

AN EVALUATION OF HOLT-WINTERS METHODS WITH DIFFERENT INITIAL TREND VALUES FOR FORECASTING CRUDE PALM OIL PRODUCTION AND PRICES IN THAILAND

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Abstract

An evaluation of the Holt- Winters methods with different initial trend values for forecasting crude palm oil production and prices in Thailand is presented in this paper. The Holt- Winters methods including well-known methods (i.e. the multiplicative Holt- Winters (MHW) and the additive Holt- Winters (AHW) methods) and the extended version of the AHW method proposed in the literature (i.e. the extended additive Holt- Winters (EAHW) method) are selected and tested, while 4 different initial trend values are set and applied for such methods. By this procedure, the major contributions of our paper are how: a) the different initial trend values that affect forecasting accuracy of the selected methods can be investigated, and b) the best forecast results determined by the optimal solution are obtained. The input data from January 2005 to February 2018 (158 months) are collected from the database of the Department of Internal Trade, Ministry of Commerce, Thailand. The results show that the EAHW method provides good accuracy as indicated by the mean absolute percentage error in forecasting crude palm oil production and prices. Additionally, the results demonstrate that, by applying the different initial trend values to the forecasting methods, the level of forecasting accuracy is significantly different. Finally, we also provide the forecast results of March 2018 to May 2018 in this paper.

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Introduction

Palm oil has become the world's leading oil crop in terms of its high yield production which is 6-10 times more than other edible oils (i.e., coconut, olive, cotton, soy, sunflower, and rapeseed) (Petchseechoung, 2017). Thailand is in third place in the world rankings of crude palm oil producers. In 2017, Thai palm oil production was 2,281,000 metric tonnes or 3% of global output (The Department of Internal Trade, 2018). The domestic consumption (88% of annual production capacity) was in the food, chemical, and biofuel industries. The supply and demand for palm oil is dependent on several factors such as economic, political, and environmental factors. Thus, its price and the production movement obviously vary based on these factors. For example, in January 2017, the palm oil production was short (total production volume of 96,750 metric tonnes) due to drought conditions, leading to the price increasing to 31.40 baht/kg. By comparison with the same month in 2018, the amount of palm oil produced increased to 222,167 metric tonnes. The price then fell to 19.36 baht/kg.

The fluctuation of the palm oil price has a significant effect on agriculturists, manufacturers, traders, and consumers who are involved in the production and the market (Kanchymalay *et al.*, 2017). The Thai government plays an important role in keeping a stable domestic price and production of palm oil by defining an appropriate policy, such as allocating the palm oil to biofuel production with suitable ratios. Therefore, an accurate forecasting strategy for palm oil prices and production using an efficient forecasting technique is imperative to assist the government's decision-making in time for uncertain situations.

To forecast time series data, the well-known Holt-Winters methods are widely used as efficient forecasting solutions (Montgomery *et al.*, 2008; Kalekar, 2004; Holt, 2004). They are used to forecast a time series without the necessity of fitting a parametric model, where

the forecasts are updated for each new incoming observation (Gelper *et al.*, 2010). The Holt-Winters methods are appropriately used when both trend and seasonality patterns are presented in the data series (Holt, 2004; Kalekar, 2004; Montgomery *et al.*, 2008). Generally, there are 2 Holt-Winters methods: the MHW and the AHW methods, depending on whether the seasonality is modeled in multiplicative or additive forms. Note that their details will be described in the next section. Although the Holt-Winters methods are not new as presented in the literature, they are popularly used in practice and in various applications, as reported (Kalekar, 2004; Montgomery *et al.*, 2008; Gelper *et al.*, 2010; Ramos *et al.*, 2015; Tratar *et al.*, 2016). Here, the Holt-Winters methods are often selected due to their simplicity, robustness, low complexity, and algorithm efficiency (Kalekar, 2004; Ramos *et al.*, 2015).

