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A Comparison of MHW and AHW Methods for Forecasting Crude Palm Oil Productions in Thailand

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

[1]*Faculty of Agro Industry, Rajamangala University of Technology Srivijaya, Nakhon Si Thammarat 80240, Thailand*
[2]*Faculty of Engineering, Thaksin University, Phatthalung 93210, Thailand*
[3]*Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, Nakhon Si Thammarat 80280, Thailand*
[4] *Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla 90112, Thailand*

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ABSTRACT

A comparison of the Multiplicative Holt-Winters method (MHW) and the Additive Holt-Winters method (AHW) as the time-series methods for forecasting crude palm oil productions in Thailand is presented in this paper. Crude palm oil productions from January 2006 to September 2018 (i.e. 153 months) as the input data are collected from the database of the Department of Internal Trade, Ministry of Commerce, Thailand. The major contribution of our paper is that the well-known MHW and AHW methods, which are appropriately used for the input data with trend and seasonality behaviors, are tested and evaluated. Therefore, the best forecast results (i.e. the forecast crude palm oil productions) by the optimal method are determined. Our study demonstrates that the AHW method shows good results in forecasting crude palm oil productions. It provides the smallest forecasting error measured by Mean Absolute Percentage Error (MAPE). Forecast results of October 2018 to December 2018 (i.e. three months) and trends of the average monthly and yearly crude palm oil productions in Thailand from the past to the present are also reported and analyzed.

Keywords: Time-series methods; Exponential smoothing; Seasonality; MAPE

***Corresponding author:** apidet.boo@gmail.com **doi:** 10.14456/scitechasia.2020.18

1. Introduction

Oil palm, as shown in Fig. 1, is an important oil crop in tropical rainforest countries. It is an attractive oil crop due to a greater palm oil yield and a lower production cost than other oil crops. Indonesia is the largest palm oil producer in the world, followed by Malaysia and Thailand, respectively [1]. In Thailand, almost 90% of crude palm oil produced is used for domestic consumption relating to food and fuel feedstock. The amount of crude palm oil consumed was increased by 1.78% per year for food product and 8.11% per year for biodiesel in the periods of 2012-2016 [2].

(a) (b)

Fig. 1. Oil palm tree (a) and oil palm fruit (b) in Thailand.

The Thai government (Ministry of Energy) allocates the flexible biodiesel-diesel blending ratio based on the volume of crude palm oil output. The varied biodiesel-diesel blending ratios of B3 to B7 (3% to 7% by volume of biodiesel blended with diesel) are regularly used in Thailand [3]. The move to raise the biodiesel-diesel blending ratio can absorb a surplus domestic crude palm oil supply, helping to obviate the problem of falling prices. In early 2017, the volume of crude palm oil output increased; then, the government announced an increase in the biodiesel-diesel blending ratio from B5 to B7 on May 2017. Therefore, an appropriate forecasting technique for crude palm oil volume is a useful tool for the government to make decisions and to arrange a suitable strategic plan of palm oil management in Thailand.

To forecast future values of stream input data, well-known exponential smoothing methods of the time-series methods are widely used: Holt's linear exponential smoothing method (or the Double Exponential Smoothing method: DES) and the Holt-Winters methods (the MHW and the AHW methods). Here, the DES method is appropriately used to forecast data which shows trend behavior, while the MHW and the AHW methods are appropriately used for data when trend and seasonality behaviors are present. Although the Holt-Winters methods are not new as introduced in the research literature, they are popularly used in practice and have many applications as demonstrated in [4-11]. Here, many works apply such methods due to their simplicity, low complexity, and method efficiency.

We note that, although the MHW and the AHW methods as the different exponential smoothing methods of the Holt-Winters family are applied and studied in this work due to their benefit as presented above, to forecast crude palm oil productions in Thailand, other forecasting techniques such as Artificial Neural Network (ANN) and Box-Jenkins Methods should also be tested. This solution is still an open research issue and needs more investigation.

