m} = L_i + mb_i + S_{i-n+m}$
IAHW	$L_i = \alpha X_i - S_{i-m} + (1-\alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1}$ $S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n}$	$L_n = \frac{X_1 + X_2 + ... + X_n}{n}$ $b_1 = \frac{X_n - X_1}{n-1}$ $S_i = X_i - L_n$	$Y_{i+m} = L_i + mb_i + S_{i-n+m}$
EAHW	$L_i = \alpha X_i - \delta S_{i-m} + (1-\alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1}$ $S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n}$	$L_n = \frac{X_1 + X_2 + ... + X_n}{n}$ $b_1 = \frac{X_n - X_1}{n-1}$ $S_i = X_i - L_n$	$Y_{i+m} = L_i + mb_i + S_{i-n+m}$

The Holt-Winters methods*:* The Holt-Winters methods are suitably used when both trend and seasonality patterns are present in the data series [9, 10, 17]. The Holt-Winters methods incorporate three equations: the first for the level, the second for the trend, and third for seasonality. Generally, there are two Holt-Winters methods: the MHW and the AHW methods, depending on whether the seasonality is modelled in multiplicative or additive forms.

The MHW method is shown in equations (6) to (9), where (7) is identical to (2), S_i is the multiplicative seasonal component, γ is the weighting factor ($0 \le \gamma \le 1$), and n is the seasonality length (the number of months in a year). As recommended by researchers [9, 10, 17-19], to initialize the level, trend and seasonal components, (10), (5) and (11) are used, respectively, where $i = 1, 2, 3, \ldots, 12$.

$$L_i = \alpha\left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{6}$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \tag{7}$$

$$S_i = \gamma\left(\frac{X_i}{L_i}\right) + (1-\gamma)S_{i-n} \tag{8}$$

$$Y_{i+m} = (L_i + mb_i)S_{i-n+m} \tag{9}$$

$$L_n = \frac{X_1 + X_2 + \ldots + X_n}{n} \tag{10}$$

$$S_i = \frac{X_i}{L_n} \tag{11}$$

For the AHW method, it is shown in equations (12) to (15), where (2), (7), and (13) are the same. As recommended by researchers [9, 10, 17- 19], the initial values for the level and trend are the same as those for the MHW method. In addition, to initialize the seasonal component, equation (16) is used instead.

$$L_i = \alpha(X_i - S_{i-m}) + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{12}$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \tag{13}$$

$$S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n} \tag{14}$$

$$Y_{i+m} = L_i + mb_i + S_{i-n+m} \tag{15}$$

$$S_i = X_i - L_n \tag{16}$$

In both MHW and AHW methods, optimal values of the weighting factors are also automatically determined during the test. They are determined by minimizing the MPAE, and the minimization problem is solved using the Solver function in Microsoft Excel.

The IAHW method*:* The IAHW method was recently introduced by Tratar in 2015 [20]. It is shown in equation (17), where the difference between the AHW and IAHW methods is only the equation for the level. The trend and seasonal components remain unchanged**.** In the IAHW method, α occurs only at the input X_i and not at the seasonal component S_{i-m}**.** Here, when $\alpha X_i > S_{i-m}$ (the smoothed value is higher than the average in its seasonality), the level increases in comparison with the level in the earlier period**.** The opposite adjustment occurs when $\alpha X_i < S_{i-m}$. For the initial values for level, trend, and seasonal components, they are the same as those for the AHW method. In addition, optimal values of the weighting factors are determined by minimizing the MPAE, where the minimization problem is solved using the Solver function in Microsoft Excel. Here, the solving method is the evolutionary algorithm, and the constraints are $0 \le \alpha, \beta, \gamma \le 1$.

$$L_i = \alpha X_i - S_{i-m} + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{17}$$

The EAWH method*:* The EAHW method was also recently proposed by Tratar in 2016 [19, 21]. It is shown in equation (18). The difference between the AHW and EAHW methods is the equation for the level**.** The EAHW allows to smooth the seasonal component more or less than the AHW method, depending on the value of δ ($1 \le \delta \le 0$). If $\delta = \alpha$, the EAHW method reduces to the AHW method. If $\delta = 1$, the EAHW method becomes the IAHW method. The initial values for the level, trend and seasonal components are identical to those for the AHW method. Also, optimal values of the weighting factors are automatically determined using the Solver function in Microsoft Excel.