Based on studies in the literature, the works related to forecasting using the Holt-Winters methods were reported in Siregar *et al.* (2017), Kanchymalay *et al.* (2017), and Wan Ahmad *et al.* (2013). Here, we concentrate on the forecasting of palm oil production and prices which directly relates to our work. In Siregar *et al.* (2017), a study of methods for forecasting palm oil production in Indonesia was presented. The input data from 2010 to 2014 (5-year data) were tested with the double exponential smoothing, MHW, and AHW methods. The authors concluded that the AHW method significantly provided more forecasting accuracy than the other methods. In Kanchymalay *et al.* (2017), the forecasting of monthly crude palm oil prices in Malaysia was presented. The forecasting methods included the multi-layer perception, the support vector regression, and the Holt-Winters methods, where the input data from January 1987 to February 2017 gathered from the Malaysian Palm Oil Council were used. The authors demonstrated that the

Holt-Winters method could be efficiently used to forecast the monthly crude palm oil prices, where the forecasting performance was evaluated through the mean absolute percentage error (MAPE) result. Finally, the work in Wan Ahmad *et al.* (2013) applied the autoregressive moving average and exponential smoothing methods to forecast crude palm oil prices in Malaysia. Here, the results also confirmed the forecasting accuracy of both selected methods.

The EAHW method was derived and proposed by Tratar in 2016 (Tratar and Srmcnik 2016; Tratar *et al.*, 2016). The EAHW method was an extended version of the traditional AHW method, where its algorithm could perform as the EAHW or the AHW adaptively, based on the pattern of the input data (its details will be described in the next section). For the EAHW's performance, the authors proved that the EAHW provided good accuracy in forecasting short and long-term heat load data (Tratar *et al.*, 2016). However, how well the EAHW method performs in the case of the crude palm oil data and during the varying initial trend values as proposed in this work had not yet been investigated.

According to the efficiency of the Holt-Winters methods in practice as described above, in this paper we apply them to forecast crude palm oil production and prices in Thailand. The MHW, the AHW, and the EAHW methods are tested, where the input data from January 2005 to February 2018 gathered from the database of the Department of Internal Trade, Ministry of Commerce are used. The major contribution of our study is that 2 well-known forecasting methods and 1 recently proposed method are tested with the crude palm oil data, while 4 different initial trend values suggested by the pioneer work in the literature are also applied and evaluated. Therefore, the best forecast results determined by the optimal solution can be obtained. Our study reveals that the EAHW method shows good accuracy both in forecasting production and prices. The findings also indicate that, using the different initial trend values, the level of forecasting accuracy is also different.

We note that, although the MHW, the AHW, and the EAHW methods as the different

exponential smoothing methods of the Holt-Winters family are applied and studied in this work because of their benefit as mentioned above, to forecast crude palm oil data other forecasting techniques such as an artificial neural network, autoregressive integrated moving average, and seasonal autoregressive integrated moving average should also be tested. This solution is still an open research issue and needs further investigation.

Materials and Methods

Input Data

The monthly crude palm oil production and monthly crude palm oil prices from January 2005 to February 2018 (158 months) as the input data for the MHW, the AHW, and the EAHW methods are collected from the database of the Department of Internal Trade (2018). They are illustrated in Figures 1 and 2, respectively.

Forecasting Methods

As introduced in the previous section, the Holt-Winters methods are appropriately used for forecasting input data which show both trends and seasonality behaviors (Montgomery *et al.*, 2008; Kalekar, 2004; Holt, 2004). The Holt-Winters methods incorporate 3 equations: the first for the level, the second for the trend, and the third for the seasonality. The MHW method is preferred when the seasonal variations are changing proportionally to the level of the series, while the AHW method is preferred when the seasonal variations are roughly constant through the series.

The MHW method is shown in Equations (1) to (4), where L_i is an estimate of the level of the data series at the sample number i , X_i is b_i the input value introduced in Figures 1 and 2, b_i is an estimate of the trend of the data series, S_i is the multiplicative seasonal component, n is the seasonality length (i.e. the number of months in a year), α , β , and γ are the weighting factors with their values between 0 and 1, and Y_{i+m} is the forecast value for the period $i+m$ (m is the number of forecast periods ahead).