Based on the studies in the literature, the works related to forecasting using Holt-Winters methods are introduced here. Note that we focus on forecasting of palm oil productions/or prices which directly relate to our work. In [12], an evaluation of the Holt-Winters methods for forecasting palm oil productions in Indonesia was presented. The five-year input data (from 2010 to 2014) were tested with the DES, the MHW, and the AHW methods, respectively. The work in [12] also concluded that the AHW showed better results than the DES and the MHW methods. In [13], exponential smoothing methods were applied to forecast crude palm oil prices in Malaysia for the year 2013. The accuracy of the exponential smoothing methods was revealed, and the authors concluded that such methods could be properly applied for the selected application. Finally, in [14], the correlation between crude palm oil price in Malaysia, selected vegetable oil prices (such as soybean oil, coconut oil, and olive oil), crude oil, and the monthly exchange rate was studied. Crude palm oil price forecasting using the Holt-Winters methods was also performed. Here, the authors demonstrated that the Holts-Winters methods could be used to forecast Malaysia's crude palm oil price.

According to the potential of the Holt-Winters methods in practice as described above, in this paper, we use them to forecast crude palm oil productions in Thailand. Thus, the MHW and the AHW methods are tested and evaluated. The input data from January 2006 to September 2018 are gathered from the database of the Department of Internal Trade, Ministry of Commerce, Thailand. Our study shows that both the MHW and the AHW methods can be properly used to forecast crude palm oil productions as indicated by the MAPE results. However, the AHW method gives smaller forecasting errors than the MHW method. Forecast results of October 2018 to December 2018 determined by the MHW and the AHW methods and the average monthly and yearly crude palm oil productions in Thailand are also reported and analyzed in the paper.

2. Materials and Methods

2.1 Input data

Monthly crude palm oil productions from January 2006 to September 2018 (i.e. 153 months) as the input data for the forecasting methods are collected from the database of the Department of Internal Trade, Ministry of Commerce, Thailand [15]. They are illustrated in Fig. 2.

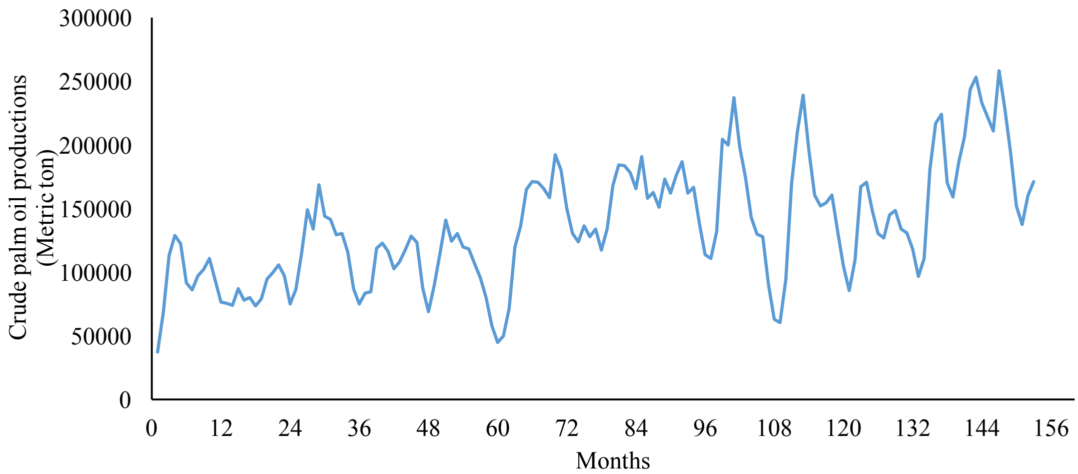


Fig. 2. Monthly crude palm oil productions (metric ton) from January 2006 to September 2018.

2.2 Holt-winters methods

The Holt-Winters methods are suitably used when both trend and seasonality patterns are present in the data series [8, 9, 16]. The Holt- Winters methods incorporate three equations: the first for the level, the second for the trend, and the third for seasonality. In general, there are two main Holt- Winters methods: the MHW and the AHW methods, depending on whether the seasonality is modeled in multiplicative or additive forms.