$$L_i = \alpha X_i - \delta S_{i-m} + (1-\alpha)(L_{i-1} + b_{i-1}) \tag{18}$$

2.3 Performance metrics

In this work, the forecasting error referred to the Mean Absolute Percentage Error or MAPE [19, 22-24] is selected as the performance metric. It is used because it provides the accurate and fair comparison of forecasting methods. The MAPE is not prone to change in the magnitude of time series to be forecasted as recommended by Gentry *et al*. [25] and Alon *et al*. [26]. Moreover, it is frequently used in practice as reported by Ravindran and Warsing [27] and Booranawong and Booranawong [28]. The MAPE is shown in equation (19), where *N* is the number of data samples, e_i is the forecasting error from $Y_i^{'} - Y_i$, $Y_i^{'}$ and Y_i are the actual data and the forecast data, respectively. The 95% confidence interval (CI) is also provided for the average results.

$$MAPE = \frac{\sum_{i=1}^{N} \left| \frac{e_i}{Y_i^{'}} \right|}{N} \times 100 \tag{19}$$

2 Results and Discussion

Figure 1 demonstrates the comparison of the MAPE results determined by the DES, the MHW, the AHW, the IAHW, and the EAHW methods with their optimal weighting factors, when 3-year data, 6-year data, 9-year data, and 12-year data are applied. Here, for fair comparison, the MAPE is calculated from the forecast results of January 2016 to December 2017 ($N = 24$). We note that for the MHW, the AHW, the IAHW, and the EAHW methods, the input data of the first years (12 months) are used for setting the initial values.

The results indicate that, to forecast crude palm oil productions, the AHW and the EAHW methods give the smallest MAPEs (i.e. 6.94 and 7.05, respectively) when 12-year data are applied. Here, by considering the 95% CI, the performance by both methods is not significantly different. In addition, the results also reveal that using more input data, the MAPE is significantly reduced in the cases of the MHW, the AHW, the IAHW and the EAHW methods. However, this is not for the case of the DES method; the MAPEs are not different.

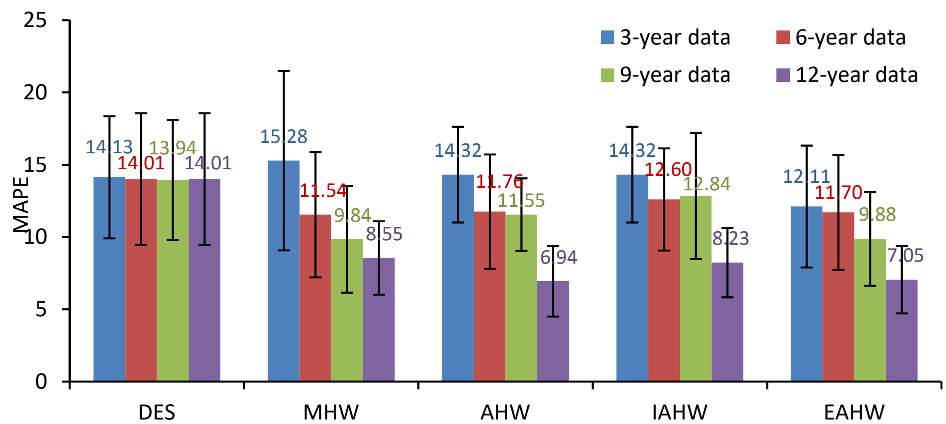
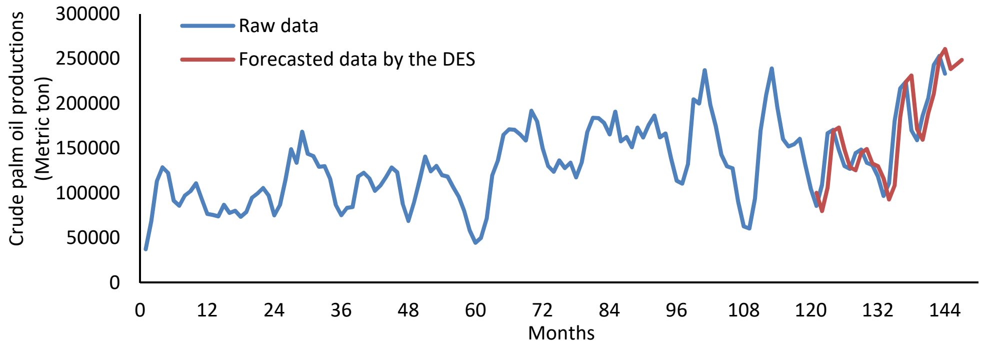
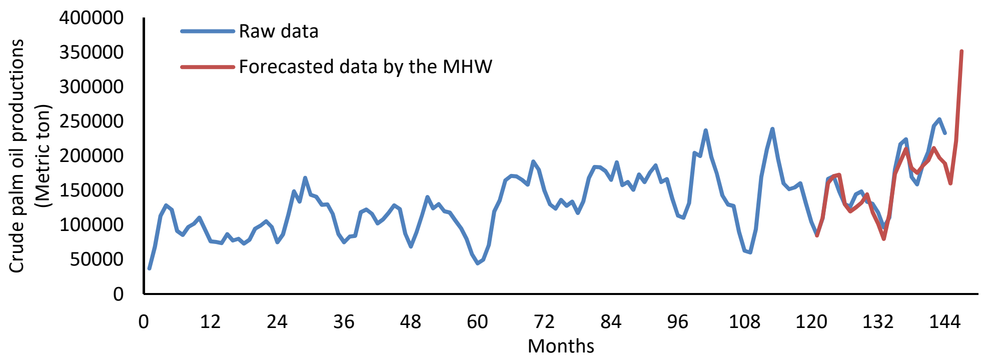


