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The Comparison of Holt-Winters Methods and α-Sutte Indicator: A Case Study

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Abstract: Forecasting tourism is one of the important areas that need to be explored, as tourism is in direct contact with society. Tourism in the region is closely related to its economy, culture and the environment. As such, it affects the economic levels of the region, for example, increasing foreign exchange in the country and creating employment opportunities. Therefore, it is very important to know how tourism will develop in the future, which depends mainly on future demand (tourist arrivals). Many publications on *tourism forecasting* have appeared during the past years. Although different forecasting techniques can be used, the major conclusions are that time series models are simplest and the least expensive. The purpose of our research is to predict foreign visitor arrivals in Indonesia, Malaysia, and Japan by using Holt-Winters Methods (Additive, Multiplicative and Extended Holt-Winters Method) and α-Sutte Indicator. Data for our research is comprised of foreign visitor arrivals in Indonesia, Malaysia, and Japan from January 2008 to November 2017. The data is divided into 2 parts, namely fitting data and testing data. Based on the results of all four forecasting methods, we conclude that the Extended Holt-Winters method is most suitable. At the end of the analysis, using the Extended Holt-Winters method, we calculate monthly forecasts of tourist arrivals for all three countries in 2018.

Key words: tourism; forecasting; foreign visitor arrivals; Holt-Winters method; α-sutte indicator

JEL codes: C61, C32, R11, Z32

1. Introduction

Things that people often dream about are traveling to foreign countries. Tourism is no longer just one of the forms of entertainment, but offers the possibility to increase knowledge about foreign countries, residents and different cultures. Tourism has become a way of life.

Tourism has many benefits for a region. For example, (1) the tourism of a region will generate large foreign exchange and will have an impact on improving the economy in an area (Cárdenas-García P. J., Sánchez-Rivero M., Pulido-Fernández J. I., 2013; Lundberg E., 2017), (2) cultural aspects — the development of tourism will provide an understanding of different cultures through the interaction of tourists with local communities (tourists

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will learn and appreciate the culture of the local community and understand the background of local culture (Nikolla I., Miko D., 2013)), (3) environmental aspects (benefits) — the local government will take care of and maintain the cleanliness of the tourist area (Nikolla I., Miko D., 2013).

From the above description, tourism is therefore very important for the area, so it needs to be carefully studied. In doing so, the forecast of the number of tourists in the region is of great help to us. Knowing the number of tourists, stakeholders in the region can adopt a policy related to the development of their territory.

Many publications on tourism forecasting have appeared during the past twenty years. The forecasting techniques can include time series models, the gravity model or expert-opinion techniques. The time series models are the simplest and least costly; the gravity model is best suited to handle international tourism flows; and expert-opinion methods are useful when data are unavailable (Sheldon P. J., Var T., 1985).

The remainder of the paper is organized as follows. We begin with the description of the forecasting procedures (see Section 2). In Section 3, we present the data, methodology and results which allow us to compare different forecasting methods and to choose the most appropriate method. Finally, in Section 4, after the conclusions of our paper some further research steps are suggested.

2. Forecasting Methods

The Holt-Winters method of exponential smoothing involves trend and seasonality and is based on three smoothing equations: equation for level, for trend and for seasonality. The decision as to which method to use depends on time series characteristics: the additive method is used when the seasonal component is constant, the multiplicative method is used when the size of the seasonal component is proportional to the trend level (Ferbar Tratar L., Mojškerc B., Toman A., 2016).

α-Sutte Indicator was developed using the principle of the forecasting method of using the previous data (Ahmar A. S., Rahman A., Mulbar U., 2018). It was developed using the adopted moving average method. The α-Sutte Indicator uses 4 previous data (Y_{t-1}, Y_{t-2}, Y_{t-3} and Y_{t-4}) as supporting data for forecasting and making the decision (Ahmar A. S., 2018).

