SIMPLE AND DOUBLE EXPONENTIAL SMOOTHING METHODS WITH DESIGNED INPUT DATA FOR FORECASTING A SEASONAL TIME SERIES: IN AN APPLICATION FOR LIME PRICES IN THAILAND

Thitima Booranawong[1] and Apidet Booranawong[2,*]

Received: April 24, 2017; Revised: October 14, 2017; Accepted: November13, 2017

Abstract

In this paper, the simple exponential smoothing (SES) and double exponential smoothing (DES) methods with designed input data are presented to forecast lime prices in Thailand during the period January 2016 to December 2016. The lime prices from January 2011 to December 2015 are the input data (i.e. seasonal data) which were gathered from the database of Simummuang market, Thailand. The major contribution of our paper is that, although, in general, the forecasting accuracy by the traditional SES and DES methods significantly decreases when those methods are used to forecast the data which show seasonality patterns, the proposed solution can properly handle such a problem. For this purpose, to forecast lime prices, 5 different input data are defined before being assigned to the SES and the DES methods: a) the monthly data of the recent year, b) the average monthly data of the past years, c) the median of the monthly data of the past years, d) the monthly data of the past years after applying the linear weighting factor, and e) the average monthly data of the past years after applying the exponential weighting factor. These designed input data are used as agents of the raw data. Our research results indicate that using the DES method with input b) and the optimal initial values to forecast lime prices during January 2016 to September 2016 significantly gives the smallest forecasting error measured by the mean absolute percentage error (MAPE). The forecast lime prices of October 2016 to December 2016 are also given. Additionally, we also demonstrate that, in our case, the SES and the DES methods with designed input data show a smaller MAPE than the methods using the multiplicative Holt-Winters and the additive Holt-Winters models which are designed for forecasting the seasonal data.

[1] *Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, Nakhon Si Thammarat 80280, Thailand. E-mail: thitima.cute@gmail.com*

[2] *Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla 90112, Thailand. E-mail: apidet.boo@gmail.com*

[*] *Corresponding author*

Keywords: Forecasting, simple and double exponential smoothing, seasonality, holt-winters, lime prices

Introduction

Currently, lime (Citrus aurantifolia Swingle) is one of the economically significant horticultural crops in Thailand (Pranamornkith, 2009; Kaewsuksang *et al.*, 2015). Limes can be grown in many regions in Thailand (i.e. in the central, the southern, and the northern regions) and produce fruits throughout the year (Pranamornkith, 2009). Because limes have their own sour taste, they can be integrated as part of various Thai foods and beverages. Also, because lime prices are very high, especially during the summer season in Thailand, it is very attractive for Thai agriculturists to sell limes to gain higher profits. Therefore, knowing the selling price and the selling trend before selling is very useful for Thai agriculturists to plan their planting and harvesting schedules.

In this work, the well-known simple exponential smoothing (SES) and double exponential smoothing (DES) methods (Brown, 1956; Hunter, 1986; Winters, 1960) are used as the time series-based methods to forecast lime prices for 2016, while the lime prices from January 2011 to December 2015 gathered from the database of Simummuang market are used as the input data. Although forecasting time series data by the SES and the DES methods is not new, as reported in the research literature, many researchers have applied such methods to their works due to the simplicity, low computational complexity, and the efficiency of the SES and the DES algorithms (Kaleker, 2004; Montgomery *et al.*, 2008; Ramos *et al.*, 2015; Tratar, 2016; Tratar *et al.*, 2016). However, the forecasting accuracy produced by both methods significantly decreases when they are applied to data which show seasonality patterns (Holt, 2004; Kaleker, 2004). To address this problem, the Holt-Winters (HW) method is introduced and used instead (Gardner, 1985; Holt, 2004; De Gooijer and Hyndman, 2006; Dhakre *et al.*, 2016;). In this work, the SES and the DES methods with designed input data (Booranawong and Booranawong, 2017) are presented to forecast the seasonal time series. The major design concept of our proposed solution is that the raw input data are redesigned before being used as the actual inputs for the SES and the DES methods. The designed input data are: a) the monthly data of the year 2015, b) the average monthly data of the years 2011 to 2015, c) the median of the monthly data of the years 2011 to 2015, d) the monthly data of the years 2011 to 2015 after applying the linear weighting factor where the higher weight value is applied to the recent data, and e) the average monthly data of the years 2011 to 2015 after applying the exponential weighting factor where the higher weight is also applied to the recent data. Our research results demonstrate that the DES method with the input b), the optimal initial values, and weighting factors provides the smallest MAPE on forecasting the lime prices. Additionally, it shows better results than the MHW and the AHW methods.