Figure 1. The comparison of the MAPE determined by each forecasting method, when 3-year data (2015-2017), 6-year data (2012-2017), 9-year data (2009-2017) and 12-year data (2006-2017) are applied.

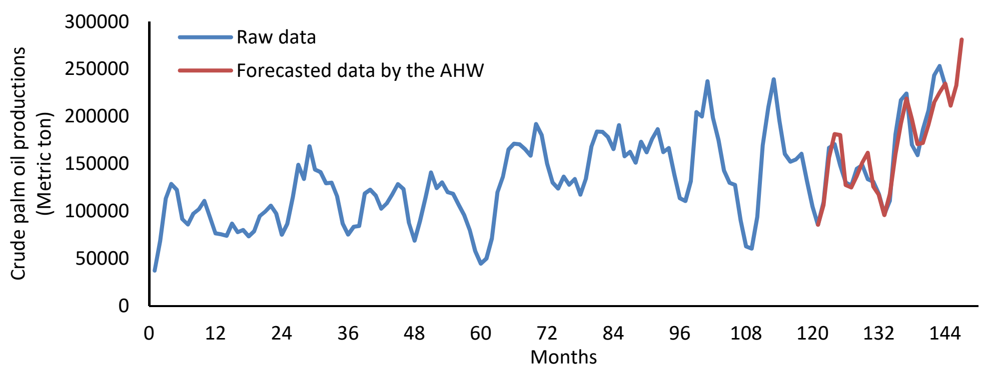
Figure 2 illustrates the comparison of the raw data shown in Table 1 and the forecast data determined by the forecasting methods with their optimal weighting factors, when 12-year data are applied. The optimal weighting factors which give the minimum of the MAPE, and the forecast results of January 2018 to March 2018 are also provided in Table 3. As seen in Figure 2, the forecast data determined by the AHW and the EAHW methods are closer to the raw data than those methods. These results relate to the MAPE results as introduced in Figure 1; a good matching result represents the small MAPE. In Figure 3, we also demonstrate the comparison of the raw data and the forecast data determined by the EAHW method, when 3-year data and 12-year data are applied. Such an example shows that the forecast result using 12-year data is closer to the raw data than using 3-year data.