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

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

$$S_i = \gamma \left(\frac{X_i}{L_i} \right) + (1 - \gamma)S_{i-n} \quad (3)$$

$$Y_{i+m} = (L_i + mb_i)S_{i-n+m} \quad (4)$$

The AHW method is shown in Equations (5) to (8), where Equation (6) is the same as Equation (2). The differences in the other equations are that the seasonal indices are added and subtracted instead of taking products and ratios.

$$L_i = \alpha(X_i - S_{i-m}) + (1 - \alpha)(L_{i-1} + b_{i-1}) \quad (5)$$

$$b_i = \beta(L_i - L_{i-1}) + (1 - \beta)b_{i-1} \quad (6)$$

$$S_i = \gamma(X_i - L_i) + (1 - \gamma)S_{i-n} \quad (7)$$

$$Y_{i+m} = L_i + mb_i + S_{i-n+m} \quad (8)$$

The EAHW method proposed by Tratar in 2016 (Tratar and Srmcnik 2016; Tratar *et al.*, 2016) is shown in Equation (9). Here, the only difference between the EAHW and the AHW methods is the equation for the level. The EAHW allows the smoothing of the seasonal component more or less than the AHW method, depending on the value of δ ($1 \leq \delta \leq 0$). If $\delta = \alpha$, the EAHW method reduces to the AHW method (or Equation (5)). In addition, if $\delta = 1$, Equation (9) is then equal to Equation (10) (Tratar *et al.*, 2016). Here, α occurs only at the input X_i and not at the seasonal component S_{i-m} . Thus, 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 $\alpha X_i < S_{i-m}$.

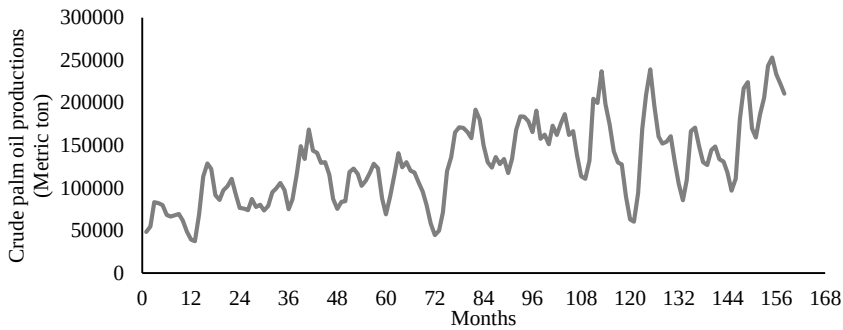


Figure 1. The monthly crude palm oil productions (metric ton) from January 2005 to February 2018 (158 months)

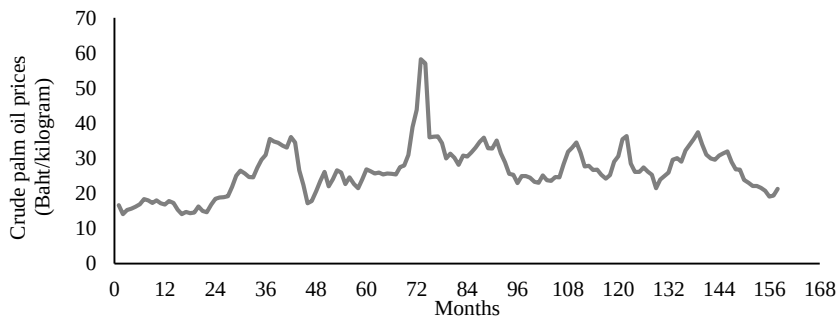


Figure 2. The monthly crude palm oil prices (Baht/kilogram) from January 2005 to February 2018 (158 month)

$$L_i = \alpha X_i - \delta S_{i-m} + (1 - \alpha)(L_{i-1} + b_{i-1}) \quad (9)$$

$$L_i = \alpha X_i - S_{i-m} + (1 - \alpha)(L_{i-1} + b_{i-1}) \quad (10)$$

As suggested by the pioneer work in the research literature (Montgomery *et al.*, 2008; Kalekar, 2004; Holt, 2004; Dhakre *et al.*, 2016; Tratar and Srmcnik 2016; Tratar *et al.*, 2016), to initialize the level and seasonal components (L_i and S_i), Equations (11) and (12) are used for the MHW method (where $i = 1, 2, 3, \dots, 12$), while Equations (11) and (13) are used for the AHW and the EAHW methods.