The structure of this paper is as follows. The next section introduces materials and methods including the detail of the input data, the designed input data, the SES and the DES methods with the designed input data, the MHW and the AHW methods, and the performance metric. The subsequent section describes the results and contains the discussion. The final section presents the limitations of the proposed solution.

Materials and Method

Input Data

The monthly lime prices as the raw data from January 2011 to September 2016 were gathered from the website of Simummuang market which is one of the big markets located in Pathum Thani, Thailand. They are given in Table 1.

Table 1. The monthly lime prices in Thai Baht units

Months	Monthly lime prices					
	2011	2012	2013	2014	2015	2016
1	71.77	265.16	235.67	236.13	261.94	210.00
2	110.00	369.66	320.00	337.14	314.29	200.00
3	269.35	502.90	558.06	505.00	398.21	320.00
4	184.83	561.33	676.67	745.00	544.83	421.67
5	169.68	336.45	542.19	622.41	581.10	500.00
6	149.33	173.00	281.67	373.33	298.33	473.33
7	113.55	163.23	251.61	187.10	200.00	264.52
8	92.90	267.74	309.35	211.29	182.26	183.87
9	84.67	295.00	300.00	289.33	200.00	270.59
10	140.00	209.03	235.45	370.97	232.26	-
11	140.00	200.00	196.00	326.33	218.33	-
12	187.00	204.84	169.03	222.58	200.00	-

Table 2. Notation of the monthly lime prices

Months	Notation of the monthly lime prices					
	2011	2012	2013	2014	2015	2016
1	A_1	B_1	C_1	D_1	E_1	F_1
2	A_2	B_2	C_2	D_2	E_2	F_2
3	A_3	B_3	C_3	D_3	E_3	F_3
4	A_4	B_4	C_4	D_4	E_4	F_4
5	A_5	B_5	C_5	D_5	E_5	F_5
6	A_6	B_6	C_6	D_6	E_6	F_6
7	A_7	B_7	C_7	D_7	E_7	F_7
8	A_8	B_8	C_8	D_8	E_8	F_8
9	A_9	B_9	C_9	D_9	E_9	F_9
10	A_{10}	B_{10}	C_{10}	D_{10}	E_{10}	-
11	A_{11}	B_{11}	C_{11}	D_{11}	E_{11}	-
12	A_{12}	B_{12}	C_{12}	D_{12}	E_{12}	-

Designed Input Data

To forecast the monthly lime prices for 2016, the monthly data of the years 2011 to 2015 are used as the input data and they are redefined before being assigned to the SES and DES methods, as presented here.

The 5 designed input data are: a) $Input_1$; the monthly data of 2015 (i.e. the recent yearly data) as shown in Equation (1), b) $Input_2$; the average monthly data of the years 2011 to 2015 as shown in Equation (2), c) $Input_3$; the median of the monthly data of the years 2011 to 2015 as shown in Equation (3), d) $Input_4$; the monthly data of the years 2011 to 2015 after applying the linear weighting factor as shown in Equation (4), and e) $Input_5$; the average monthly data of the years 2011 to 2015 after applying the exponential weighting factor as also shown in Equation (4). The notation of the monthly lime prices from January 2011 to September 2016 is illustrated in Table 2.

$$Input_1 = [E_1, E_2, \ldots E_{12}] \quad (1)$$

$$Input_2 = [Mean(A, B_1, C_1, D_1, E_1), Mean(A_2, B_2, C_2, D_2, E_2), \ldots, Mean(A_{12}, B_{12}, C_{12}, D_{12}, E_{12})] \quad (2)$$

$$Input_3 = [Median(A, B_1, C_1, D_1, E_1), Median\ (A_2, B_2, C_2, D_2, E_2), \ldots, Median\ (A_{12}, B_{12}, C_{12}, D_{12}, E_{12})] \quad (2)$$