(a) Forecast data by the DES method; 12-year data

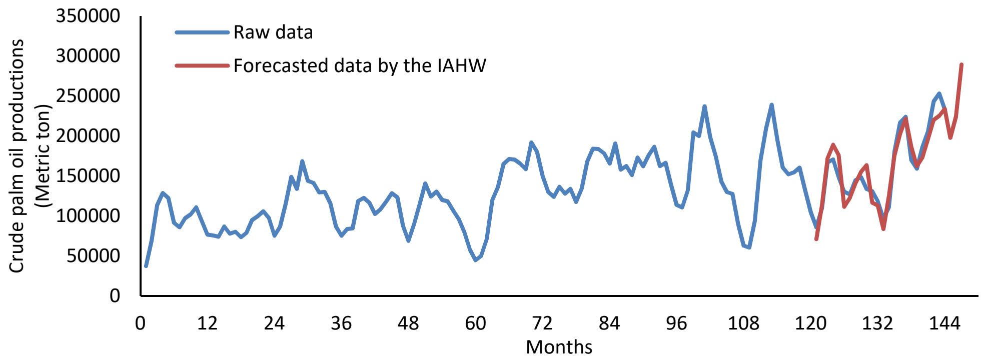


(b) Forecast data by the MHW method; 12-year data

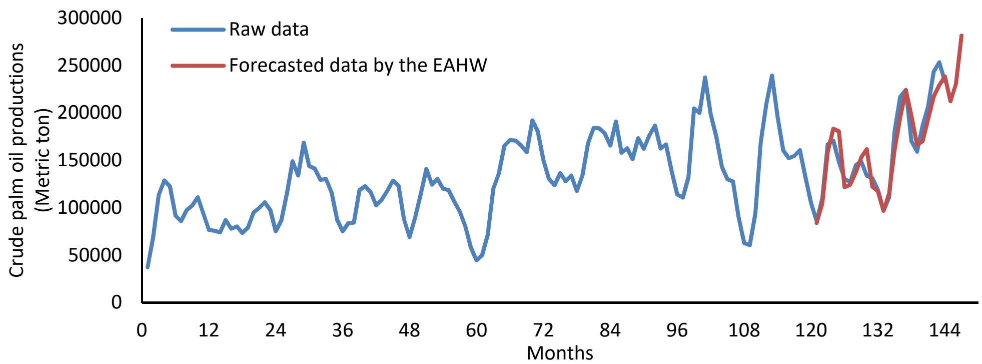


(c) Forecast data by the AHW method; 12-year data

Figure 2. The comparison of the crude palm oil productions between the raw data and the forecast data determined by each forecasting method, when 12-year data are applied.



(d) Forecast data by the IAHW method; 12-year data



(e) Forecast data by the EAHW method; 12-year data

Figure 2. (cont.) The comparison of the crude palm oil productions between the raw data and the forecast data determined by each forecasting method, when 12-year data are applied.

Table 3. The optimal weighting factors and the forecast data of January 2018 to March 2018

Methods	Optimal weighting factors				Forecasted productions (2018)		
	α	β	γ	δ	Jan.	Feb.	March
DES	1	0.0905	-	-	238,388	243,520	248,652
MHW	0.3085	0.2655	0.0990	-	160,258	221,592	351,574
AHW	0.7975	≈0	0.1719	-	**211,328**	**232,285**	**281,082**
IAHW	0.9718	0	1	-	197,820	224,201	289,507
EAHW	0.9303	0	0.5615	0.9344	**211,991**	**230,492**	**281,301**

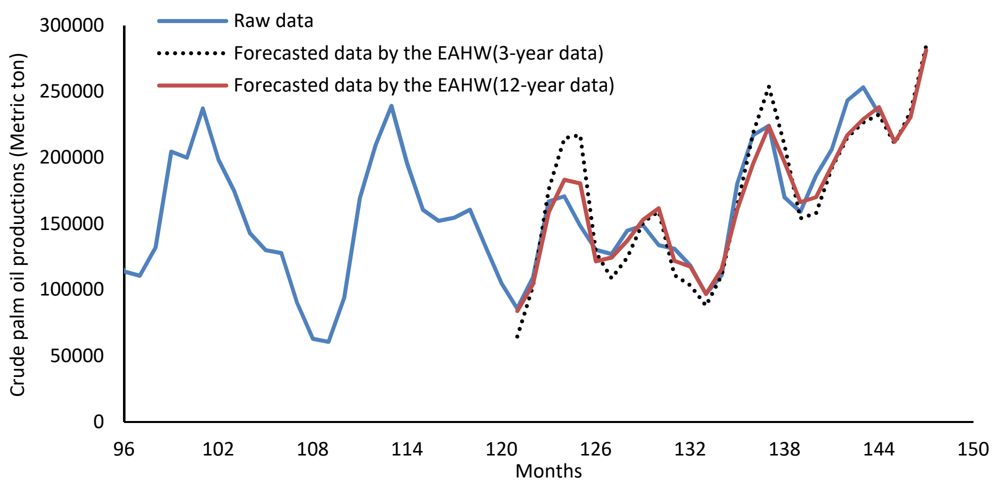
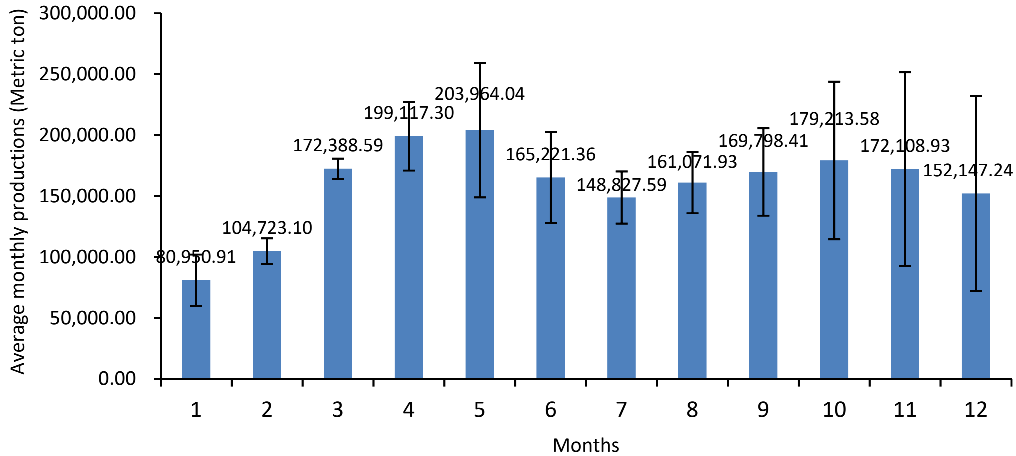