$$L_n = \frac{(X_1 + X_2 + \dots + X_n)}{n} \quad (11)$$

$$S_i = \frac{X_i}{L_n} \quad (12)$$

$$S_i = X_i - L_n \quad (13)$$

Additionally, to initialize the trend value (b_i) for the MHW, the AHW, and the EAHW

methods, the works in Montgomery *et al.* (2008), Kalekar (2004), Holt (2004), Dhakre *et al.* (2016), Tratar and Srmcnik (2016), Tratar *et al.* (2016) also suggested that Equations (14) to (17) should be used (i.e. options 1 to 4). In this paper these 4 suggested equations will be tested. Therefore, how such different initial values influence the accuracy level of the MHW, the AHW, and the EAHW methods with the crude palm oil data will be investigated, and the best forecast results provided by the optimal solution will also be determined.

$$\text{Option 1; } b_1 = \frac{(X_n - X_1)}{(n-1)}; n = 12 \quad (14)$$

$$\text{Option 2; } b_1 = X_2 - X_1 \quad (15)$$

$$\text{Option 3; } b_1 = \frac{[(X_2 - X_1) + (X_3 - X_2) + (X_4 - X_3)]}{3} \quad (16)$$

$$\text{Option 4; } b_1 = 0 \quad (17)$$

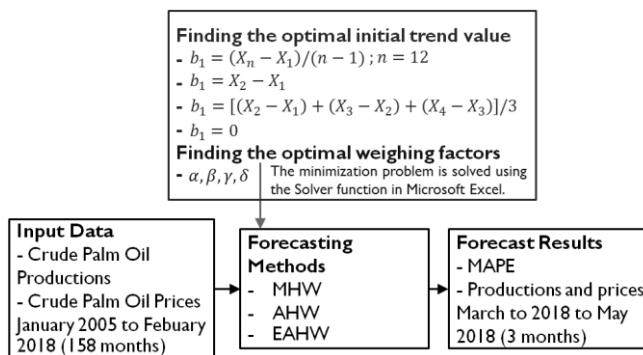


Figure 3. The forecasting system proposed in this paper

Table 1. Summary of the MHW, the AHW, and the EAHW methods

Methods	Level, trend, and seasonal components	Initial values	Forecast value
MHW	$L_i = \alpha \left(\frac{X_i}{S_{i-m}} \right) + (1 - \alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1 - \beta)b_{i-1}$ $S_i = \gamma \left(\frac{X_i}{L_i} \right) + (1 - \gamma)S_{i-n}$	$L_n = (X_1 + X_2 + \dots + X_n)/n$ $S_i = X_i/L_n$ $b_1 = (X_n - X_1)/(n - 1)$ $b_1 = X_2 - X_1$ $b_1 = [(X_2 - X_1) + (X_3 - X_2) + (X_4 - X_3)]/3$ $b_1 = 0$	$Y_{i+m} = (L_i + mb_i)S_{i-n+m}$
AHW	$L_i = \alpha(X_i - S_{i-m}) + (1 - \alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1 - \beta)b_{i-1}$ $S_i = \gamma(X_i - L_i) + (1 - \gamma)S_{i-n}$	$L_n = (X_1 + X_2 + \dots + X_n)/n$ $S_i = X_i - L_n$ $b_1 = (X_n - X_1)/(n - 1)$ $b_1 = X_2 - X_1$	$Y_{i+m} = L_i + mb_i + S_{i-n+m}$
EAHW	$L_i = \alpha X_i - \delta S_{i-m} + (1 - \alpha)(L_{i-1} + b_{i-1})$ $b_i = \beta(L_i - L_{i-1}) + (1 - \beta)b_{i-1}$ $S_i = \gamma(X_i - L_i) + (1 - \gamma)S_{i-n}$	$b_1 = [(X_2 - X_1) + (X_3 - X_2) + (X_4 - X_3)]/3$ $b_1 = 0$	

Finally, as mentioned before, α , β , γ , and δ are the weighting factors with their values between 0 and 1. In this paper, the optimal values of all weighting factors are automatically determined during the test. They are determined by minimizing the MAPE results, and the minimization problem is solved using the Solver function in Microsoft Excel (Booranawong *et al.*, 2017b; Tratar and Srmcnik 2016; Tratar *et al.*, 2016). We note that the MHW, the AHW, and the EAHW methods introduced in this work are also implemented in the Excel program. We also note that a summary of the MHW, the AHW, and the EAHW methods are also illustrated in Table 1.