2.1 Holt-Winters' Additive Procedure (AHW)

The basic equations for the AHW method are:

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \quad (3)$$

$$F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (4)$$

where are L_t – estimation of variable in time *t*, Y_t – observed value, b_t – trend estimation of time series in time *t*, S_t – estimation of seasonality in time *t*, F_{t+m} – forecast in time *t* for *m* period ahead, *α, β, γ* – smoothing parameters in the interval [0, 1], m – number of forecasted periods, *s* – duration of seasonality (for example, number of months or quarters in a year).

For initialization of the additive method initial values of variable L_t, trend estimation b_t and seasonality estimation S_t are needed. To determine initial estimates we need at least one whole data season (that is, *s* data). Initialization of variable L_s is calculated with the formula:

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \dots + Y_s) \quad (5)$$

For trend initialization it is more suitable if we use two whole seasons (that is, 2s data):

$$b_s = \frac{1}{s}\left(\frac{Y_{s+1}-Y_1}{s} + \frac{Y_{s+2}-Y_2}{s} + \dots + \frac{Y_{s+s}-Y_s}{s}\right) \tag{6}$$

Seasonal indices are calculated as differences between observed value and variable estimation:

$$S_1 = Y_1 - L_s,\ S_2 = Y_2 - L_s,\ \dots,\ S_s = Y_s - L_s \tag{7}$$

The method is proved to be (regarding costs and calculation itself) comparable with more complex methods (for example Box-Jenkins); in some cases the results gained with the Holt-Winters were even better than more complex methods (Ferbar Tratar L., Mojškerc B., Toman A., 2016).

2.2 Extended Holt-Winters' Procedure (EHW)

The EHW method differs from AHW only in the equation for the level (1); all other equations remain the same as with the AHW (2-7). The equation for level now contains an additional smoothing parameter δ:

$$L_t = \alpha Y_t - \delta S_{t-s} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{8}$$

This method allows to smooth the seasonal factors more or less than the AHW method, depending on the value of the parameter δ (Ferbar Tratar L., Mojškerc B., Toman A., 2016).

2.3 Holt-Winters' Multiplicative Procedure (MHW)

The basic equations for the MHW method are as follows:

$$L_t = \alpha(Y_t/S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{9}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{10}$$

$$S_t = \gamma(Y_t/L_t) + (1-\gamma)S_{t-s} \tag{11}$$

$$F_{t+m} = (L_t + b_t m) \cdot S_{t-s+m} \tag{12}$$

The second of this equation (10) is identical to the second equation (2) of AHW. The only differences in the other equations are that the seasonal components are now in the form of products and ratios instead of being added and subtracted.

2.4 α-Sutte Indicator (SUTTE)

The equation of SUTTE method is (Ahmar A. S., 2018; Sutiksno D. U., Ahmar A. S., Kurniasih N., Susanto E., Leiwakabessy A., 2018):

$$F_t = \frac{1}{3}\left[\alpha\left(\frac{\alpha-\delta}{((\alpha+\delta)/2)}\right) + \beta\left(\frac{\beta-\alpha}{((\beta+\alpha)/2)}\right) + \gamma\left(\frac{\gamma-\beta}{((\gamma+\beta)/2)}\right)\right] \tag{13}$$

where $\alpha = Y_{t-3}, \beta = Y_{t-2}, \gamma = Y_{t-1}, \delta = Y_{t-4}$ and Y_{t-k} is observed data in period $(t-k)$.

3. Case Study

3.1 Data

For research we used monthly data of foreign visitor arrivals in Indonesia, Malaysia, and Japan from January 2008 to November 2017. We acquired data from the website: (1) Badan Pusat Statistik (BPS-Statistics Indonesia); (2) Tourism Malaysia of Ministry of Tourism and Culture Malaysia; and (3) Statistics Bureau of Ministry of Internal Affairs and Communications, Japan.

Figure 1 shows the number of foreign visitor arrivals in Indonesia, Malaysia, and Japan between the years 2008 and 2017. It is evident that a growing trend and comprehensive (random) fluctuations are present in the data.

