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Forecasting Movie Demand Using Total and Split Exponential Smoothing

(Ramalan Permintaan Filem Menggunakan Kaedah Exponential Smoothing)

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ABSTRACT

In the motion picture industry, the movie market players always rely on accurate demand forecasts. Distributors require the demand forecasts to decide the best release date of the new movies that arguably the most difficult decision. Thus, forecasting methods which are able to capture historical patterns can be relied on to produce an accurate prediction. Exponential smoothing methods are the common methods, but there is limited study using this technique in movie demand forecasting. In this paper, we study the performance of a newly proposed seasonal exponential smoothing method that previously has been considered for forecasting daily supermarket sales. It is known as total and split exponential smoothing, and apply it to daily box office from the United States market. The resulting forecasts are compared against other exponential smoothing methods, seasonal adjustment, non-seasonal, and seasonal exponential smoothing methods. Overall, total and split exponential smoothing with optimised parameters separately for each lead time is performing good, followed by seasonal (damped trend) exponential smoothing method (DA-A). The identification of the best performing method assists distributors to make a decision on the best release date for their new movies earlier than the competitors.

Keywords: Forecasting; exponential smoothing; movie demand; time series

ABSTRAK

Dalam industri filem, para pemain di pasaran filem sentiasa bergantung pada ramalan permintaan yang tepat. Para pengedar memerlukan ramalan permintaan untuk menentukan tarikh pelepasan yang terbaik bagi filem-filem baru yang boleh dikatakan merupakan keputusan yang paling sukar. Oleh itu, kaedah ramalan yang dapat menangkap corak sejarah boleh dipercayai untuk menghasilkan ramalan yang tepat. Kaedah exponential smoothing adalah pilihan umum, tetapi terdapat kajian terhad menggunakan teknik ini dalam ramalan permintaan filem. Dalam kajian ini, kita mengkaji prestasi kaedah exponential smoothing yang baru yang pernah digunakan untuk meramalkan jualan harian di pasaraya sebelum ini. Ia dikenali sebagai total and split exponential smoothing, dan meggunakan kaedah ini pada jualan box office harian dari pasaran Amerika Syarikat. Ramalan yang dihasilkan berbanding dengan kaedah-kaedah exponential smoothing lain, kaedah seasonal adjustment, kaedah non-seasonal dan seasonal exponential smoothing. Secara keseluruhan, total and split exponential smoothing dengan parameter yang dioptimumkan secara berasingan bagi setiap masa yang diimplementasikan adalah terbaik, diikuti dengan kaedah seasonal (damped trend) exponential smoothing method (DA-A). Pengenalpastian kaedah terbaik membantu para pengedar untuk membuat keputusan pada tarikh pelepasan terbaik untuk filem-filem baru mereka lebih awal daripada pesaing.

Kata Kunci: Ramalan; exponential smoothing; permintaan filem; siri masa

INTRODUCTION

The motion picture industry is a multi-billion dollar business. Global box office for all films released worldwide reached $38.3 billion in 2015, up 5% over 2014's total ($36.4 billion) (MPAA 2016). The demand for movies has been significantly increased due to the increment of a personal desire for cultural life. Most cultural products except books are defined as experience goods with short product life cycle, thus, it is difficult to forecasts their demands (Chang & Ki 2005). The movie industry believes that each film is unique, which make forecasting demand very tricky because consumers have difficulty evaluating the quality of a movie before viewing the film (Marshall et al. 2013).

President of MPAA, Jack Valenti (1978) gave a speech regarding the uncertainty and unpredictability associated with investments in a motion picture (pg. 7):

"With all of the experience, with all the creative instincts of the wisest of people in our business, no one, absolutely no one can tell you what a movie is going to do in the marketplace… Not until the film open in darkened theatre and sparks fly up between the screen and the audience can you say this film is right… Excellence is a fragile substance."

As a consequence, the motion picture industry is emerging to become an area of interest to scholar and researchers. An early and accurate forecast of box-office demand in this industry is a valuable tool in planning and decision making (Marshall et al. 2013). The ability to accurately predict the box office revenues for a movie will help the distribution companies to determine the release timing, marketing strategy and cost, period of showing the movie and number of screens. The release date of a movie is arguably the most difficult decision facing the distributors (Radas & Shugan 1998). For distributors, the release date of a new movie is their major focus as the first-week opening accounted for 40% of the box office revenues of average movies. Studios will compete with each other for the movie's release date especially seasonal holidays (Einav 2007). So, a forecasting tool that able to capture the seasonality and generate reliable forecasts can be relied on, such as exponential smoothing methods, to give a general idea of the future demand for the movies. Nevertheless, there is limited literature regarding the application of exponential smoothing methods in movie demand forecasting. Therefore, our work intends to forecast the movie demand in the evaluation period by using various exponential smoothing models and attempts to compare their forecasting performance to better support movie distributors' decisions.

Box office forecasting has always been a major concern in the motion picture business (Jun et al. 2011). There are three areas of decisions relating to producing and distributing a motion picture: revenue projection, marketing decision, and distribution decision. To properly address each decision, one must understand that different decisions, even in different categories, may be related (Torres 2004). Litman (1983) also identified three decision-making areas: creative sphere, the scheduling and release pattern, and the marketing effort. Thus, having an accurate box office forecasts in an early stage of screening is extremely important, because marketing activities in this period decide the success of motion pictures (Sawhney & Eliashberg 1996). In addition, producers and exhibitors can benefit from accurate forecasts. It allows them to make appropriate managerial decisions concerning the budget allocations for additional marketing activities and screen allocation across movie theatres (Kim et al. 2015).