Performance Metrics

The MAPE (Chatfield, 2001; Tratar *et al.*, 2016; Booranawong *et al.*, 2017a) referring to the forecasting error is selected as the performance metric. It is used in this paper because it provides an accurate and fair comparison of forecasting methods. The MAPE is not prone to change in the magnitude of the time series to be forecasted as reported by Gentry *et al.* (1995) and Alon *et al.* (2001). Also, it is frequently used in practice as reported by Ravindran and Warsing (2013). The MAPE is expressed in Equation (18), where e_i is the error which is the different level between the actual data and the forecast data;

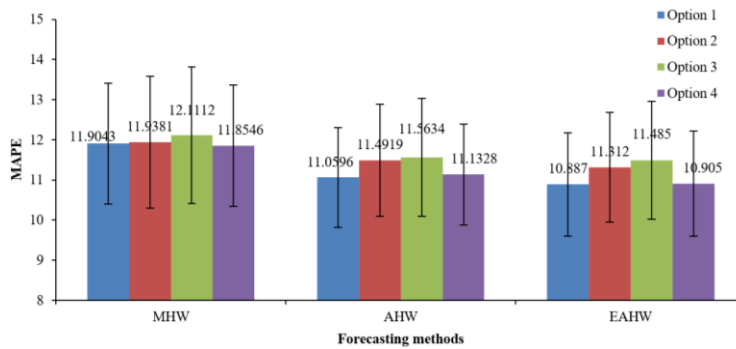


Figure 4. The comparison of the MAPE determined by each forecasting method for the case of the crude palm oil productions, when the initial trend values in Equations (14) to (17) are applied

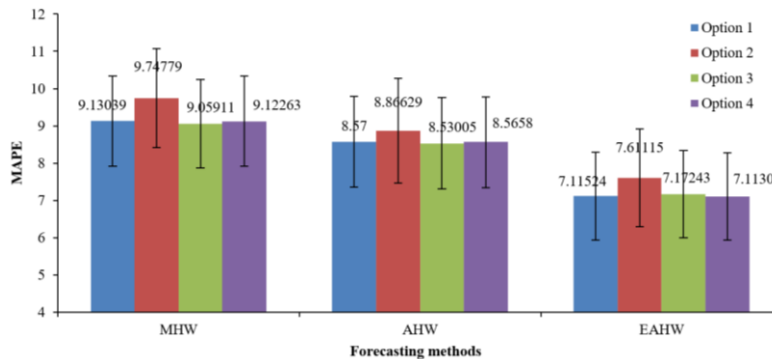


Figure 5. The comparison of the MAPE determined by each forecasting method for the case of the crude palm oil prices, when the initial trend values in Equations (14) to (17) are applied

$e_i = \hat{Y}_i - Y_i$, and N is the number of data samples. The 95% confidence interval (CI) is also provided for the average results.

$$MAPE = \frac{\sum_{i=1}^N \left| \frac{e_i}{Y_i} \right|}{N} \times 100 \quad (18)$$

In summary, the forecasting system proposed in this work is summarized in Figure 3. The input data are the monthly crude palm oil production and prices (158-month data). The forecasting methods are the MHW, the AHW, and the EAHW methods. The optimal initial values for the trend component and the optimal weighting factors for the level, trend, and seasonal components are determined. Finally,

the MAPE and the forecast results (3-month data) are reported.

Results and Discussion

Figures 4 and 5 show the comparison of the MAPE results determined by the MHW, the AHW, and the EAHW methods with their optimal weighting factors, when the initial trend values in Equations (14) to (17) (options 1 to 4) are applied. We note that the MAPE is calculated from the forecast results of January 2006 to February 2018 ($N = 146$ to $N = 144$), where the input data of the first years (January 2005 to December 2005) are employed for

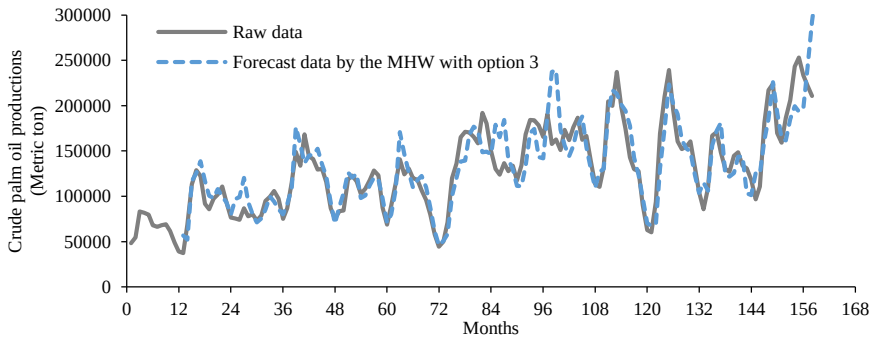


Figure 6. The comparison of the crude palm oil productions between the raw data and the forecast data determined by the MHW method with Equation (16) (option 3)