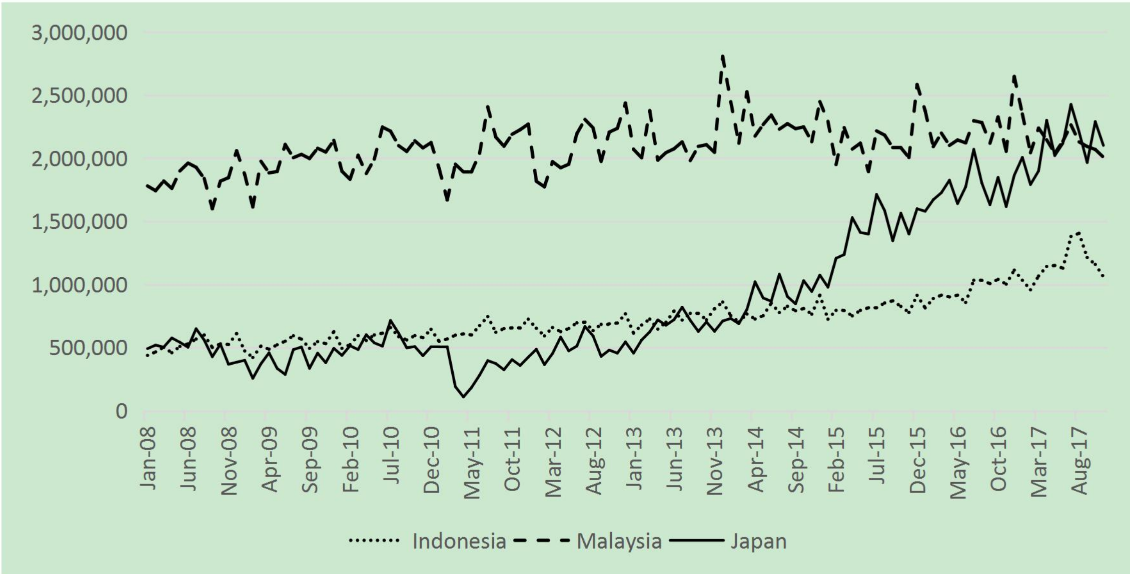

Figure 1 Foreign Visitor Arrivals in Indonesia, Malaysia, and Japan from January 2008 to November 2017

3.2 Methodology

The obtained data of each time series were split into initialization (the first two years, from January 2008 to December 2009), fitting (period from January 2008 to December 2016), and testing subset (period from January 2017 to November 2017). Fitting subset was used for method learning. With the testing subset we checked a time series learning ability. We calculated forecasting values for testing subset and then compare these values to independent-real data. To calculate forecasting values of testing subset we use a long-term forecasting approach for eleven (m = 11) months ahead:

$$F_{t+m}, \quad m = 1, 2, \ldots, 11 \text{ (monthly forecasting)} \qquad (14)$$

where t represents December 2016. Monthly long-term forecasting is important for the strategic planning decisions in the future.

For the evaluation of the forecasting methods we applied two forecasting accuracy measures, Mean Squared Error (MSE) and Mean Absolute Error (MAE):

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{N}(Y_t - F_t)^2 \qquad (15)$$

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}|Y_t - F_t| \qquad (16)$$

where Y_t represents actual value, F_t forecasted value and N number of samples. MSE penalizes the errors proportional to their squares. Minimizing MSE therefore leads to smoothing parameters that produce fewer large errors at the expense of tolerating several small errors. The MAE penalty is proportional to the error itself. Minimizing MAE therefore leads to more small errors but also more frequent large errors. We use both objective functions as both aspects are important in practice. Of course, the lower values of MSE and MAE represent a better forecasting performance.