Table 3. Designed input data

	Designed input data				
Months	**$Input_1$**	**$Input_1$**	**$Input_1$**	**$Input_1$**	**$Input_1$**
1	261.94	214.13	236.13	237.55	244.97
2	314.29	290.22	320.00	315.29	317.04
3	398.21	446.70	502.90	464.03	448.92
4	544.83	542.53	561.33	602.77	601.06
5	581.10	450.37	542.19	524.29	554.33
6	298.33	255.13	281.67	288.35	301.16
7	200.00	183.09	187.10	196.22	197.69
8	182.26	212.71	211.29	220.86	208.91
9	200.00	233.80	289.33	248.79	238.22
10	232.26	237.54	232.26	260.64	263.17
11	218.33	216.13	200.00	234.99	238.88
12	200.00	196.69	200.00	199.61	201.57

Table 4. Forecasting by the SES method

	Forecasting by the SES method	
Month	**Input**	**Forecast results (Y_i)**
1	X_1	$Y_1 = X_1$
2	X_2	$Y_2 = \alpha X_2 + (1-\alpha)Y_1$
.	.	.
.	.	.
.	.	.
12	X_{12}	$Y_{12} = \alpha X_{12} + (1-\alpha)Y_{11}$

$$Input_{4\text{ and }5} = [((A_1\, W_1)+(B_1\, W_2)+(C_1\, W_3)+(D_1\, W_4)+(E_1\, W_5)),((A_2\, W_1)+(B_2\, W_2)+(C_2\, W_3)+(D_2\, W_4)+(E_2\, W_5)),\ldots,((A_{12}\, W_1)+(B_{12}\, W_2)+(C_{12}\, W_3)+(D_{12}\, W_4)+(E_{12}\, W_5))] \quad (3)$$

For $Input_4$ and $Input_5$, the monthly data of the years 2011, 2012, 2013, 2014, and 2015 are multiplied by the weighting factors. W_1, W_2, W_3, W_4 and W_5 are the weighting factors, where 0 ≤ weighting factor ≤ 1 $W_1 \leq W_2 \leq W_3 \leq W_4 \leq W_5$ and $W_1 + W_2 + W_3 + W_4 + W_5$. For $Input_4$, W_1, W_2, W_3, W_4 and W_5 are set to 0.06667 (e.g. W_1 = 1/(1+2+3+4+5)), 0.13333, 0.20000, 0.26667, and 0.33333 (e.g. W_5 = 1/(1+2+3+4+5)), respectively (i.e. the linear weighting values). For $Input_5$, W_1, W_2, W_3, W_4 and W_5 are set to 0.03750 (e.g. $W_1 = (1/2)^5 + 0.00625$), 0.06875, 0.13125, 0.25625, and 0.50625 (e.g. $W_1 = (1/2)^1 + 0.00625$), respectively (i.e. the exponential weighting values). By our setting, the weighting factor with a high value is applied to the input data of the recent year. This will give high priority to recent input data. The 5 designed input data in Equations (1) to (4) are also shown in Table 3.

The SES and the DES Methods with the Designed Input Data

The SES Method

The forecast result by the SES method is shown in Equation (5), where Y_i is the forecast value at the sample number i (i.e. the month), X_i is the input value as introduced in Table 3, Y_{i-1} is the forecast value at the sample number i-1 (i.e. the latest month), and α is the weighting factor. By Equation (5), the forecast result directly depends on the previous forecast value and the recent input value multiplied by the weighting factor, where $0 \leq \alpha \leq 1$. Here, α close to 1 gives high priority to recent changes in the input value, while α close to 0 indicates that the previous forecast value plays a role in the calculation. In this work, the optimal value of α is determined by minimizing the forecasting error (i.e. the MAPE) (Trater and Srmcnik, 2016). The minimizing problem is automatically solved by using the Solver function in Microsoft Office Excel, version 2013. More details on this can be found in Trater and Srmcnik (2016). An example of the forecasting by the SES method is also illustrated in Table 4.