With regard to the importance of movie demand forecasts, researchers have undertaken the task of predicting movie success using various approaches. They attempted to predict box office revenues or theatre admissions. Models such as econometric and behavioural models are widespread in the study of motion pictures (Sharda & Delen 2006). The most common method is incorporating the variables in the development of forecasting models (Hur et al. 2016). Exploring the variables influencing the box office performance is the first priority when analysing the motion picture industry because it is a basic foundation for movie-related policy establishment (Yoo 2002). The impact of various explanatory variables on movie performance has been investigated in research studies: genre (Eliashberg et al., 2014; Litman 1983;), sequel (Litman & Kohl 1989; Nelson & Glotfelty 2012; Prag & Casavant1994; Terry et al. 2011;), star power (Basuroy et al. 2003; Elberse 2007; Ghiassi et al. 2015; Smith & Smith 1986; Sochay 1994;), date, timing, or season of release (Litman 1983; Sawhney & Eliashberg 1996; Sharda & Delen 2006; Zufryden 2000;), reviews by critics (Dellarocas et al. 2007; Elberse & Eliashberg 2003; Goetzman et al. 2013; Litman 1983; Wallace et al. 1993), MPAA rating (Gopinath et al. 2013; Moon et al 2010; Ravid 1999; Walls 2005), award or nomination (Litman & Kohl 1989; Nelson et al. 2001; Sochay 1994), the number of screens (McKenzie 2013; Neelamegham & Chintagunta 1999;), film budget and marketing budget (Gopinath et al. 2013; Litman & Kohl 1989; Prag & Casavant 1994; Stimpert et al. 2008), distributor (Litman 1983), competition (Kulkarni et al. 2012; Litman & Kohl 1989), and word-of-mouth (Kim et al. 2015; Liu 2006; Mestyán et al. 2013). Indeed, the incorporating of variables in movie forecasting improve the accuracy of models (Kim et al. 2015; Lee & Chang 2009; Sharda & Delen 2006). However, our study does not consider these variables. We only considered time series analysis based on historical data patterns to predict the future market behaviour by using exponential smoothing methods.

The main aim of this paper is to provide insight into the usefulness of the newly proposed total and split exponential smoothing method. The method was developed for daily sales forecasting and involves smoothing both the total weekly sales and the split of the total sales for each day of the week. Total and split exponential smoothing method performed well for daily supermarket sales forecasting, particularly for early lead times considered. In this paper, we apply this method to a dataset consisting of daily box office taken from the website. In addition, we compare the accuracy of this method against other exponential smoothing methods. Exponential smoothing is particularly popular due to its impressive performance in empirical studies (Gardner 2006). In their survey of sales forecasting practitioners, McCarthy et al. (2006) reported a greater level of satisfaction with exponential smoothing than any other method used. In movie demand forecasting, various approaches were implemented and their accuracy has been proven. To our knowledge, the empirical application of exponential smoothing models is scarce in the motion picture industry. Exponential smoothing models are expected to be able to better capture the seasonality in the time series and forecast the movie demand. Thus, the inclusion of traditional exponential smoothing methods and comparison with the total and split exponential smoothing method in this study is of particular interest.

The models are presented in the following first and second sections. The third section gives the descriptive of the study including the background of the daily movie sales data and methodology used in this study. All the results will be discussed in the fourth section. The conclusion is presented in the final section.

FORECASTING MODELS

EXPONENTIAL SMOOTHING MODELS

The exponential smoothing methods act as benchmarks to compare the performance of the total and split exponential smoothing method. Although the movie demand series showed seasonality (Einav 2007; Gong et al. 2011; Kim et al. 2015; Litman 1983; Litman & Kohl 1989), we included non-seasonal together with seasonal methods in the forecast comparison. Demand cannot attain negative values. Thus, for all methods, if a forecast produced negative value, that forecast is set to zero. In addition, seasonal methods were very sensitive to the approach used to initialise the seasonal indices. In this paper, all exponential smoothing methods initialise the method using simple averages based on the early observations in the series (Taylor 2011).

Non-Seasonal Methods Naïve – All forecasts for the future are equal to the last observed value of the series. Given that:

$$\hat{X}_t\,(m) = X_t \tag{1}$$

where $\hat{X}_t\,(m)$ is forecast for m periods ahead from origin t, X_t is the observed value of the time series at time t and m is a lead time, This method assumes that the current observation is the only important one and all previous observations provide no information for the future (Hyndman & Athanasopoulos 2014).

Simple exponential smoothing (N-N) – This method is suitable for forecasting data with no trend and seasonal pattern as indicated by "N-N". It involves smoothing the level of the series through the use of a single smoothing parameter, α (Hyndman et al., 2002). Given that:

$$\text{Level: } S_t = \alpha X_t + (1 - \alpha)S_{t-1} \tag{2}$$

$$\text{Forecast: } \hat{X}_t\,(m) = S_t \tag{3}$$

where S_t is smoothed level of the series, computed after X_t is observed, X_t is observed value of the time series at time t, $\hat{X}_t\,(m)$ is forecast for m periods ahead from origin t, m is a lead time and α is the smoothing parameter for the level of the series ($0 \leq \alpha \leq 1$).

Trend exponential smoothing (A-N) – This method is also known as Holt's linear trend method. It involves smoothing the level and trend of the series through the use of two parameters, α and β. The notation "A-N" indicates an additive trend and no seasonal component.

$$\text{Level: } S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + T_{t-1}) \tag{4}$$

$$\text{Trend: } T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1} \tag{5}$$

$$\text{Forecast: } \hat{X}_t\,(m) = S_t + mT_t \tag{6}$$

where S_t is smoothed level of the series, T_t is smoothed additive trend at the end of period t, X_t is observed value of the time series at time t, $\hat{X}_t\,(m)$ is forecast for m periods ahead from origin t, m is a lead time and α and β are the smoothing parameter for the level and trend of the series respectively with $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$.

Damped trend exponential smoothing (DA-N) –The notation "DA-N" indicates a damped additive trend and no seasonal component. This method smoothed the level and additive trend of the series and dampens the trend in the forecast function. Methods that include a damped trend have proven to be successful as reported in a number of empirical studies (Gardner 2006).

$$\text{Level: } S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + \phi T_{t-1}) \tag{7}$$

$$\text{Trend: } T_t = \beta(S_t - S_{t-1}) + (1 - \beta)\phi T_{t-1} \tag{8}$$

$$\text{Forecast: } \hat{X}_t\,(m) = S_t + \Sigma_{i=1}^{m}\phi T_t \tag{9}$$

where S_t is smoothed level of the series, T_t is smoothed additive trend at the end of period t, X_t is observed value of the time series at time t, $\hat{X}_t\,(m)$ is forecast for m periods ahead from origin t, m is a lead time and α and β are the smoothing parameter for the level and trend of the series respectively with $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$, while ϕ is the damping parameter with $0 \leq \phi \leq 1$.

Seasonal Adjustment In forecasting seasonal time series, the common approach is to seasonally adjust the data, then apply a non-seasonal method to produce forecasts, and finally incorporate seasonality into the forecasts. We used the seasonal adjustment method based on ratio-to-moving averages. In the analysis, we considered the non-seasonal exponential smoothing methods: simple (N-N), the trend (A-N), and damped trend (DA-N).

Seasonal Methods Seasonal naïve – Each forecast value to be equal to the last observed value from the same season of the year (Hyndman & Athanasopoulos, 2014). For example, with daily data, the forecast for all future first-day values of the week is equal to the last observed first day of the week. The forecast is written as:

$$\hat{X}_t\,(m) = X_{t-p+m} \tag{10}$$

where $\hat{X}_t\,(m)$ is forecast for m periods ahead from origin t and X_t is observed value of the time series at time t, m is the lead time, and p is the number of periods in the seasonal cycle.