The MHW method is shown in Eq. (2.1) to Eq. (2.4), 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 productions in Fig. 1.), b_i is the estimate of the trend of the data series, S_i is the multiplicative seasonal component, n is the seasonality length (the number of months in a year), α, β, and γ are the weighting factors with values between 0 and 1, and, finally, 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. As recommended by [8, 9, 16- 18], the initial values for L_i, b_1 and S_i are set using Eq. (2.5), Eq. (2.6), and Eq. (2.7), respectively, where *i = 1, 2, 3,…, 12.*

$$L_i = \alpha\left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha)(L_{i-1} + b_{i-1}) \quad (2.1)$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \quad (2.2)$$

$$S_i = \gamma\left(\frac{X_i}{L_i}\right) + (1-\gamma)S_{i-n} \quad (2.3)$$

$$Y_{i+m} = (L_i + mb_i)S_{i-n+m} \quad (2.4)$$

$$L_n = \frac{X_1 + X_2 + \ldots + X_n}{n} \quad (2.5)$$

$$b_1 = \frac{X_n - X_1}{n-1} \quad (2.6)$$

$$S_i = \frac{X_i}{L_n} \quad (2.7)$$

The AHW method is shown in Eq. (2.8) to Eq. (2.11), where Eq. (2.9) and Eq. (2.2) are the same. Also, as recommended by [8, 9, 16-18], the initial values for the level and the trend are the same as those for the MHW method. In addition, to initialize the seasonal component, Eq. (2.12) is used instead.

$$L_i = \alpha(X_i - S_{i-m}) + (1-\alpha)(L_{i-1} + b_{i-1}) \quad (2.8)$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \quad (2.9)$$

$$S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n} \quad (2.10)$$

$$Y_{i+m} = L_i + mb_i + S_{i-n+m} \quad (2.11)$$

$$S_i = X_i - L_n \quad (2.12)$$

In both the MHW and the AHW methods, optimal values of the weighting factors $(\alpha, \beta,$ and $\gamma)$ are automatically determined during the test. They are determined by minimizing the MAPE results [18], and the minimization problem is solved using the Solver function in Microsoft Excel. We note that, for our test, we use a Dell Inspiron 5480 laptop with the Intel core I7-8565U CPU and 8 GB DDR4 RAM, and the Microsoft Excel version 2016.

We also note that for the equations Eq. (2.1), Eq. (2.2), Eq. (2.3), Eq. (2.8), Eq. (2.9), and Eq. (2.10), they are in the form of the exponential weighted function, where the weighting for each older datum decreases exponentially (see an example as the derivation of Eq. (2.8); by assuming $S_{i-m} = a$ and $b_{i-1} = b$ and substituting X_{i-1}, X_{i-2},... X_1 and L_{i-1}, L_{i-2},... L_1 into Eq. (2.8), the general form can be written by Eq. (2.13)) as follows:

$$
\begin{aligned}
L_i &= \alpha(X_i - a) + (1-\alpha)(L_{i-1} + b) \\
&= \alpha \times (X_i - a) + (1-\alpha) \times \left[\alpha \times (X_{i-1} - a) + (1-\alpha) \times (L_{i-2} + b)\right] \\
&= \alpha \times (X_i - a) + \alpha \times (1-\alpha) \times (X_{i-1} - a) + (1-\alpha)^2 \times (L_{i-2} + b) \\
&= \alpha \times (X_i - a) + \alpha \times (1-\alpha) \times (X_{i-1} - a) + (1-\alpha)^2 \times \left[\alpha \times (X_{i-2} - a) + (1-\alpha) \times (L_{i-3} + b)\right] \\
&= \alpha \times (X_i - a) + \alpha \times (1-\alpha) \times (X_{i-1} - a) + \alpha \times (1-\alpha)^2 \times (X_{i-2} - a) + (1-\alpha)^3 \times (L_{i-3} + b) \\
&= \alpha \times (X_i - a) + \alpha \times (1-\alpha) \times (X_{i-1} - a) + \alpha \times (1-\alpha)^2 \times (X_{i-2} - a) + \ldots + \alpha \times (1-\alpha)^{i-1} \times L_1
\end{aligned}
\tag{2.13}
$$