Figure 3. The comparison of the crude palm oil productions between the raw data and the forecast data determined by the EAHW method, when 3-year data and 12-year data are applied.

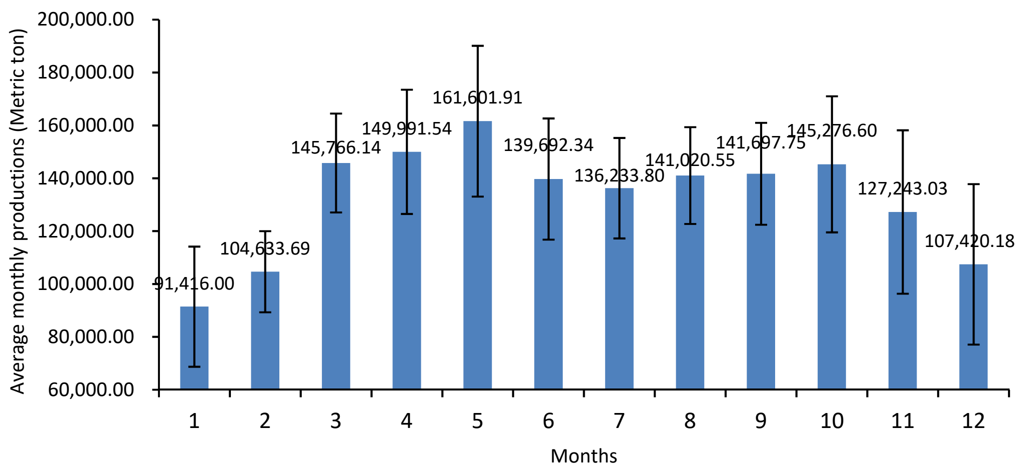
As shown in Table 3, the results reveal that the forecast data of January 2018 to March 2018 by all forecasting methods have the same trend**.** The crude palm oil production increases. Here, the results by the AHW and the EAHW methods are more reliable, since they provide the smallest MAPEs as presented before.

The average monthly productions of the crude palm oil using 3-year data and 12-year data are illustrated in Figure 4. The results demonstrate that the trends of the average monthly productions using 3-year data and 12-year data are likely the same. They follow the circle pattern. We can also observe that the forecast results of January 2018 to March 2018 as seen in Table 3 are consistent with the average monthly productions of January to March as seen in Figure 4.

The average yearly productions of the crude palm oil using 12-year data are also illustrated in Figure 5. A four-order polynomial trend line is fitted to the average results, and the R-squared value is also provided. The result indicates that the average yearly production of the crude palm oil during 2006 to 2017 have increased. There is more possibility that in 2018, the productions of the crude palm oil will increase.



(a) 3-year data (2015-2017); there is more variation during October to December



(b) 12-year data (2006-2017)

Figure 4. The average monthly productions of the crude palm oil.