Seasonal (no trend) exponential smoothing (N-A & N-M) – Two methods are under this category, additive and multiplicative seasonality formulations. The notation "N-A" indicates no trend and additive seasonality, while notation "N-M" indicates no trend and multiplicative seasonality. The following showed the formulations for N-A and N-M respectively.

N-A

Level: $S_t = \alpha(X_t - I_{t-p}) + (1 - a)S_{t-1}$ (11)

Seasonal: $I_t = \Upsilon(X_t - S_t) + (1 - \Upsilon)I_{t-p}$ (12)

Forecast: $\hat{X}_t (m) = S_t + I_{t-p+m}$ (13)

N-M

Level: $S_t = \alpha(X_t/I_{t-p}) + (1 - a)S_{t-1}$ (14)

Seasonal: $I_t = \Upsilon(X_t/S_t) + (1 - \Upsilon)I_{t-p}$ (15)

Forecast: $\hat{X}_t (m) = S_t I_{t-p+m}$ (16)

where S_t is smoothed level of the series, I_t is smoothed seasonal index at the end of period t, $\hat{X}_t (m)$ is forecast for m periods ahead from origin t, X_t is the observed value of the time series at time t, m is a lead time, p is the number of periods in the seasonal cycle, α and ϒ are the smoothing parameter for the level and seasonal indices of the series respectively with $0 \leq \alpha \leq 1$ and $0 \leq \Upsilon \leq 1$.

Seasonality trend exponential smoothing (A-A & A-M) – Two methods are under this category, with additive and multiplicative seasonality formulations. The notation "A-A" indicates an additive trend and additive seasonality, while notation "A-M" reflects additive trend and multiplicative seasonality. This method smoothed the level, trend, and seasonality through the use of three smoothing parameters (α, β, and Υ). The following showed the formulation for A-A and A-M respectively.

A-A

Level: $S_t = \alpha(X_t - I_{t-p}) + (1 - a)(S_{t-1} + T_{t-1})$ (17)

Trend: $T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$ (18)

Seasonal: $I_t = \Upsilon(X_t - S_t) + (1 - \Upsilon)I_{t-p}$ (19)

Forecast: $\hat{X}_t(m) = S_t + mT_t + I_{t-p+m}$ (20)

A-M

Level: $S_t = \alpha(X_t/I_{t-p}) + (1 - a)(S_{t-1} + T_{t-1})$ (21)

Trend: $T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$ (22)

Seasonal: $I_t = \Upsilon(X_t/S_t) + (1 - \Upsilon)I_{t-p}$ (23)

Forecast: $\hat{X}_t (m) = (S_t + mT_t)I_{t-p+m}$ (24)

where S_t is smoothed level of the series, T_t is smoothed additive trend at the end of period t, I_t is smoothed seasonal index at the end of period t, $\hat{X}_t$ is forecast, $\hat{X}_t (m)$ is forecast for m periods ahead from origin t, X_t is the observed value of the time series at time t, m is a lead time, p is the number of periods in the seasonal cycle, α, β and Υ are the smoothing parameter for the level, trend and seasonal indices of the series respectively with $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$ and $0 \leq \Upsilon \leq 1$.

Seasonal damped trend exponential smoothing (DA-A & DA-M) –Both DA-A and DA-M are damped additive trend with additive seasonality and multiplicative seasonality respectively. This method smoothed the level, trend, and seasonality and dampens the trend in the forecast function. It involves three smoothing parameters (α, β, and Υ) and a damping parameter (ϕ). Given that:

DA-A

Level: $S_t = \alpha(X_t - I_{t-p}) + (1 - a)(S_{t-1} + \phi T_{t-1})$(25)

Trend: $T_t = \beta(S_t - S_{t-1}) + (1 - \beta)\phi T_{t-1}$ (26)

Seasonal: $I_t = \Upsilon(X_t - S_t) + (1 - \Upsilon)I_{t-p}$ (27)

Forecast: $\hat{X}_t (m) = S_t + \Sigma_{i=1}^{m}\phi^i T_t + I_{t-p+m}$ (28)

DA-M

Level: $S_t = \alpha(X_t/I_{t-p}) + (1 - a)(S_{t-1} + \phi T_{t-1})$ (29)

Trend: $T_t = \beta(S_t - S_{t-1}) + (1 - \beta)\phi T_{t-1}$ (30)

Seasonal: $I_t = \Upsilon(X_t/S_t) + (1 - \Upsilon)I_{t-p}$ (31)

Forecast: $\hat{X}_t (m) = (S_t + \Sigma_{i=1}^{m}\phi^i T_t)I_{t-p+m}$ (32)

where S_t is smoothed level of the series, T_t is smoothed additive trend at the end of period t, I_t is smoothed seasonal index at the end of period t, $\hat{X}_t (m)$ is forecast for m periods ahead from origin t, X_t is the observed value of the time series at time t, m is a lead time, p is the number of periods in the seasonal cycle, α, β and Υ are the smoothing parameter for the level, trend and seasonal indices of the series respectively with $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$ and $0 \leq \Upsilon \leq 1$, while ϕ is the damping parameter with $0 \leq \phi \leq 1$.

TOTAL AND SPLIT EXPONENTIAL SMOOTHING

The total and split smoothing method is presented by Taylor (2007) in daily supermarket sales data and Taylor (2011) in monthly sales series of the publishing company. Taylor (2007) reported that the method performing well for daily supermarket sales data, particularly for short lead times. Other than these two papers, there is no other empirical evidence regarding the method. In this paper, we apply the method to daily movie sales. For a series of daily observations, y_t, the method involves smoothing the total weekly sales, W_t, and the split, L_t, of the weekly sales across the days of the week. The method has the following formulation:

$$W_t = \alpha\Sigma_{i=1}^{6} y_{t-i} + (1 - \alpha)W_{t-1} \quad (33)$$

$$L_t = \frac{\Upsilon y_t}{\Sigma_{i=1}^{6} y_{t-i}} + (1 - \Upsilon)L_{t-6} \quad (34)$$

where α and Υ are smoothing parameters with $0 \leq \alpha \leq 1$ and $0 \leq \Upsilon \leq 1$. The forecasts, $\hat{y}_t (m)$ are given by:

$$\hat{y}_t(m) = W_t L_{t+m-7} \text{ for } m = 1 \text{ to } 7 \quad (35)$$

$$\hat{y}_t(m) = W_t L_{t+m-14} \text{ for } m = 8 \text{ to } 14 \quad (36)$$

where m is the lead time.