2.3 Performance metrics

As mentioned before, in this work, the forecasting error referred to the Mean Absolute Percentage Error or MAPE [18-21] is selected as the performance metric. The MAPE is used because it provides the accurate and fair comparison of forecasting methods. It is not prone to change in the magnitude of time series to be forecasted as recommended by [22, 23]. Moreover, it frequently is used in practice as reported by [24, 25]. The MAPE is expressed in Eq. (2. 14), where N is the number of data samples, e_i is the forecasting error calculated from $\acute{Y}_i - Y_i$, $\acute{Y}_i$ and Y_i are the actual data and the forecast data, respectively. The 95% confidence interval (CI) is also given for average results.

$$
MAPE = \frac{\sum_{i=1}^{N} \left| \frac{e_i}{Y_i} \right|}{N} \times 100, \tag{2.14}
$$

3. Results and Discussion

Fig. 3. shows the comparison of the MAPE results determined by the MHW and the AHW methods with their optimal weighting factors (the minimization problem solved by the Solver function in Microsoft Excel). Here, the MAPEs are calculated from the forecast results of January 2007 to September 2018 (N = 141). We note that the input data of the first year (January 2006 to December 2006; 12 months) are used for setting the initial values for the MHW and the AHW methods. The results demonstrate that, to forecast crude palm oil productions the AHW method gives the smallest MAPE result. It is 13.490, where the MAPE result provided by the MHW method is 16.060. Here, by considering the 95% CI, the AHW method, that the seasonality is modeled in an additive form, significantly shows better performance than the MHW method.

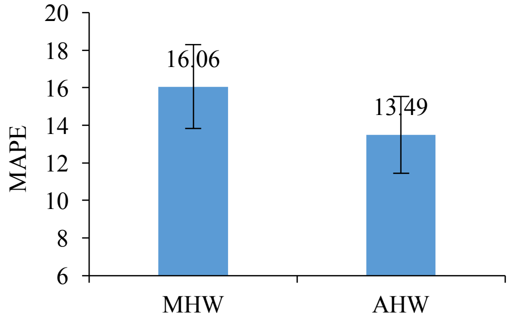


Fig. 3. The comparison of the MAPE determined by the MHW and the AHW methods.

The comparison of the raw data shown in Fig. 1. and the forecast data determined by the MHW and the AHW methods with their optimal weighting factors is illustrated in Fig. 4. The optimal weighting factors which give the minimum of the MAPE result, and the forecast results of October 2018 to December 2018 are also provided in Table 1. As shown in Fig. 4., the forecast data determined by the AHW method are closer to the raw data than the MHW method. Such results correlate with the MAPE results as introduced in Fig. 3.

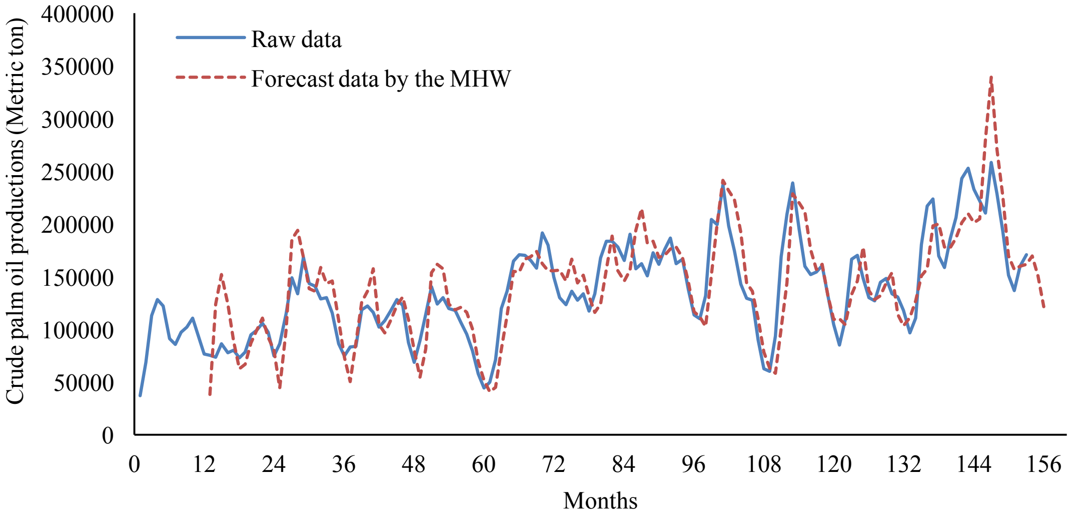
above; where a good matching result represents the small MAPE.