$$Y_i = \alpha X_i + (1-\alpha)\, Y_{i-1} \quad (5)$$

We note that by substituting $Y_{i-1}, Y_{i-2}, \ldots Y_1$, into Equation (5), the general form of the SES method can be written by Equation (6), where the weighting for each older datum decreases exponentially. According to Equation (6), an illustration of the forecast result of month 12 is shown in Equation (7).

$$\begin{aligned} Y_i &= \alpha X_i + (1-\alpha)\,[\alpha X_{i-1} + (1-\alpha)\, Y_{i-2}] \\ &= \alpha X_i + \alpha(1-\alpha)\, X_{i-1} + (1-\alpha)^2 Y_{i-2} \\ &= \alpha X_i + \alpha(1-\alpha)\, X_{i-1} + (1-\alpha)^2[\alpha X_{i-2} + (1-\alpha) Y_{i-3}] \\ &= \alpha X_i + \alpha(1-\alpha)\, X_{i-1} + \alpha(1-\alpha)^2 X_{i-2} + (1-\alpha)^3 Y_{i-3} \end{aligned}$$

$$Y_i = \alpha X_i + \alpha(1-\alpha)\, X_{i-1} + \alpha(1-\alpha)^2 X_{i-2} + \cdots + \alpha(1-\alpha)^{i-1} Y_1\text{, where } Y_1 = X_1 \quad (6)$$

$$Y_{12} = \alpha X_{12} + \alpha(1-\alpha)X_{11} + \alpha(1-\alpha)^2 X_{10} + \cdots + \alpha(1-\alpha)^{11} X_1 \quad (7)$$

The DES Method

The DES method, also known as Holt's linear exponential method, is appropriately used to forecast the data which show the trend (Holt, 2004; Kaleker, 2004; Montgomery *et al.*, 2008). The DES method adds a trend factor to the equation as a way of adjusting for the trend. Three equations are incorporated in this method as written in Equations (8) to (10), where L_i is an estimate of the level of the data series at the sample number i, X_i is the input value as introduced in Table 3, b_i is an estimate of the trend of the data series at the sample number i, α and β are the weighting factors with values between 0 and 1, and Y_{i+m} is the forecast value for the period (where $m > 0$).

$$Li = \alpha X_i + (1 - \alpha)(L_{i-1} + b_{i-1}) \quad (8)$$

$$b_i = \beta(L_i - L_{i-1}) + (1 - \beta)b_{i-1} \quad (9)$$

$$Y_{i+m} = L_i + mb_i \quad (10)$$

As suggested by Kaleker (2004), Montgomery *et al.* (2008), Dhakre *et al.* (2016) and Trater and Srmcnik (2016), to set the initial values for L_i and b_i, we use Equations (11), (12), (13), and (14). For b_i, the one that gives the minimum forecasting error is selected. In addition, optimal values of α and β are also automatically determined. They are selected when the forecasting error (i.e. the MAPE) is minimized (Trater and Srmcnik,

Table 5. Forecasting by the DES method with L_i Equation (11) and b_i in Equation (14)

		Forecasting by the DES method		
Month	***Input***	L_i	b_i	Y_i
1	X_1	$L_1 = X_1$	$b_1 = (X_{12} - X_1)/(12 - 1)$	-
2	X_2	$L_2 = \alpha X_2 + (1 - \alpha)(L_1 + b_1)$	$b_2 = \beta(L_2 - L_1) + (1 - \beta)b_1$	$Y_2 = L_1 + b_1$
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
12	X_{12}	$L_{12} = \alpha X_{12} + (1 - \alpha)(L_{11} + b_{11})$	$b_{12} = \beta(L_{12} - L_{11}) + (1 - \beta)b_{11}$	$Y_{12} = L_{11} + b_{11}$

2016), where the minimizing problem is solved by using the Solver function in Microsoft Office Excel (Trater and Srmcnik, 2016). An illustration of the forecasting by the DES method with L_1 in Equation (11) and b_1 in Equation (14) is shown in Table 5.