The method can be viewed as a hybrid of the ratio-to-moving average seasonal adjustment procedure and Holt-Winters exponential smoothing with multiplicative seasonality and no trend (N-M exponential smoothing) The total and split is a method to replace the Holt-Winters smoothing of the level by smoothing of the weekly total. In the ratio-to-moving average seasonal adjustment approach, the total and split method can be viewed as replacing simple averages by exponentially weighted moving averages (Taylor, 2007).

We used simple averages of the first few observations to calculate initial values for the smoothed components. Taylor (2007) reported in the paper that the supermarket company used subjectively chosen parameter values for all the series, α=0.7 and Υ=0.1, and optimised values. In this study, it is also applied to this method and other exponential smoothing methods.

DATA AND METHODOLOGY

The data used in this paper is daily movie sales in the United States from Box Office Mojo (www.boxofficemojo.com). This data was collected from 1 January 2002 to 31 December 2016, with a total of 5479 observations.

Time series plot is presented in Figure 1 to show some of the features in the data. The data does not show an obvious trend but the sales showed a slight increase in the long-term horizon. In addition, there are some outliers in the series. As shown in Figure 1, the series seemed to possess yearly seasonality. Every year, the peak seasons can be seen around the month of January, May to August and December. Some studies (see, Litman, 1983; Litman & Kohl, 1989; Einav, 2007; Gong, Young, & der Stede, 2011; Kim et al., 2015) indicated that there is seasonality in movie sales, especially around Easter months (March and April), summer months (May through August) and Christmas time (November and December) and other special holidays (e.g. President's Day and Memorial Day) in United States.

We estimated method parameters using the first 80% of observations of the series (in-sample). The final 20% of the observations used as post-sample forecast evaluation (as shown in Figure 2). In movie demand, a forecast of the weekend (Friday, Saturday, and Sunday) was of most importance. However, in this paper, we considered forecast horizons of 14 days in the study. Taylor (2007) used a rolling origin for each series in generating a forecast for each lead time. For each series, they rolled the forecast origin forward through the post-sample evaluation to produce a collection of forecasts from each model for each horizon. Nevertheless, we did not apply this approach. We generated a series of forecasts for each lead time.

In this paper, for all exponential smoothing methods, we optimised parameters by minimising the sum of squared forecast errors (SSE) of estimation samples, as well as minimising the sum of absolute errors (SAE). The results reported that it was preferable to minimise the SAE over SSE in estimating the parameters of the exponential smoothing methods (Taylor, 2011).

Fildes et al. (1998) revealed that using commonly occurring exponential smoothing parameters for all series can be preferable to use the values optimised for each series. Taylor (2007) reported the optimised parameters was more useful in the early lead times, it may be due to the parameter optimization using one-step ahead errors. Thus, he suggested optimising parameters separately for each lead time using in-sample forecast errors corresponding to that lead time. For simplicity in the remainder of this report, we present results in terms of only the RMSE and Theil-U based on RMSE. The relative performances of the methods were broadly similar when compared using the MAE and Theil-U.

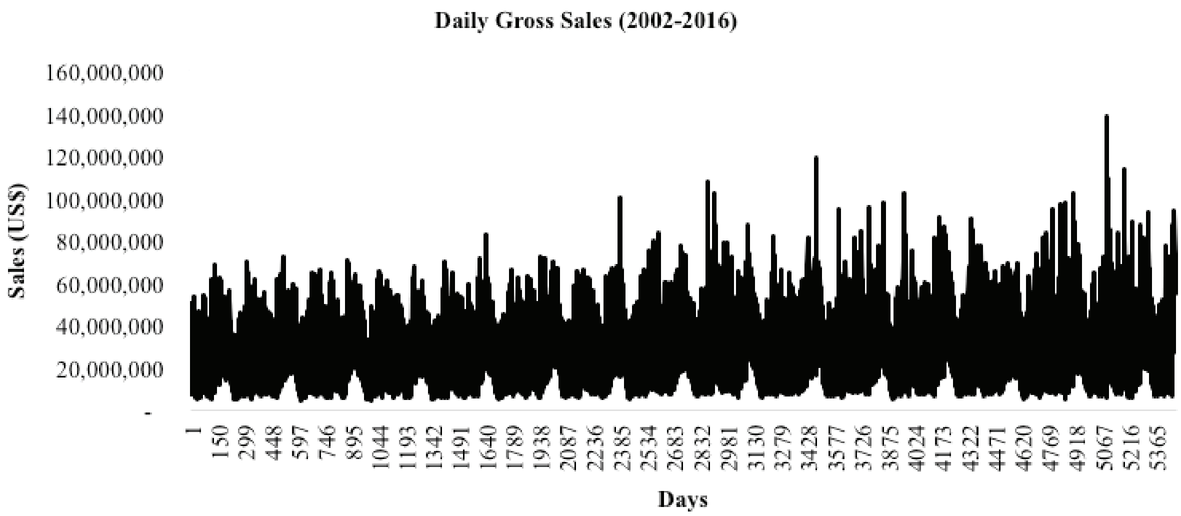

FIGURE 1. Time series plot for daily movie sales from year 2002 to 2016.

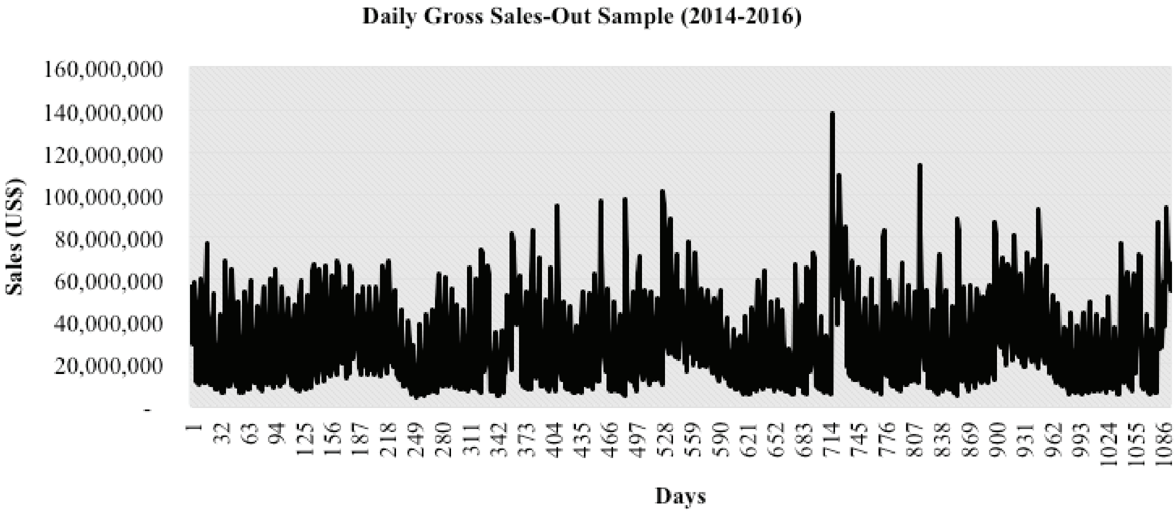

FIGURE 2. Time series plot for daily movie sales (out-sample) from year 2014 to 2016.