Fig. 5. also demonstrates the comparison of the MAPE for each input sample determined by the MHW and the AHW methods. Such a result reveals that the forecasting errors by both methods decrease when more input data are inserted into the forecasting methods. We can see that, for example, the MAPE of January 2007 (i. e. month 13) is higher than the MAPE of September 2018 (month 153). Here, the MAPEs of January 2007 and September 2018 are 48.892 and 5.278 for MHW method, and they are 46.031 and 3.656 for the AHW method.

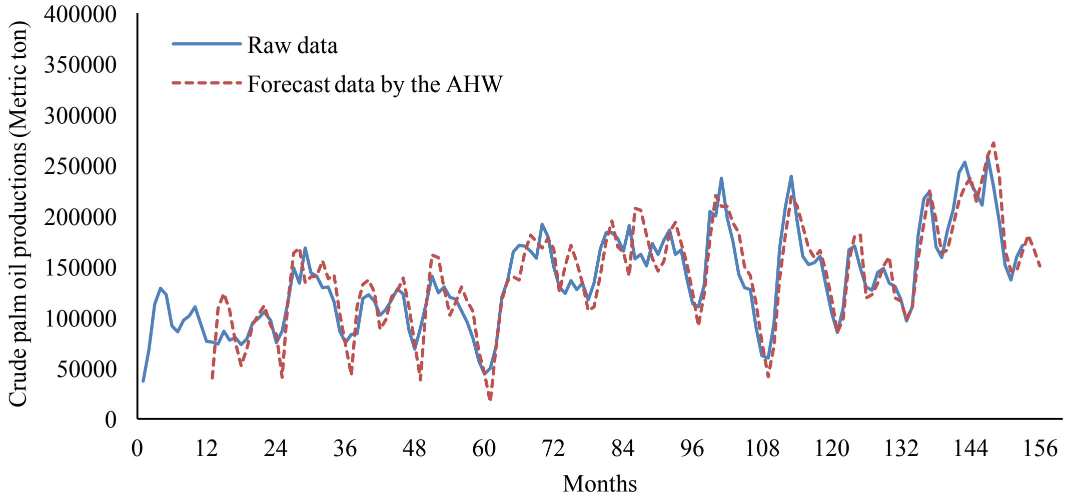
As shown in Table 1, the results reveal that the forecast data of October 2018 to December 2018 for both the MHW and the AHW methods show the same trend. However, the results for the AHW method are more reliable than the MHW method, since they provide the smallest MAPE as presented in Fig. 3. and Fig. 5. From the results in Table 1, on average, the crude palm oil productions in Thailand are still high at the end of the year compared with the productions during July 2018 to September 2018 (137,307.96, 159,832.62, 171,085.95 metric ton, respectively)

The average monthly productions of the crude palm oil using 12-year data (2006 to 2017) are illustrated in Fig. 6. The results demonstrate that the trend of the average monthly productions follows the circle pattern. The average yearly productions of the crude palm oil using 12-year data (2006 to 2017) are also illustrated in Fig. 7. The linear trend line is fitted to the average result, and the R-squared value is also included. The result shows that the average yearly production of the crude palm oil during 2006 to 2017 increased. There is more possibility that in 2018 and 2019, the production of the crude palm oil will also increase.