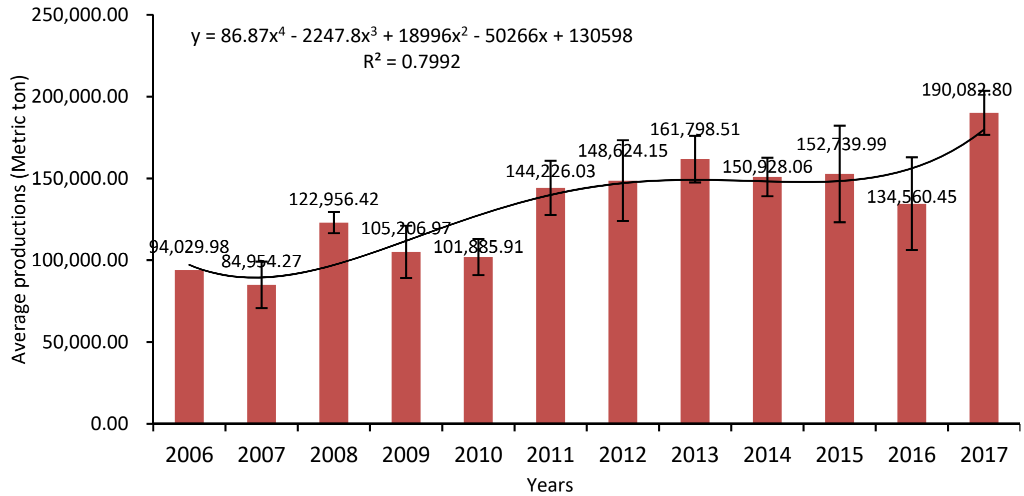


Figure 5. The average yearly productions of the crude palm oil; 12-year data (2006-2017)

The findings as presented in this work can be useful as an information for planning a suitable strategy of the Thai agriculturist and government. For example, if crude palm oil productions in Thailand markets can be accurately predicted, an appropriate plan for managing the use of biodiesel can be immediately set. As announced by the Thai governments during 2015 to 2017, the biodiesel blending ratio was changed from 3.5% to 6% by volume of diesel (or B3.5 to B6) during April 2015, 7% to 5% during July 2016, and 5% to 7% during May 2017 to present. Here, the change depends on the number of crude palm oil productions in Thailand markets. As shown by the forecast results in Table 3, we found that the crude palm oil productions of January 2018 to March 2018 will increase. Consequently, to handle such a situation, the biodiesel blending ratio should be kept at 7% or higher, and the exportation of crude palm oil productions should be more supported (to prevent the decrease of crude palm oil prices).

3 Conclusions

In this work, several exponential smoothing methods including the DES, the MHW, the AHW, the IAHW, and the EAHW methods are employed to forecast crude palm oil productions in Thailand during January 2018 to March 2018. The input data from January 2006 to December 2017 are collected from the Department of Internal Trade, Ministry of Commerce, Thailand. Our study demonstrates that the well-known AHW and the recently proposed EAHW methods provide the smallest forecasting error (i.e. MAPEs are 6.94 and 7.05 for the AHW and the EAHW methods, respectively). Our study also reveals that both forecasting methods show more accurate results when more input data are used; the forecast results using 12-year data are closer to the observed data than using 9-year data, 6-year data, and 3-year data. Additionally, the trends of average monthly and yearly crude palm oil productions are also reported in this paper.

In the future work, to enhance the forecasting accuracy, other input data related to the crude palm oil production will be selected and tested, and more efficient forecasting methods will also be proposed.

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Appendix

An example of the implementation of the DES method in Excel program

The implementation of the DES method and the use of the Solver function in Excel program are illustrated as an example here. More details can be found in [19, 21]. A snapshot of Excel spreadsheet is shown in Figure 6, where L_i, b_i, L_1, b_1, and Y_{i+m} are calculated. Such calculations are corresponding to equations (1), (2), (4), (5), and (3), as presented in Section 2. In Figure 7, the Solver optimization tool with setting is shown. The MAPE is minimized by adjusting the values of the weighting factors, where they are in the range between 0 and 1 and their optimal values are automatically determined.