3.3 Forecasts for Indonesia

Table 1 shows MSE and MAE results for fitting set obtained with four different methods and the percentage of improvement of MSE and MAE, calculated by using the EHW method compared to the AHW, MHW and

SUTTE method. EHW method is identified as the best method, not just in case of fitting set but also for testing set (see Table 2 and Figure 2). It is obvious that with the EHW method a considerable reduction in the MSE and MAE can be reached. The results show that with the EHW method the MSE for testing set is reduced by more than 14% (25%, 30%) in comparison with AHW (MHW, SUTTE) method.

Table 1 MSE and MAE Results of Forecasting for Indonesia, Fitting Data

Indonesia			Improvement	
Fitting set (2010-2016)	**MSE**	**MAE**	**MSE**	**MAE**
EHW	1,637,964,823.77	32,475.14	EHW/method	EHW/method
AHW	1,719,966,909.50	32,846.82	4.77%	1.13%
MHW	1,856,432,284.95	34,574.22	11.77%	6.07%
SUTTE	6,037,728,179.53	59,829.34	72.87%	45.72%

Table 2 MSE and MAE Results of Forecasting for Indonesia, Testing Data

Indonesia			Improvement	
Testing set (Jan-Nov 2017)	**MSE**	**MAE**	**MSE**	**MAE**
EHW	12,522,672,017.26	97,694.25	EHW/method	EHW/method
AHW	14,667,585,431.30	100,606.20	14.62%	2.89%
MHW	16,847,254,534.97	110,122.94	25.67%	11.29%
SUTTE	18,032,018,775.72	111,326.00	30.55%	12.24%

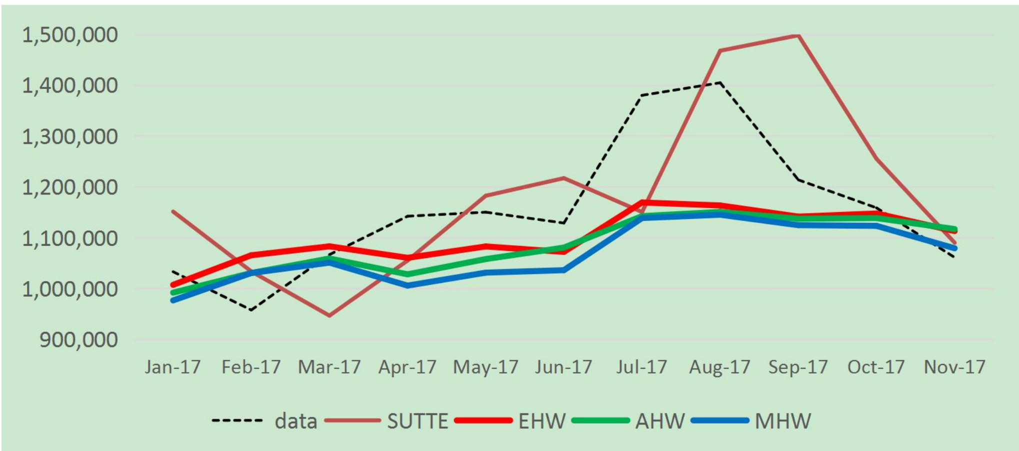

Figure 2 Forecast for Foreign Visitor Arrivals in Indonesia, Testing Subset

3.4 Forecasts for Malaysia

The best fitting and testing result for MSE and MAE is reached by EHW method (Table 3 and Table 4). It is just a little bit lower than fitting performance, but significantly lower than testing performance of AHW and MHW method (see Figure 3).

Table 3 MSE and MAE Results of Forecasting for Malaysia, Fitting Data

Malaysia			Improvement	
Fitting set (2010-2016)	**MSE**	**MAE**	**MSE**	**MAE**
EHW	21,624,253,750.05	109,285.24	EHW/method	EHW/method
AHW	21,882,965,131.56	109,458.78	1.18%	0.16%
MHW	22,528,196,047.93	109,529.26	4.01%	0.22%
SUTTE	70,618,631,313.33	199,981.72	69.38%	45.35%