$$L_1 = X_1 \quad (11)$$

$$b_1 = 0 \quad (12)$$

$$b_1 = X_2 - X_1 \quad (13)$$

$$b_1 = (X_n - X_1) / (n - 1) \quad (14)$$

The MHW and the AHW Methods

To investigate and evaluate the performance of our methods presented above, we compared them with the Holt-Winters method's models (Holt, 2004; Kaleker, 2004; Montgomery *et al.*, 2008) which are directly used when both trend and seasonality patterns are present in the data series. The Holt-Winters models incorporate 3 equations: first for the level, second for the trend, and third for the seasonality. Generally, there are two Holt-Winters models: the MHW method and the AHW method, depending on whether the seasonality is modelled in multiplicative or additive forms. They are described in detail below.

The MHW Method

The MHW method is shown in Equations (15) to (18); note that Equation (16) is the same as Equation (9), where S_i is the multiplicative seasonal component, γ is the weighting factor with its value between 0 and 1, and n is the seasonality length (i.e. the number of months in a year). We note that the input X_i inserted to the MHW and the AHW methods is the raw data (i.e. the lime prices from January 2011 to September 2016), as presented in Table 1.

$$L_i = \alpha\left(\frac{X_i}{S_{i-m}}\right) + (1-\alpha)(L_{i-1} + b_{i-1}) \quad (15)$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \quad (16)$$

$$S_i = \gamma\left(\frac{X_i}{L_i}\right) + (1-\gamma)S_{i-n} \quad (17)$$

$$Y_{i+m} = (L_i + mb_i)S_{i-n+m} \quad (18)$$

As suggested by Montgomery *et al.* (2008), Kaleker (2004), Holt (2004), Dhakre *et al.* (2016), and Trater and Srmcnik (2016), to initialize the level, we use Equation (19) with n = 12. To initialize the trend, we use Equations (12) to (14) and the one that gives the minimum forecasting error is also selected. Finally, to initialize the seasonal components, we use Equation (20), where i = 1,2,3,…,12.

$$L_n = (X_1 + X_2 + \cdots + X_n)/n \quad (19)$$

$$S_i = X_i/L_n \quad (20)$$

The AHW Method

The AHW method is expressed in Equations (21) to (24); note that Equations (22), (16), and (9) are the same.

$$L_i = \alpha(X_i - S_{i-m}) + (1-\alpha)(L_{i-1} + b_{i-1}) \quad (21)$$

$$b_i = \beta(L_i - L_{i-1}) + (1-\beta)b_{i-1} \quad (22)$$

$$S_i = \gamma(X_i - L_i) + (1-\gamma)S_{i-n} \quad (23)$$

$$Y_{i+m} = L_i + mb_i + S_{i-n+m} \quad (24)$$

The initial values for the level and the trend are the same as those for the MHW method. In addition, to initialize the seasonal components (Holt, 2004; Kaleker, 2004; Montgomery *et al.*, 2008; Dhakre *et al.*, 2016; Trater and Srmcnik, 2016), we use Equation (25), where i = 1,2,3,…,12.

$$S_i = X_i - L_n \quad (25)$$

In both the MHW and the AHW methods, optimal values of α, β, and γ are automatically determined during the test. The parameters α, β, and γ are determined by minimizing the MPAE, and the minimizing problem is also solved by using the Solver function in Microsoft Office Excel.

Table 6. The optimal weighting factors and the forecast prices of October 2016 to December 2016 in the cases of the SES method with input 2, the DES method with input 2 and the initial value in Equation (14), the MHW method, and the AHW method

Methods	Optimal weighting factors			Forecast prices (2016)		
	α	β	γ	Oct.	Nov.	Dec.
SES with input 2	0.42626	-	-	241.779	230.847	216.287
DES with input 2 and Equation (14)	0.94467	≈ 0	-	230.878	235.587	215.623
MHW	0.04250	0	0.54920	259.750	236.156	203.187
AHW	0.04522	≈ 0	0.62632	252.417	229.754	192.843