In this work, the knowledge findings are useful information for the government to prepare a strategic plan to maintain the stability of crude palm oil productions in Thailand. In case that the data of crude palm oil productions are accurately predicted, a suitable implement of palm oil based biodiesel and biodiesel-diesel blending ratio policy can also be set. As announced by the Thai governments during 2015 to 2017, the biodiesel-diesel blending ratio was increased from B3.5 to B6 on April 2015, then increased from B6 to B7 on August 2015, after that decreased from B7 to B5 on July 2016, and increased from B5 to B7 on May 2017 (to present). Here, the biodiesel-diesel blending ratio variation depends on the volume of crude palm oil productions in Thailand markets. Regarding the forecast results in Table 1, Thailand's crude palm oil production, on average, is still on a high level for the last 3 months of 2018. Thus, the constant biodiesel-diesel blending ratio of B7 or a bit higher should be suitable for this situation. Moreover, the exportation of crude palm oil policy should be considered to prevent the decrease in crude palm oil prices as well.



(a) Forecast data by the MHW method



(b) Forecast data by the AHW method

Fig. 4. The comparison of the crude palm oil productions between the raw data and the forecast data determined by the MHW and the AHW methods.

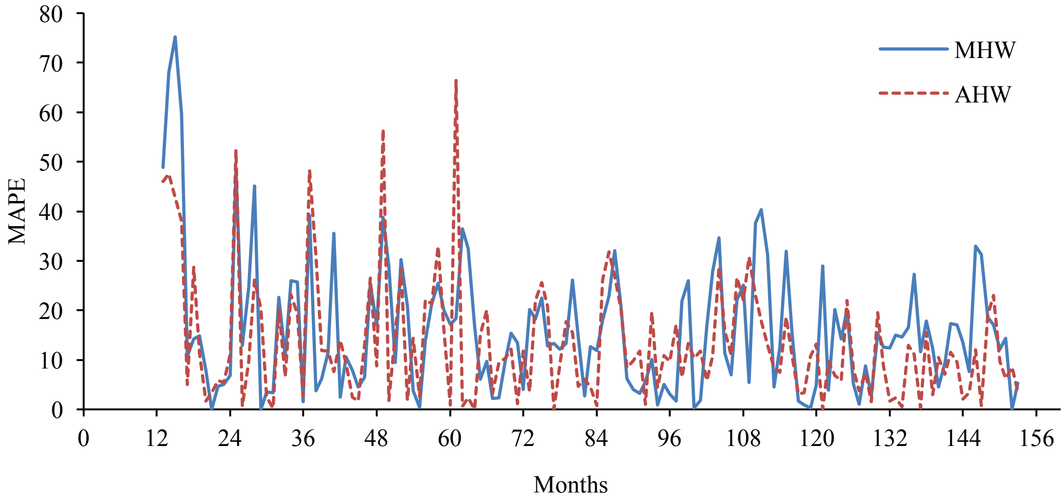


Fig. 5. The comparison of the MAPE of each input sample determined by the MHW and the AHW methods.

Table 1. The optimal weighting factors and the forecast data of October 2018 to December 2018.

Methods	**Optimal weighting factors**			**Forecast productions (2018)**		
	α	β	γ	Oct.	Nov.	Dec
MHW	0.7023	0.0516	1.0000	160,258	151,082	121,856
AHW	0.9497	0.0063	1.0000	181,044	167,334	151,132