Table 4 MSE and MAE Results of Forecasting for Malaysia, Testing Data

Malaysia			Improvement	
Testing set (Jan-Nov 2017)	MSE	MAE	MSE	MAE
EHW	25,234,146,629.73	83,289.63	EHW/method	EHW/method
AHW	43,942,291,730.75	103,486.76	42.57%	19.52%
MHW	46,409,847,320.42	142,211.72	45.63%	41.43%
SUTTE	43,615,238,632.09	146,375.90	42.14%	43.10%

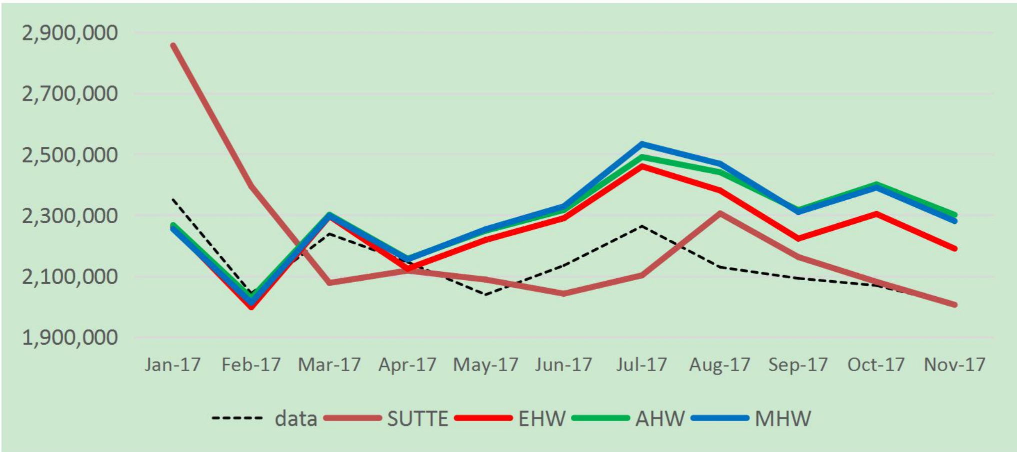

Figure 3 Forecast for Foreign Visitor Arrivals in Malaysia, Testing Subset

3.5 Forecasts for Japan

Again, the excellent performance for fitting and testing set shows the EHW method. Although the results of the fitting set for the EHW and AHW method are very similar (Table 5), the EHW method turns out to be significantly better for the testing set (Table 6 and Figure 4).

Table 5 MSE and MAE Results of Forecasting for Japan, Fitting Data

Japan			Improvement	
Fitting set (2010-2016)	MSE	MAE	MSE	MAE
EHW	8,266,955,513.84	69,989.42	EHW/method	EHW/method
AHW	8,338,841,226.96	70,150.57	0.86%	0.23%
MHW	10,655,274,437.07	86,882.46	22.41%	19.44%
SUTTE	24,049,780,653.84	129,433.68	65.63%	45.93%

Table 6 MSE and MAE Results of Forecasting for Japan, Testing Data

Japan			Improvement	
Testing set (Jan-Nov 2017)	MSE	MAE	MSE	MAE
EHW	15,319,208,751.29	129,427.98	EHW/method	EHW/method
AHW	22,753,518,944.41	139,454.62	32.67%	7.19%
MHW	80,530,197,423.19	1,116,039.96	80.98%	88.40%
SUTTE	69,466,709,126.94	225,004.39	77.95%	42.48%