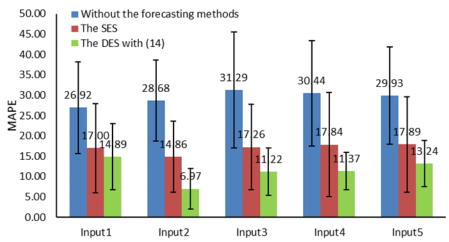


Figure 1. The MAPE by applying inputs 1 to 5

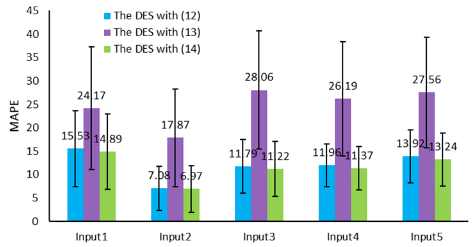


Figure 2. The MAPE by applying inputs 1 to 5 to the DES method with the initial values in Equations (12), (13), and (14)

Performance Metric

The forecasting error represented by the MAPE (Trater and Srmcnik, 2016; Chatfield, 2001) is chosen as the performance metric. The MAPE is selected because it provides an accurate and fair comparison of the forecasting methods, and it is not prone to change in the magnitude of time series to be forecast (Gentry *et al*., 1995; Alon *et al*. 2001). Also, it is frequently used in practice (Ravindran and Warsing, 2013). The MAPE is expressed in Equation (26), where N is the number of the data samples, e_i is the forecasting error from $\acute{Y}_i - Y_i$ as shown in Equation (27), $\acute{Y}_i$ is the actual data, and Y_i is the forecast data determined by the forecasting methods. The 95% confidence interval is also provided for the average results. We note that, in our proposed solutions, N is 9 months and refers to F_1 to F_9 as shown in Table 2. In the MHW and the AHW methods, N is also 9 months and refers $\acute{Y}_i$ to F_1 to F_9 when compared with our proposed solutions. However, we also show their forecasting results during January 2012 to December 2016.

$$MAPE = \frac{\sum_{i=1}^{N}\left|\frac{e_i}{\acute{Y}_i}\right|}{N} \times 100 \qquad (26)$$

$$e_i = \acute{Y}_i - Y_i \qquad (27)$$

Results and Discussion

The MAPE results by applying the inputs 1 to 5 to the SES and the DES methods are presented in Figure 1, and the results without applying any forecasting methods are also compared. Note that without applying the forecasting methods means that the input values are directly used as the forecast values. Figure 2 shows the MAPE results by the DES method with the initial values in Equations (12), (13), and (14), respectively. The results reveal that the DES method with the input 2

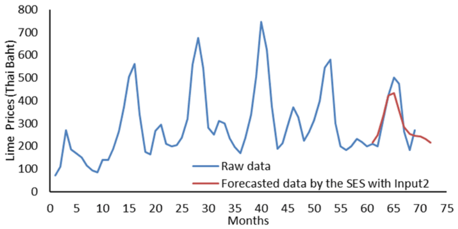


Figure 3. The comparison of the lime prices between the raw data and the forecast data determined by the SES method with input 2

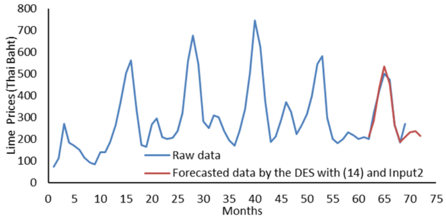


Figure 4. The comparison of the lime prices between the raw data and the forecast data determined by the DES method with input 2

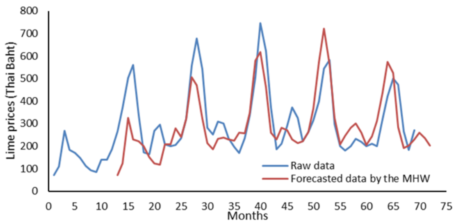


Figure 5. The comparison of the lime prices between the raw data and the forecast data determined by the MHW method