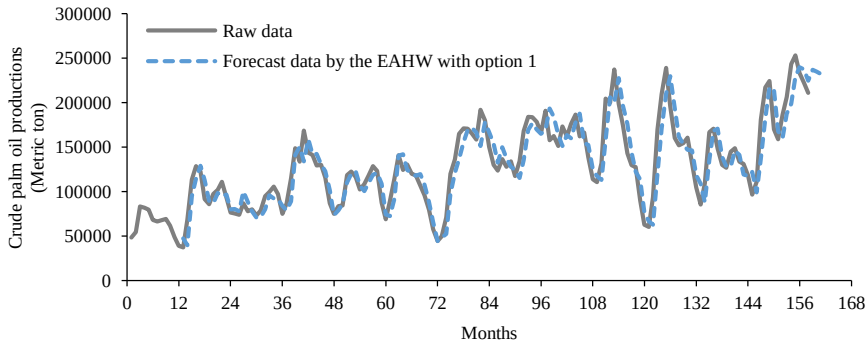


Figure 7. The comparison of the crude palm oil productions between the raw data and the forecast data determined by the EAHW method with Equation (14) (option 1)

setting the initial values for the level, trend, and seasonal components as shown in Equations (11) to (17).

The results in Figure 4 demonstrate that, to forecast crude palm oil production, the AHW and the EAHW methods give the smallest MAPE results when the initial trend values from Equations (14) and (17) or options 1 and 4 are applied. We note that by considering the 95% CI for this case, the performance by the AHW and the EAHW methods is not significantly different. The results in Figure 4 also indicate that using Equations (14) and (17), the MAPE results are significantly smaller than in the case of using Equations (15) and (16) or options 2 and 3. For the case of the crude palm oil prices in Figure 5, the results

also reveal that the EAHW method with the initial trend values in Equations (14) and (17) also provide the smallest MAPE results. Therefore, by Figures 4 and 5, we can conclude that, to obtain the best forecasting accuracy, selecting and using the optimal initial trend value (like Equations (14) and (17)), and the optimal forecasting method (like the EAHW method) for forecasting crude palm oil productions and prices are required.

Figures 6 and 7 illustrate the comparison of the raw data (crude palm oil production) and the forecast data determined by the MHW method with the optimal weighting factors and Equation (16) (i.e. the worst case) and the EAHW method with the optimal weighting factors and Equation (14) (i.e. the best case).

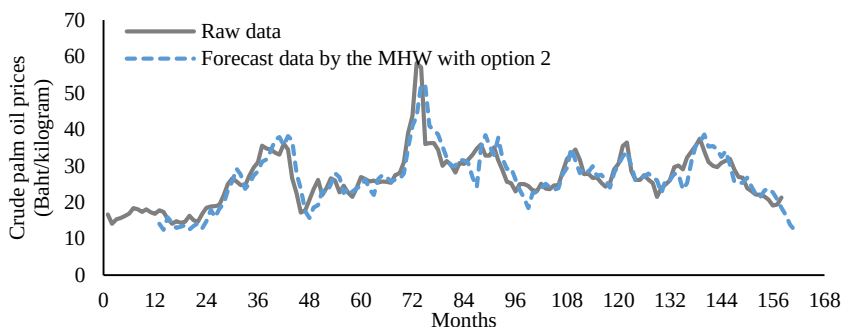


Figure 8. The comparison of the crude palm oil prices between the raw data and the forecast data determined by the MHW method with Equation (15) (option 2)