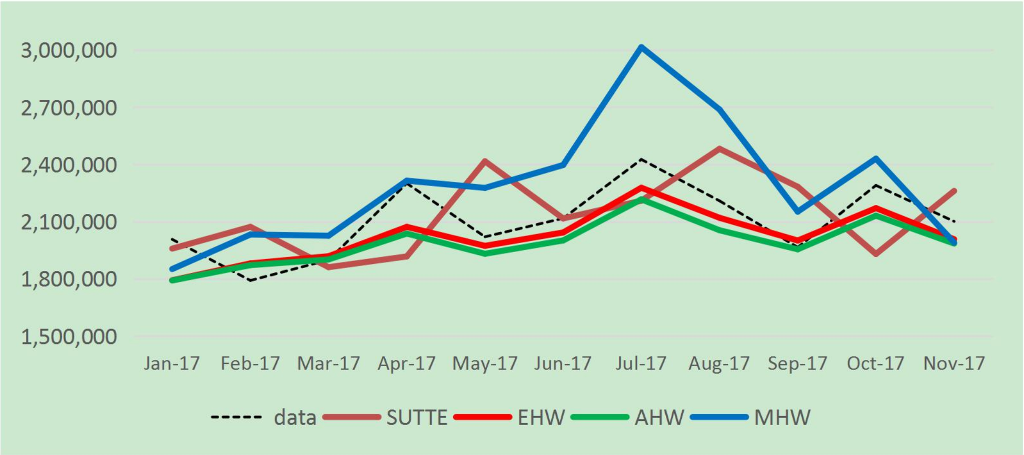

Figure 4 Forecast for Foreign Visitor Arrivals in Japan, Testing Subset

3.6 Research Findings

The best forecasting method is the method that has the smallest MSE and MAE value on the fitting and testing subset. Based on MSE and MAE as performance measures, the EHW method is identified as the best forecasting method for foreign visitor arrivals data in Indonesia, Malaysia and Japan (see Tables 1-6). As the EHW method is the most appropriate method for all three time series, this method is used for forecasts of the foreign visitor arrivals in Indonesia, Malaysia and Japan from January to December 2018 (see Figure 5). Due to the dynamics of the time series, the authors propose a re-analysis when new data is available.

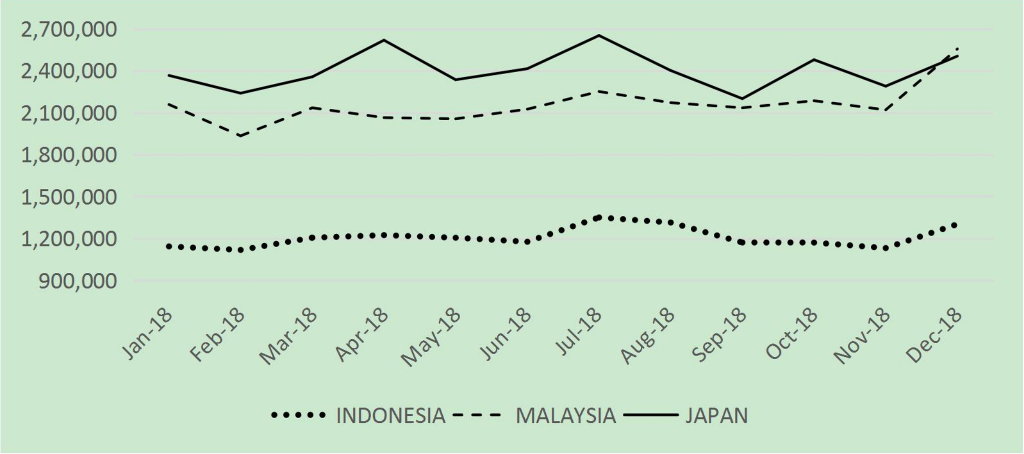

Figure 5 Forecast for Foreign Visitor Arrivals in Indonesia, Malaysia, and Japan from January to December 2018

4. Conclusion and Further Research

Tourism is a very important thing to be studied in various countries/regions because it is related to income and social economy in the region. The data on tourism that need to be explored are strongly connected to the number of tourists. Forecasts of the number of tourists in the future can affect tourism management so that stakeholders can adopt a policy that relates to tourists and tourism. In order to forecast the arrival of foreign visitors to Indonesia, Malaysia and Japan from January to December 2018, the EHW method proved to be more appropriate than other methods (AHW, MHW and SUTTE).

For further research, authors suggest that additional optimization using the initial parameters is used with Holt-Winters methods. Also, the possible way to improve SUTTE method would be to upgrade it by introducing seasonal variations.

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