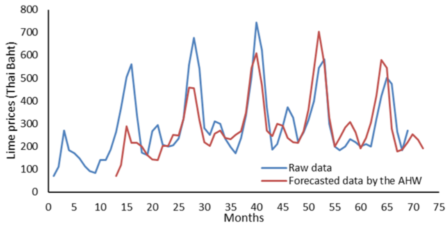


Figure 6. The comparison of the lime prices between the raw data and the forecast data determined by the AHW method

(i.e. the average monthly data of the years 2011 to 2015) and the initial value in Equation (14) significantly gives a smaller MAPE (i.e. MAPE = 6.97) than the other methods. Also, the results here indicate that using the optimal designed input data and initial values can help to increase the forecasting accuracy. The optimal weighting factors, which give the minimum MAPE in the case of the SES method with input 2 and in the case of the DES method with input 2 and the initial value in Equation (14), are shown in Table 6.

The comparisons of the monthly lime prices in Thai Baht units between the raw data (as given in Table 1) and the forecast data determined by the proposed solutions, the MHW method and the AHW method with their optimal initial values and weighting factors, are demonstrated in Figures 3, 4, 5, and 6, respectively. The optimal weighting factors and the forecast prices of October 2016 to December 2016 are shown in Table 6. Here, the results confirm that the methods presented in the previous sections, especially the DES method with input 2 and the initial value in Equation (14), can be properly applied to forecast the monthly lime prices of 2016, although the raw input data to be forecast shows the seasonality pattern. We note that the results also illustrated that the monthly lime prices are very high during the summer season, March to May, in every year.

Figure 7 shows the comparison of the MAPE results determined by the SES method with the input 2 (i.e. method 1), the DES method with the input 2 and the initial value in Equation (14) (i.e. method 2), the MHW method (i.e. method 3), and the AHW method (i.e. method 4), where the MAPE is calculated from the forecast data of the months 62 to 69 (i.e. February 2016 to September 2016). The results confirm that the SES and the DES methods with designed input data provide better performances than the MHW and the AHW methods which are designed by taking the seasonality behavior of the data into considerations.

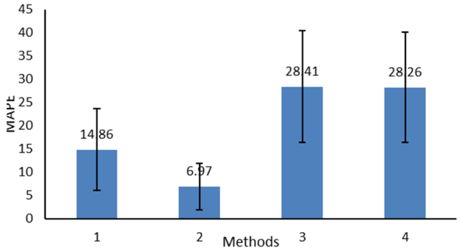
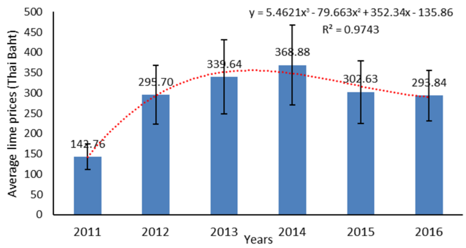


Figure 7. The comparison of the MAPE determined by the SES method with input 2 (i.e. method 1), the DES method with input 2 and the initial value in Equation (14) (i.e. method 2), the MHW method (i.e. method 3), and the AHW method (i.e. method 4)



Figures 8. The year's average prices of the lime

Finally, Figure 8 demonstrates the yearly average prices of the lime during 2011 to 2016. We note that for 2016 we use the raw data (i.e. January 2016 to September 2016) in the last column of Table 1 and the forecast data (i.e. October 2016 to December 2016) determined by the DES method with the input 2 and the initial value in Equation (14). The three-order polynomial trend line is fitted to the average results, and the R-squared value is also provided. Here, the results reveal that the yearly average lime prices' increase during 2011 to 2014 and then the decrease during 2014 to 2016. By the trend line, there is more possibility that average lime prices of 2017 may not be different from 2016.

Conclusions

In this paper, the SES and the DES methods with the designed input data are used to forecast monthly lime prices in Thailand. We show that our proposed solution can be suitably used to forecast the time series data which show the seasonality pattern. Our results demonstrate that the DES method with the optimal designed input data, initial values, and weighting factors shows a better forecasting performance than the MHW and the AHW methods which are directly designed to forecast the seasonal data. We believe that our research methodology proposed in this work can be applied to forecast monthly lime prices for the next year and that it can also be applied for other high-value agricultural products. Also, our results are useful for Thai agriculturists to plan their work schedules and sales.