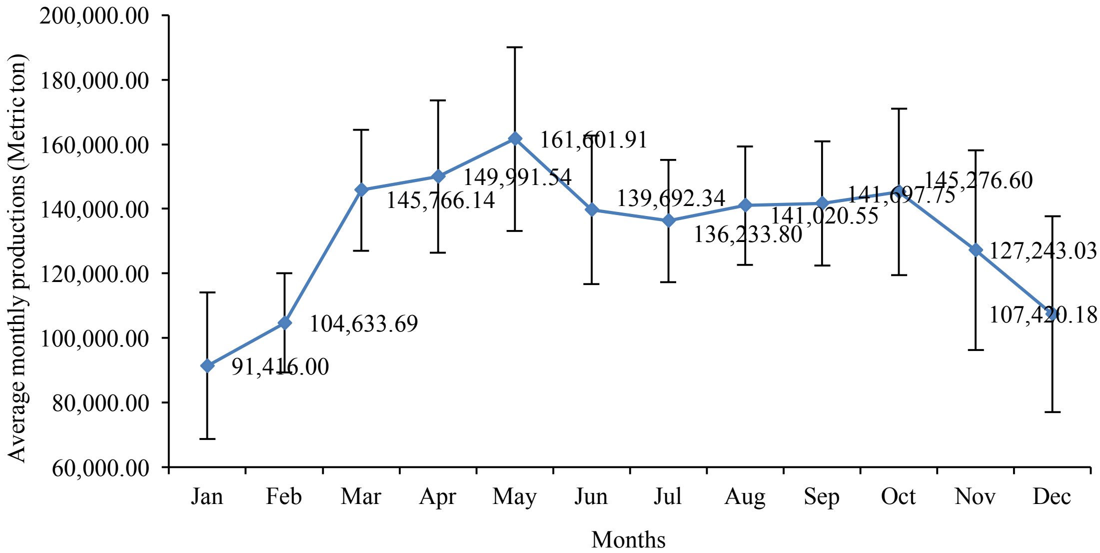


Fig. 6. The average monthly productions of the crude palm oil; 12-year data (2006–2017).

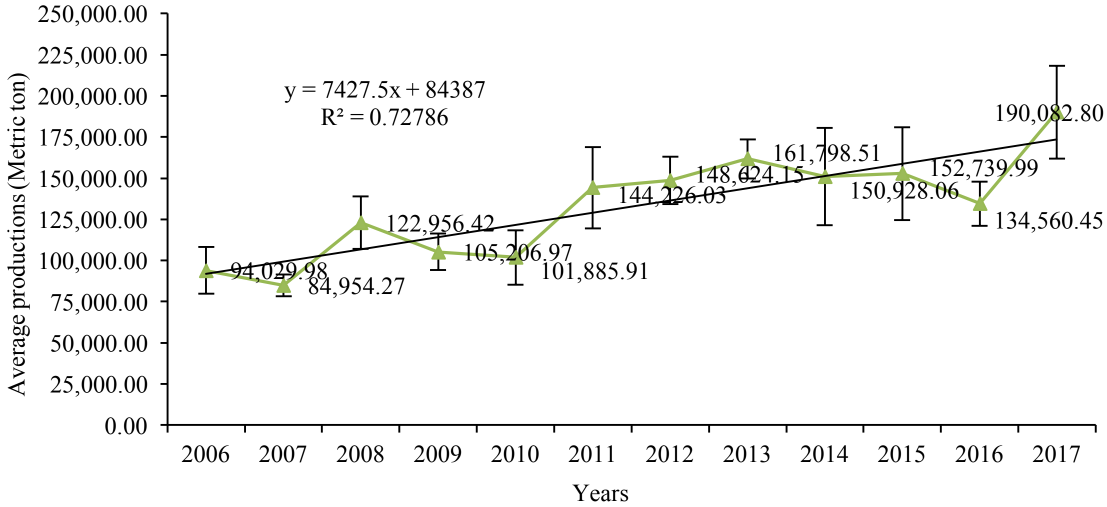


Fig. 7. The average yearly productions of the crude palm oil; 12-year data (2006–2017).

4. Conclusion

In this work, the well-known Holt-Winters methods including the MHW and the AHW methods are employed to forecast crude palm oil productions in Thailand during October 2018 to December 2018. The input data from January 2006 to September 2018 are collected from the Department of Internal Trade, Ministry of Commerce, Thailand. Our study demonstrates that the AHW method provides smaller forecasting error as measured by Mean Absolute Percentage Error than the MHW method. We also show the trends of average monthly and yearly crude palm oil productions in Thailand.

In the future work, to increase the forecasting accuracy, other input data related to the crude palm oil production will be selected and tested. In addition, although the MHW and the AHW methods provide good accuracy in the case of short-term forecasting (i.e. three months), how well they work for one-year ahead should be studied. Finally, more efficient forecasting methods should also be included.