EMPIRICAL RESULTS

We evaluated post-sample forecasting performance for each forecast horizon using root mean squared error (RMSE) and Theil-U measure based on RMSE. Table 1(a) and Table 1(b) reports the RMSE of post-sample results for methods that the parameters were optimised separately by minimising the sum of absolute error (SAE) and Table 2 presents the one by minimising the sum of squared error (SSE). Each table includes the total and splits exponential smoothing methods that had parameters estimated by minimising the sum of squared errors (SSE) and the sum of absolute errors (SAE) for the purpose of comparison. Both tables showed the average of the accuracy measure for pairs of forecast horizons, and the first four lowest values are presented in bold. The final column of the table presents the average of the accuracy measure across the 14 horizons.

OPTIMISED PARAMETERS BY MINIMISING SUM OF ABSOLUTE ERROR (SAE)

The tables showed the average of the accuracy measure for pairs of forecast horizons, and the first four lowest values are presented in bold. The final column of the table presents the average of the accuracy measure across the 14 horizons. Based on the results in Table 1, the non-seasonal exponential smoothing methods performed very poorly. The first four methods with lowest forecast errors fell into seasonal methods. It reflects that the time series has a seasonal effect. RMSE suggest that the total and split exponential smoothing with optimised parameter separately by SSE is the best performing method.

Forecasting accuracies of non-seasonal exponential smoothing methods improved by implementing methods with seasonal adjustment. The addition of damp parameter (ϕ) in damped trend exponential smoothing improved forecasting accuracy. This parameter dampens the trend to a flat line some time in the future (Gardner & McKenzie 1985), in which it plays the role to avoid over-forecast, especially for longer forecast horizon. As we can see from the results, the error becomes almost constant for longer forecast horizon. The seasonal naïve method has the lowest forecasting errors compared to the naïve method. It reflects that there is seasonality in the time series.

Comparing the results for exponential smoothing methods with additive seasonality formulations, N-A, A-A, and DA-A, indicates that N-A and DA-A performed better than A-A. Overall, DA-A is the best performing method followed by N-A. The seasonal (no trend) exponential smoothing (N-M) and seasonal damped trend exponential smoothing (DA-M) were more successful than the similar method with the additive trend (A-M). For the first 3 days of the forecast horizon, N-M method outperformed DA-M method. Beyond 3 days ahead, DA-M was a most accurate method. Overall, exponential smoothing with additive seasonality formulations, N-A, A-A, and DA-A, performed better than with multiplicative seasonality formulations (N-M, A-M, & DA-M), especially seasonal (no trend) exponential smoothing (N-A) and damped trend exponential smoothing (DA-A). In the comparison of the results for the six seasonal exponential smoothing methods, N-M, A-M, DA-M, N-A, A-A, and DA-A with the results for the corresponding three methods that involve seasonal adjustment, N-N, A-N, and DA-N, the seasonal exponential smoothing methods were performed better than seasonal adjustment for all three cases, especially with additive seasonality formulations. It is expected that the implementation of seasonality adjustment is preferable to using the seasonal smoothing methods (see, Makridakis & Hibon 2000).

Total and split exponential smoothing with subjectively chosen parameters, $\alpha = 0.7$ and $\Upsilon = 0.1$ were outperformed by the methods with parameters optimised separately for each lead time, where the optimisation was performed by minimising SAE and SSE. In the paper by Taylor (2011), the outcome of the optimised value only useful for the first few periods, but beyond that, the subjectively chosen values was most accurate. It may be due to parameter optimisation using one-step ahead errors. Thus, this study performed optimisation separately for each lead time using in-sample forecast errors corresponding to that lead time, and the results showed the performance with subjectively chosen parameters was the poorest. The RMSE results (Table 1(a)) showed that estimating the parameters of total and split exponential smoothing by minimising the sum of squared errors (SSE) were performing better than those by minimising the sum of absolute errors (SAE) across all the lead times. Overall, the best result across all lead times was achieved by total and split exponential smoothing with optimised parameters separately by minimising SSE. Seasonal damped trend exponential smoothing with additive trend (DA-A) and seasonal (no trend) exponential smoothing (N-A) performed well in earlier lead time but beyond 7 days ahead, they are outperformed by total and split exponential smoothing with optimised parameters separately by minimising SAE. N-A and DA-A outperformed this total and split exponential smoothing method at the earlier lead time (especially minimising SSE). Beyond 5 days ahead, total and split exponential smoothing methods can forecast better than both methods.

Table 1(b) summarized the post sample accuracy of various exponential smoothing methods employed in this study. Theil-U measure has been employed to summarize the relative performances of the forecasting methods. It is calculated as the ratio of RMSE for a particular method to the RMSE for the naïve model. The lower the value of Theil-U, the better the model it is. Based on the results, the total and split exponential smoothing method optimised by minimising SSE dominated the other forecasting methods in terms of mean Theil-U in post sample period. It is followed by seasonal damped trend exponential smoothing with the additive trend (DA-A) and seasonal (no trend) exponential smoothing (N-A). Nevertheless, beyond 5 days ahead, Theil-U measures of total and split exponential smoothing (SSE) are the lowest.

OPTIMISED PARAMETERS BY MINIMISING SUM OF SQUARED ERROR (SSE)

Taylor (2011) assumed that it is preferable to optimise exponential smoothing parameters by minimising the SAE of sample errors over minimising SSE. In this study, optimise exponential smoothing parameters by minimising SSE of sample errors also consider in the analysis. The results in Table 2 (a & b) are almost consistent with the results in Table 1. This section discussed the results that were different from the results of Table 1.