	A	B	C	D	E	F	G
1	DES METHOD					95%CI	4.554186
2			Alpha	0.999996		SD	11.383303
3			Beta	0.090526		MAPE	14.008253
4	Month	Xi	Li	bi	Yi	ei (Error)	Abs%Error
5	1	37235.8	37235.8	3582.61			
6	2	68668.1	68667.98	6103.719			
7	3	113396.9	=$D$2*B7+(1-$D$2)*(C6+D6)				
8	4	128698.6	128698.6	10116.43			
9	5	122438.9	122439	8633.971			

(a) The calculation of L_i, where C7 = $D$2*B7 + (1-$D$2)*(C6+D6) refers to $L_3 = \alpha X_3 + (1-\alpha)(L_2 + b_2)$

	A	B	C	D	E	F	G
1	DES METHOD					95%CI	4.554186
2			Alpha	0.999996		SD	11.383303
3			Beta	0.090526		MAPE	14.008253
4	Month	Xi	Li	bi	Yi	ei (Error)	Abs%Error
5	1	37235.8	37235.8	3582.61			
6	2	68668.1	68667.98	6103.719			
7	3	113396.9	113396.7	=$D$3*(C7-C6)+(1-$D$3)*D6			
8	4	128698.6	128698.6	10116.43			
9	5	122438.9	122439	8633.971			

(b) The calculation of b_i, where D7 = $D$3*(C7-C6) + (1-$D$3)*D6 refers to $b_3 = \beta(L_3 - L_2) + (1-\beta)b_2$

	A	B	C	D	E	F	G
1	DES METHOD					95%CI	4.554186
2			Alpha	0.999996		SD	11.383303
3			Beta	0.090526		MAPE	14.008253
4	Month	Xi	Li	bi	Yi	ei (Error)	Abs%Error
5	1	37235.8	=B5	3582.61			
6	2	68668.1	68667.98	6103.719			
7	3	113396.9	113396.7	9600.288			
8	4	128698.6	128698.6	10116.43			
9	5	122438.9	122439	8633.971			

(c) The calculation of L_1, where C5 = B5 refers to $L_1 = X_1$

Figure 6. Implementation of the DES method in Excel program

	A	B	C	D	E	F	G
1	DES METHOD					95%CI	4.554186
2			Alpha	0.999996		SD	11.383303
3			Beta	0.090526		MAPE	14.008253
4	Month	*Xi*	*Li*	*bi*	*Yi*	*ei* (Error)	Abs%Error
5	1	37235.8	37235.8	=(B16-B5)/11			
6	2	68668.1	68667.98	6103.719			
7	3	113396.9	113396.7	9600.288			
16	12	76644.51	76644.6	1276.109			
17	13	75633.14	75633.15	1069.026			

(d) The calculation of b_1, where D5 = (B16-B5)/11 refers to $b_1 = (X_{12}-X_1)/(12-1)$

	A	B	C	D	E	F	G
1	DES METHOD					95%CI	4.554186
2			Alpha	0.999996		SD	11.383303
3			Beta	0.090526		MAPE	14.008253
4	Month	*Xi*	*Li*	*bi*	*Yi*	*ei* (Error)	Abs%Error
5	1	37235.8	37235.8	3582.61			
6	2	68668.1	68667.98	6103.719			
7	3	113396.9	113396.7	9600.288			
125	121	85652.25	85652.31	-5806.31	100381	-14728.8	17.196001
126	122	109332.8	109332.7	-3137	=C125+(1*D125)		26.969745
127	123	166879.1	166878.9	2356.408	106195.7	60683.48	36.363731

(e) The calculation of Y_{122}, where E126 = C125 + (1*D125) refers to $Y_{122}=L_{121} + (1*b_{121})$

Figure 6. (cont.) Implementation of the DES method in Excel program

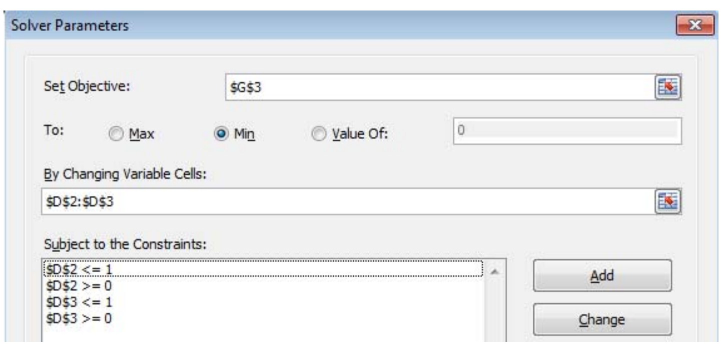

Figure 7. Excel solver setting.