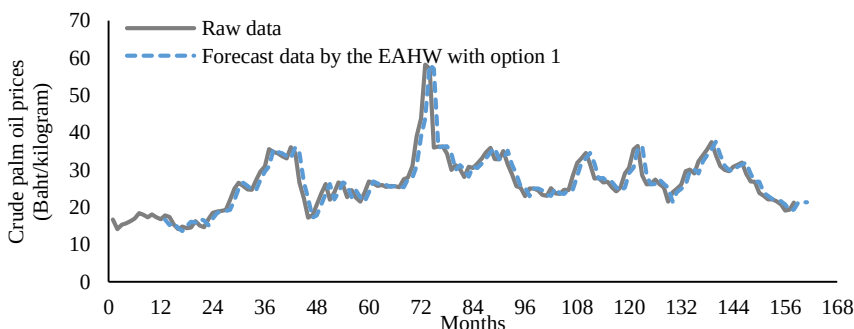


Figure 9. The comparison of the crude palm oil prices between the raw data and the forecast data determined by the EAHW method with Equation (14) (option 1)

Figures 8 and 9 also illustrate the comparison of the raw data (crude palm oil prices) and the forecast data determined by the MHW method with the optimal weighting factors and Equation (15) (i.e. the worst case) and the EAHW method with the optimal weighting factors and Equation (14) (i.e. the best case). These examples demonstrate that the forecast data by the optimal solution are closer to the raw data. This directly relates to the MAPE results which are introduced in Figures 4 and 5; a good matching result represents the small MAPE.

The optimal weighting factors, which give the minimum of the MAPE determined by the Solver function in Microsoft Excel, and the forecast results of March 2018 to May 2018 in the case of the EAHW method with the different initial trend values are also illustrated in Tables 2 and 3, respectively. For the crude palm oil production, as shown in Table 2, the forecast data by using Equations (14) and (17) show the same trend. The forecast values of the oil palm production decrease; they are 236,985.9, 234,875.6, and 231,847.8, respectively (by Equation (14)), and 237,303.7, 236,025.3, and 233,829.0, respectively (by Equation (17)). For the crude palm oil prices in Table 3,

they are 21.29517, 21.31068, and 21.32624, respectively (by Equation (14)), and they are 21.27948, 21.27962, and 21.27987, respectively (by Equation (17)). Here, the forecast values of crude palm oil prices are little increased. The results provided above reveal the correlation between the production and prices.

Conclusions

In this paper, an evaluation of the Holt-Winters methods with different initial trend values for forecasting crude palm oil production and prices in Thailand is proposed. The MHW, the AHW, and the EAHW methods are tested, and 4 different initial trend values are applied for such forecasting methods. Our study demonstrates that the EAHW method shows good accuracy both in forecasting crude palm oil production and prices. In addition, applying the different initial trend values, the forecasting accuracy is also different. Therefore, selecting the optimal initial trend value and the optimal forecasting method is required for testing in practice. Finally, the forecast results of March 2018 to May 2018 are also reported in this paper. In future work, to

Table 2. The optimal weighting factors and the forecast data of March 2018 to May 2018 determined by the EAHW method; crude palm oil productions

Methods	Optimal weighting factors				Forecasted productions (2018)		
	α	β	γ	δ	March	April	May
Option 1	0.99994	3.642e-5	0.00015	0.81874	236985.9	234875.6	231847.8
Option 2	0.99999	0.04670	7.95e-6	0.83927	240310.9	241321.1	241413.5
Option 3	1	0.07043	8.59e-5	0.85350	240872.4	242311.6	242833.3
Option 4	0.99999	1.68e-6	0	0.76424	237303.7	236025.3	233829.0

Table 3. The optimal weighting factors and the forecast data of March 2018 to May 2018 determined by the EAHW method; crude palm oil prices

Methods	Optimal weighting factors				Forecasted prices (2018)		
	α	β	γ	δ	March	April	May
Option 1	0.99994	0	0.99991	8.1e-6	21.29517	21.31068	21.32624
Option 2	0.99983	0.18448	1	0.35644	21.05049	20.82299	20.59515
Option 3	1	0.00080	0.99999	3.49e-5	21.15510	21.03019	20.90529
Option 4	0.99988	7.96e-6	1	4.95e-5	21.27948	21.27962	21.27987

validate the selected Holt- Winters methods with different initial trend values and to enhance the forecasting accuracy, more updated crude palm oil data, other input data related to crude palm oil production and prices, and more efficient forecasting techniques will be included and evaluated.

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