Comparing the results of exponential smoothing methods with multiplicative seasonality formulations (N-M, A-M & DA-M), DA-M outperformed the other two methods for all lead times. Overall, exponential smoothing with additive seasonality formulations, N-A, A-A, and DA-A, performed better than with multiplicative seasonality formulations, N-M, A-M, and DA-M, with DA-A method was the most accurate followed by N-A. N-A and DA-A method able to forecast accurately in the earlier lead times, however, with a longer forecast horizon, it is slowly outperformed by DA-M methods.

Overall, the best results across all lead times were achieved by seasonal damped trend exponential smoothing with the additive trend (DA-A), followed by total and split exponential smoothing with optimised parameters by minimising SSE and seasonal (no trend) exponential smoothing (N-A). However, N-A method performed well in the earlier lead time, it was then outperformed by other methods; while total and split methods outperformed the other two methods in the later lead times (beyond 9 days ahead).

Based on the outcomes of the Theil-U measure, the seasonal damped trend exponential smoothing with the additive trend (DA-A) dominated the other forecasting methods in terms of mean Theil-U in post sample period. It is followed by seasonal (no trend) exponential smoothing (N-A) and total and split exponential smoothing with optimised parameters by minimising SSE. These two methods (DA-A and N-A) performed well in the earlier lead times. However, beyond 9 days ahead, the Theil-U measures of total and split (SSE) are the lowest among all other methods.

CONCLUSION

We have investigated the forecasting performance of newly proposed exponential smoothing presented by Taylor (2007) and compared with other exponential smoothing methods using daily movie sales series. Four different groups of exponential smoothing mothods are being employed in our empirical study. Overall, the best result in our study was achieved by total and split exponential smoothing method with optimised parameters by minimising the sum of squared errors. Other methods that produced competitive results are total and split method with optimised parameters by minimising the sum of absolute errors, seasonal damped trend exponential smoothing (DA-A), and seasonal (no trend) exponential smoothing (N-A). For total and split exponential smoothing, the results showed that subjectively chosen values achieved the poorest accuracy as compared to those optimised separately for each lead time corresponding to their lead time.

We could not employ regression and Box-Jenkins methods in this study. The main reason is regression and Box-Jenkins were designed by assuming that the pattern of time series is stationary (Nanda 1988). There are not suitable for non-stationary data like movie demand. Box-Jenkins required the most time in the application. The time includes for looking at the graph of each series, the autocorrelation functions, identifying appropriate models, estimating parameters, and diagnosis checking on the residual autocorrelation. The exponential smoothing methods were completely run on an automatic basis. The data series was put into the models, and forecasts were generated without human interference. The model selection and parameters estimation were done automatically, and the forecasts were not modified afterwards through any human interference (Makridakis et al. 1982). Unlike exponential smoothing, when new data become available, the entire procedure must be repeated. In the movie industry where a decision has to be made constantly, they required a forecasting method that can give them reliable forecasts in a shorter time, so exponential smoothing methods are the suitable choice.

Together with the newly proposed method, researchers able to evaluate and identify the best performing method in movie demand forecasting. The findings of this study allowed the distributors to identify a new way to generate reliable forecasts and predict the future demand based on historical sales data. The application of best performing forecasting method is important to distributors and production companies in the movie industry to make managerial decisions at the post-production stage concerning release timing and marketing strategy. Two important considerations for the release date are the strong seasonal effects in demand and the possibility of competition throughout the movie run (Einav 2007). The distributors have to compete with each other to get the best release timing, so as to reap a high revenue in the opening week. For them, the best release timing is the highest admission of the weekend. They tend to release their movies at the beginning of summer and during the Christmas holiday. These are the times when consumers have more free time and likely to go to the movies. Nevertheless, there is fierce competition among distributors for these peak times, because the movie sales in these holiday weeks are the highest, compared to other non-holiday weeks. Thus, strong seasonal effects in demand will be encountered throughout the movie's run (Moul & Shugan 2005). However, they have to aware of the possibility of similar movies release in the same period. Distributors often change the release dates in response to such information. To avoid such competition, they will announce the movie's release date early (Einav 2007). They should use exponential smoothing methods that were known for their simplicity and reliable forecasts in capturing various patterns in time series. The exponential smoothing methods are relatively simple but robust approaches to forecasting (Billah et al. 2006). They are inexpensive to use and require little data storage (Gardner 1985; Mentzer & Gomes 1989). In addition, the forecasts generated was to give a general idea of the expected number of admission every day. It does not indicate the sales estimation of the individual movie. However, based on this information, distributors able to decide on the best release date and negotiate with the exhibitors regarding the contract and screening period earlier than their competitors.

In comparison to other empirical papers, the results of this study cannot be generalised. Unlike results reported in the previous study (see Taylor 2007), our study only involve one time series data. Thus, further study can involve a number of time series data to gain robust results on the accuracy of the total and split exponential smoothing methods. We also aware of the double seasonal total and split exponential smoothing method (see Taylor 2010) and exponential smoothing with multiplicative and damped multiplicative trend (see Pegels 1969; Taylor 2003). However, double seasonal total and split exponential smoothing method is not applicable as we lack intraday dataset. While the application of multiplicative trend method has received very little attention, we only involve traditional exponential methods in this study. Therefore, the application of multiplicative trend methods in movie demand forecasting is suggested to compare with total and split exponential smoothing methods.

Further work in this area of research would be to investigate the variables influence the movie demand. In the movie industry, there are variables that influence the movie demand, such as movie characteristics, special holidays/events, public holidays, and so forth. In addition, movie demand showed yearly seasonality, as some authors (e.g. Litman 1983; Kim et al. 2015) mentioned, there are peak periods in movie sales, Christmas, summer, Easter and other special holidays in the United States. There may be a benefit in modelling the exponential smoothing methods to capture the yearly seasonality in movie demand. In addition, an event study or addition of dummy variables in the models are recommended to gain optimal results in movie demand forecasting. To our knowledge, there are only two empirical studies (Taylor 2007; 2010) investigated the forecasting performance of the newly proposed methods. So, it is suggested to explore more of this new method by applying it to different time series, such as stock prices and housing prices, to see whether any characteristics or patterns of the different series will influence the performance of the model.

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APPENDIX A

TABLE 1(a). Post-sample comparison of methods for 1096 daily observations using Root Mean Square Error (RMSE). The exponential smoothing methods estimated using absolute errors (Lower values are better. Bold indicates four lowest values in each column.)