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References

[1] Thailand industry outlook 2017-19: oil palm industry [Internet]. [cited 2018 Feb 10]. Available from: https://www.krungsri.com/bank/getmedia/ac87c171-db74-442b-ae29-5b69572896ca/IO_Oil_Palm_2017_EN.aspx

[2] Agricultural commodity situation and trend (2017) [Internet]. [cited 2018 Feb 10]. Available from: http://www.oae.go.th/assets/portals/1/files/ebook/agri_situation2560.pdf

[3] Agricultural commodity situation and trend (2018) [Internet]. [cited 2018 Feb 10]. Available from: http://www.oae.go.th/assets/portals/1/files/ebook/agri_situation2561.pdf

[4] Brown RG. Exponential smoothing for predicting demand. The 10th National Meeting of the Operations Research Society of America, San Francisco; 1956;14-15 November; San Francisco, USA.

[5] Winters P. Forecasting sales by exponentially weighted moving averages. Manag Sci 1960;6:324-42.

[6] Gardner ES. Exponential smoothing: the state of the art. J Forecast 1985;4:1–28.

[7] Hunter JH. The exponentially weighted moving average. J Qual Tech 1986;18(4):203-10.

[8] Kalekar PS. Time series forecasting using holt-winters exponential smoothing. Kanwal Rekhi School of Information Technology 2004;1-13.

[9] Montgomery DC, Jennings CL, Kulahci M. Introduction to time series analysis and forecasting. Wiley Series in Probability and Statistics: John Wiley and Sons; 2008.

[10] Gelper S, Fried R, Croux C. Robust forecasting with exponential and Holt-winters smoothing. J Forecast 2010; 29:285-300.

[11] Ramos P, Santos N, Rebelo R. Performance of state space and ARIMA models for consumer retail sales forecasting. Robot Comput Integrated Manuf 2015; 34(2015):151-63.

[12] Siregar B, Butar-Butar IA, Rahmat RF, Andayani U, Fahmi F. Comparison of exponential smoothing methods in forecasting palm oil real production. IOP Conf Series: J Phys 2017; 801(2017):1-9.

[13] Wan Ahmad WKA, Ahmad S. Arima model and exponential smoothing method: a comparison. API Conference Proceedings 2013;1522:1312-21.

[14] Kanchymalay K, Salim N, Sukprasert A, Krishnan R, Raba'ah Hashim U. Multivariate time series forecasting of crude palm oil price using machine learning techniques. 2017 IOP Conf Ser: Mater Sci Eng 226 012117.

[15] Prices and situation of agricultural commodities (oil palm) [Internet]. [cited 2018 Feb 10]. Available from: http://www.dit.go.th/

[16] Holt CC. Forecasting seasonals and trends by exponentially weighted moving averages. Int J Forecast 2004;20(1):5-10.

[17] Dhakre DS, Sarkar KA, Manna S. Forecasting price of Brinjal by Holt-winters method in west Bengal using MS Excel. Int J Bio-res Env Agril Sci 2016;2(1):232-5.

[18] Tratar LF, Srmcnik E. The Comparison of Holt-winters method and multiple regression methods: a case study. Energy 2016;109(2016):266-76.

[19] Booranawong T, Booranawong A. An exponentially weighted moving average method with designed input data assignments for forecasting lime prices in Thailand. Jurnal Teknologi 2017;79(6):53-60.

[20] Booranawong T, Booranawong A. Simple and double exponential smoothing methods with designed input data for forecasting a seasonal time series: in an application for lime prices in Thailand. Suranaree J Sci Technol 2017;24(3):301-10.

[21] Chatfield C. Time-series forecasting. New York: Chapman & Hall; 2001.

[22] Alon I, Qi M, Sadowski RJ. Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods. J Retailing Consum Serv 2001;8(3):147-56.

[23] Gentry TW, Wiliamowski BM, Weatherford LR. A comparison of traditional forecasting techniques and neural networks. Intelligent Engineering Systems through Artificial Neural Networks 1995;5:765-70.

[24] Ravindran A, Warsing DP. Supply chain engineering: models and applications. New York: NY: CRC Press; 2013.

[25] Booranawong T, Booranawong A. Double exponential smoothing and Holt-Winters methods with optimal initial values and weighting factors for forecasting lime, Thai chili and lemongrass prices in Thailand. Eng Appl Sci Res 2018;45(1):32-38.