To apply our proposed solution with other time series data, we have some recommendations. First, since the designed input data (i.e. the inputs 1 to 5) are determined from the past years' data (i.e. dataset), the forecasting accuracy strongly depends on the numbers of the dataset. Using small numbers for the dataset to determine the designed input data may lead to low forecasting accuracy. Second, among 5 different inputs, the input which gives the better performance should be determined. This is because the different datasets have different characteristics.

Acknowledgements

We express our thanks to the Faculty of Management Sciences, Nakhon Si Thammarat Rajabhat University, and the Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, for supporting this research.

References

Alon, I., Qi, M., and Sadowski, R.J. (2001). Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods. Journal of Retailing and Consumer Services, 8(3):147-156.

Booranawong, T. and Booranawong, A. (2017). An exponentially weighted moving average method with designed input data assignments for forecasting lime prices in Thailand. J. Teknol., 79(6):53-60.

Brown, R.G. (1956). Exponential smoothing for predicting demand. Proceedings of the 10th National Meeting of the Operations Research Society of America; November 16, 1956; San Francisco, CA, USA, p. 1-15.

Chatfield, C. (2001). Time-series Forecasting. Chapman & Hall, NY, USA, 280p.

De Gooijer, J.G. and Hyndman, R.J. (2006). 25 years of time series forecasting. Int. J. Forecasting, 22(3):443-473.

Dhakre, D.S., Sarkar, K.A., and Manna, S. (2016). Forecasting price of Brinjal by Holt Winters method in west Bengal using MS Excel. Inter. J. Bio-res., Environ. Agri. Sci., 2(1):232-235.

Gardner, E.S. (1985). Exponential smoothing: the state of the art. J. Forecasting, 4:1-28.

Gentry, T.W., Wiliamowski, B.M., and Weatherford, L.R. (1995). A comparison of traditional forecasting techniques and neural networks. Intelligent Engineering Systems through Artificial Neural Networks, 5:765-770.

Holt, C.C. (2004). Forecasting seasonals and trends by exponentially weighted moving averages. Int. J. Forecasting, 20(1):5-10.

Hunter, J.H. (1986). The exponentially weighted moving average. J. Qual. Technol., 18(4):203-210.

Kaewsuksaeng, S., Tatmala, N., Srilaong, V., and Pongprasert, N. (2015). Postharvest heat treatment delays chlorophyll degradation and maintains quality in Thai lime (Citrus aurantifolia Swingle cv. Paan) fruit. Postharvest Biol. Tec., 100:1-7.

Kalekar, P.S. (2004). Time series forecasting using Holt-Winters exponential smoothing. Kanwal Rekhi School of Information Technology, Mumbai, India, 13p.

Montgomery, D.C., Jennings, C.L., and Kulahci, M. (2008). Introduction to Time Series Analysis and Forecasting. John Wiley and Sons, Hoboken, NJ, USA, 472p.

Pranamornkith, T. (2009). Effects of postharvest treatments on storage quality of lime (Citrus latifolia Tanaka) fruit, [Ph.D. thesis]. Massey University, Wellington, New Zealand, 261p.

Ramos, P., Santos, N., and Rebelo, R. (2015). Performance of state space and ARIMA models for consumer retail sales forecasting. Robot. Cim-Int. Manuf., 34:151-163.

Ravindran, A. and Warsing, D.P. (2013). Supply chain engineering: models and applications. CRC Press, NY, USA, 548p.

Tratar, L.F. (2016). Forecasting method for noisy demand. Int. J. Prod. Econ., 161:64-73.

Tratar, L.F., Mojskerc, B., and Toman, A. (2016). Demand forecasting with four-parameter exponential smoothing. Int. J. Prod. Econ., 181:162-173.

Tratar, L.F. and Srmcnik, E. (2016). The comparison of Holt-Winters method and regression methods: a case study. Energy, 109:266-276.

Winters, P. (1960). Forecasting sales by exponentially weighted moving averages. Manage. Sci., 6:324-342.