	RMSE Forecast lead time							
	1-2	3-4	5-6	7-8	9-10	11-12	13-14	All
Non-seasonal methods								
Naïve	25,577,843.09	34,600,916.23	27,641,925.11	19,709,714.99	34,196,258.81	34,690,852.81	21,762,727.48	28,311,462.65
Simple ES (N-N)	21,188,026.50	21,803,844.74	19,253,946.68	19,676,138.55	21,892,406.65	22,156,366.68	18,980,121.03	20,707,264.40
Trend ES (A-N)	21,695,840.00	22,602,048.26	19,914,167.25	20,320,717.01	24,050,120.62	23,767,169.22	20,214,731.22	21,794,970.51
Damped trend ES (DA-N)	21,355,589.59	22,174,485.46	18,640,846.32	19,664,405.79	22,328,242.27	22,683,126.87	18,792,640.75	20,805,619.58
Methods using seasonal adjustment								
Simple ES (N-N)	16,791,569.86	16,791,093.42	16,155,997.69	15,956,818.25	16,398,107.39	16,318,104.23	16,398,274.55	16,401,423.63
Trend ES (A-N)	18,292,977.43	19,729,641.79	17,782,094.89	19,461,137.88	22,577,440.18	21,693,894.42	21,681,695.10	20,174,125.95
Damped trend ES (DA-N)	16,791,053.29	16,665,959.13	16,151,115.81	15,924,556.92	16,332,919.35	16,215,646.20	16,278,675.42	16,337,132.30
Seasonal methods								
Seasonal naïve	15,456,611.99	15,456,611.99	15,456,611.99	16,799,006.94	18,141,401.88	18,141,401.88	18,141,401.88	16,799,006.94
Seasonal (no trend) ES (N-A)	**11,073,371.42**	**13,093,775.45**	**13,783,622.34**	**13,964,350.79**	**14,176,138.81**	**14,325,861.18**	**14,377,305.85**	**13,542,060.84**
Seasonal trend ES (A-A)	**11,029,493.05**	**13,213,261.20**	14,065,836.23	14,570,817.32	14,956,840.58	15,311,456.13	15,578,323.47	14,103,718.29
Seasonal damped trend ES (DA-A)	**11,073,304.87**	**13,093,589.59**	**13,778,799.22**	**13,964,245.44**	**14,176,723.58**	**14,328,361.23**	**14,376,884.15**	**13,541,701.15**
Seasonal (no trend) ES (N-M)	15,611,034.68	13,891,606.95	13,888,514.81	14,187,444.46	14,506,548.36	14,506,548.33	14,506,547.87	14,442,606.50
Seasonal trend ES (A-M)	15,803,839.69	14,322,167.03	14,237,807.21	14,779,828.05	15,213,072.24	15,070,276.13	15,170,163.29	14,942,450.52
Seasonal damped trend ES (DA-M)	15,714,481.71	13,890,180.94	**13,885,614.05**	14,172,840.27	14,468,435.37	14,468,436.37	14,467,538.19	14,438,218.13
Total and split ES (optimised using SAE)	13,739,279.09	13,832,434.62	14,009,704.16	**13,961,236.30**	**13,584,848.84**	**13,599,533.85**	**14,018,665.72**	**13,739,279.09**
Total and split ES (optimised using SSE)	**13,332,897.28**	**13,522,711.44**	**13,659,213.55**	**13,585,973.79**	**13,414,202.36**	**13,413,374.98**	**13,412,521.93**	**13,332,897.28**
Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$)	14,373,783.04	15,380,433.15	15,579,810.38	16,632,667.14	17,783,058.18	17,558,432.22	17,115,421.00	14,373,783.04

*Table 1(a): Overall, the total and split exponential smoothing method using optimised parameters (SSE) is the best performing model. This new model was performed poorly in the earlier lead time. Beyond 5 days ahead, it has the lowest error among all the methods.

TABLE 1(b). Theil-U of the methods based on Root Mean Squared Error (RMSE). The exponential smoothing methods estimated using absolute errors (Lower values are better.)

	RMSE Forecast lead time							
	1-2	3-4	5-6	7-8	9-10	11-12	13-14	Mean Theil's U
Non-seasonal methods								
Naïve	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Simple ES (N-N)	0.8284	0.6302	0.6965	0.9983	0.6402	0.6387	0.8721	0.7578
Trend ES (A-N)	0.8482	0.6532	0.7204	1.0310	0.7033	0.6851	0.9289	0.7957
Damped trend ES (DA-N)	0.8349	0.6409	0.6744	0.9977	0.6529	0.6539	0.8635	0.7597
Methods using seasonal adjustment								
Simple ES (N-N)	0.6565	0.4853	0.5845	0.8096	0.4795	0.4704	0.7535	0.6056
Trend ES (A-N)	0.7152	0.5702	0.6433	0.9874	0.6602	0.6253	0.9963	0.7426
Damped trend ES (DA-N)	0.6565	0.4817	0.5843	0.8080	0.4776	0.4674	0.7480	0.6033
Seasonal methods								
Seasonal naïve	0.6043	0.4467	0.5592	0.8523	0.5305	0.5229	0.8336	0.6214
Seasonal (no trend) ES (N-A)	0.4329	**0.3784**	0.4986	0.7085	0.4146	0.4130	0.6606	0.5010
Seasonal trend ES (A-A)	**0.4312**	0.3819	0.5089	0.7393	0.4374	0.4414	0.7158	0.5223
Seasonal damped trend ES (DA-A)	0.4329	**0.3784**	0.4985	0.7085	0.4146	0.4130	0.6606	0.5009
Seasonal (no trend) ES (N-M)	0.6103	0.4015	0.5024	0.7198	0.4242	0.4182	0.6666	0.5347
Seasonal trend ES (A-M)	0.6179	0.4139	0.5151	0.7499	0.4449	0.4344	0.6971	0.5533
Seasonal damped trend ES (DA-M)	0.6144	0.4014	0.5023	0.7191	0.4231	0.4171	0.6648	0.5346
Total and split ES (optimised using SAE)	0.5372	0.3998	0.5068	0.7083	0.3973	0.3920	0.6442	0.5122
Total and split ES (optimised using SSE)	0.5213	0.3908	**0.4941**	**0.6893**	**0.3923**	**0.3867**	**0.6163**	**0.4987**
Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$)	0.5620	0.4445	0.5636	0.8439	0.5200	0.5061	0.7865	0.6038

*Table 1(b): The results in Table 1(a) can be see clearly by looking at Theil-U measure. The total and split exponential smoothing method using optimised parameters (SSE) is the best performing model. This new model was performed poorly in the earlier lead time. Beyond 5 days ahead, it has the lowest Theil-U value among all the methods.

TABLE 2(a). Post-sample comparison of methods for 1096 daily observations using Root Mean Square Error (RMSE). The exponential smoothing methods estimated using square error (Lower values are better. Bold indicates four lowest values in each column.)

	RMSE Forecast lead time							
	1-2	3-4	5-6	7-8	9-10	11-12	13-14	All
Non-seasonal methods								
Naïve	25,577,843.09	34,600,916.23	27,641,925.11	19,709,714.99	34,196,258.81	34,690,852.81	21,762,727.48	28,311,462.65
Simple ES (N-N)	21,254,747.21	21,874,283.42	19,108,860.51	18,605,246.30	21,899,772.66	21,971,187.30	18,852,320.75	20,509,488.31
Trend ES (A-N)	21,649,969.59	22,566,260.43	19,474,228.88	19,843,335.49	24,439,926.79	23,571,707.57	20,277,966.57	21,689,056.48
Damped trend ES (DA-N)	21,188,755.71	21,831,540.37	18,534,499.60	18,602,173.17	21,894,992.45	22,038,280.22	18,721,297.73	20,401,648.46
Methods using seasonal adjustment								
Simple ES (N-N)	16,438,715.85	16,374,331.03	16,125,277.77	15,941,349.67	15,987,838.80	15,929,321.66	15,943,657.34	16,105,784.59
Trend ES (A-N)	17,853,619.76	19,517,086.99	17,824,366.97	20,666,250.59	22,966,925.40	21,900,969.53	22,470,124.32	20,457,049.08
Damped trend ES (DA-N)	16,432,519.80	16,366,574.50	16,114,294.74	15,923,628.98	15,961,191.43	15,906,776.18	14,715,625.99	15,917,230.23
Seasonal methods								
Seasonal naïve	15,456,611.99	15,456,611.99	15,456,611.99	16,799,006.94	18,141,401.88	18,141,401.88	18,141,401.88	16,799,006.94
Seasonal (no trend) ES (N-A)	**10,923,029.35**	**12,846,426.50**	**13,489,910.07**	**13,774,004.92**	14,132,693.41	14,261,195.90	14,302,663.81	**13,389,989.14**
Seasonal trend ES (A-A)	**10,950,224.73**	**12,956,104.86**	13,840,118.56	14,297,724.34	14,856,919.14	15,131,009.49	15,262,535.44	13,899,233.80
Seasonal damped trend ES (DA-A)	**10,923,029.35**	**12,846,500.93**	**13,487,862.50**	**13,771,576.20**	14,129,251.35	**13,574,408.43**	**13,574,410.46**	**13,186,719.89**
Seasonal (no trend) ES (N-M)	13,470,633.83	13,569,351.83	**13,561,029.27**	13,914,332.38	**13,584,975.99**	**13,584,976.33**	**13,584,977.24**	13,610,039.55
Seasonal trend ES (A-M)	14,389,217.09	14,740,856.66	14,549,821.18	14,782,645.45	16,507,008.99	16,223,161.16	18,388,738.55	15,654,492.73
Seasonal damped trend ES (DA-M)	13,466,942.27	13,566,371.76	**13,558,471.13**	**13,561,910.92**	**13,565,111.55**	**13,565,072.26**	**13,565,136.36**	**13,549,859.46**
Total and split ES (optimised using SAE)	13,739,279.09	13,832,434.62	14,009,704.16	13,961,236.30	**13,584,848.84**	13,599,533.85	14,018,665.72	13,739,279.09
Total and split ES (optimised using SSE)	**13,332,897.28**	**13,522,711.44**	13,659,213.55	**13,585,973.79**	**13,414,202.36**	**13,413,374.98**	**13,412,521.93**	**13,332,897.28**
Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$)	14,373,783.04	15,380,433.15	15,579,810.38	16,632,667.14	17,783,058.18	17,558,432.22	17,115,421.00	14,373,783.04

*Table 2(a): There is not much different in the results, compared to results in Table 1(a). The total and split exponential smoothing method using optimised parameter (SSE) was the best performing model. In the earlier lead time, the method outperformed by traditional methods. But, beyond 9 days ahead, it has the lowest RMSE.

TABLE 2(b). Theil-U of the methods based on Root Mean Squared Error (RMSE). The exponential smoothing methods estimated using square error (Lower values are better).

	RMSE Forecast lead time							
	1-2	3-4	5-6	7-8	9-10	11-12	13-14	Mean Theil's U
Non-seasonal methods								
Naïve	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Simple ES (N-N)	0.8310	0.6322	0.6913	0.9440	0.6404	0.6333	0.8663	0.7484
Trend ES (A-N)	0.8464	0.6522	0.7045	1.0068	0.7147	0.6795	0.9318	0.7908
Damped trend ES (DA-N)	0.8284	0.6310	0.6705	0.9438	0.6403	0.6353	0.8602	0.7442
Methods using seasonal adjustment								
Simple ES (N-N)	0.6427	0.4732	0.5834	0.8088	0.4675	0.4592	0.7326	0.5953
Trend ES (A-N)	0.6980	0.5641	0.6448	1.0485	0.6716	0.6313	1.0325	0.7558
Damped trend ES (DA-N)	0.6425	0.4730	0.5830	0.8079	0.4668	0.4585	0.6762	0.5868
Seasonal methods								
Seasonal naïve	0.6043	0.4467	0.5592	0.8523	0.5305	0.5229	0.8336	0.6214
Seasonal (no trend) ES (N-A)	**0.4271**	**0.3713**	0.4880	0.6988	0.4133	0.4111	0.6572	0.4953
Seasonal trend ES (A-A)	0.4281	0.3744	0.5007	0.7254	0.4345	0.4362	0.7013	0.5144
Seasonal damped trend ES (DA-A)	**0.4271**	**0.3713**	**0.4879**	0.6987	0.4132	0.3913	0.6237	**0.4876**
Seasonal (no trend) ES (N-M)	0.5267	0.3922	0.4906	0.7060	0.3973	0.3916	0.6242	0.5041
Seasonal trend ES (A-M)	0.5626	0.4260	0.5264	0.7500	0.4827	0.4676	0.8450	0.5800
Seasonal damped trend ES (DA-M)	0.5265	0.3921	0.4905	**0.6881**	0.3967	0.3910	0.6233	0.5012
Total and split ES (optimised using SAE)	0.5372	0.3998	0.5068	0.7083	0.3973	0.3920	0.6442	0.5122
Total and split ES (optimised using SSE)	0.5213	0.3908	0.4941	0.6893	**0.3923**	**0.3867**	**0.6163**	0.4987
Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$)	0.5620	0.4445	0.5636	0.8439	0.5200	0.5061	0.7865	0.6038

*Table 2(b): We can see clearly that the total and split exponential smoothing with optimised parameter (SSE) was the best performing method relative to other methods. It has the lowest Theil-U measure beyond 9 days ahead.