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# Forecasting Monthly Data Using Total and Split 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 make decisions such as marketing strategy and costs, number of screens, and release timing. Movie demand is known to show seasonality. Thus, forecasting methods which are able to capture such patterns can be relied on to produce an accurate prediction. In this paper, we study the performance of the recently proposed exponential smoothing method. It is known as total and split exponential smoothing, and applies it to box office from the United States on monthly basis. The forecasts are evaluated against other seasonal exponential smoothing methods. Overall, total and split exponential smoothing with subjectively chosen parameters was performing well, followed by seasonal damped trend exponential smoothing method (DA-M).

**JEL Classification:** M20, M21,

**Keywords:** Forecasting; exponential smoothing; motion pictures; movie demand; time series

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## INTRODUCTION

The motion picture industry is a multi-billion dollar business. Motion Picture Association of America (MPAA) stated that global box office for all films released worldwide reached $40.6 billion in 2017, up 5% over 2016's total (US$38.8 billion) (2018). The demand for movies has been significantly increased due to the increment of a personal desire for cultural life. Demand for the new movie is uncertain, as movies are experiential products. Most cultural products except books are defined as experience goods with short product life cycle (Chang and Ki, 2005). The challenge of demand forecasting in the movie industry was believed to be due to the uniqueness of each movie (Marshall et al., 2013). For these reasons, it is difficult for consumers to evaluate the movie until they have actually experienced it (Hirschman and Holbrook, 1982; Eliashberg and Sawhney, 1994; Marshall et al., 2013). Ultimately, the audiences will decide the fate of the movies (De Vany and Walls, 1999).

With reference to this issue, President of MPAA, Jack Valenti (1978) gave a speech regarding the uncertainty and unpredictability related to 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.*"

This statement was supported by Goldman (1983). They stated that no one knows anything about the new movies until the audiences go and see it for themselves. As a consequence, the motion picture industry is emerging to become an area of interest to scholar and researchers. Box office forecasting has always been a major concern in the motion picture business (Jun et al., 2011). With the importance of new movies and uncertainty in predicting the box office performance of these new movies, the value of accurate box office forecasts is extremely high in this industry (Sawhney and Eliashberg, 1996).

With regard to the importance of movie demand forecasts, various approaches have been applied by researchers in past studies to predict movie success. 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 and Delen, 2006). The most common method is incorporating the variables into the forecasting models. When analysing the motion picture industry, it is crucial to explore the factors influencing the box office performance because it is a basic foundation for movie-related policy establishment (Yoo, 2002). Basically, the variables came from the theories of motion picture success stated by Litman (1983). He identified three areas involved in decision making process that drives the success of movies: the creative sphere, the scheduling and release pattern, and the marketing effort. The impact of various factors to movie sales, such as consumer behaviour, MPAA rating, director, star, distributor, genre, degree of competition, word-of-mouth (WOM) and critique, advertising spending, country of origin, external events, seasonality, and number of screens has been investigated (e.g. Litman, 1983; Jones and Ritz, 1991; Sawhney and Eliashberg, 1996; Eliashberg and Shugan, 1997; Ravid, 1999; Holbrook, 1999; Elberse and Eliashberg, 2003; Liu, 2006; Dellarocas et al., 2007; Einav, 2007; Elberse, 2007; Moon et al., 2010; Marshall et al., 2013; Kim et al., 2015). Indeed, the incorporating of variables in movie forecasting improves the accuracy of models (Sharda and Delen, 2006; Lee and Chang, 2009; Kim et al., 2015).

Movie demand forecasting is an important task but challenging for distributors. In the decision making process, forecasting of movie demand is inevitable (Jun et al., 2011). When they distribute a film to theatres, distributors are required to make appropriate managerial decisions to maximize the profit. The ability to accurately predict the box office revenues will help the distribution companies to determine the release timing, marketing strategy and cost, period of showing the movie and number of screens. The date of launching of a film is arguably the extremely difficult decision facing the distributors (Radas and Shugan, 1998). The date of release of a new movie is the main focus because the first-week opening accounted for 40% of the box office revenues of average movies. Studios will compete with each other for the best movie's release date especially seasonal holidays (Einav, 2007). The movie has a short exhibition period and can last for less than 15 weeks in domestic theatrical release. Normally, distributors have 3 to 5 new movies available for release into the market in a weekly basis, and the exhibitors (theatres) need to decide the number of screens and play time for these movies (Eliashberg et al., 2009). However, movie distributors will face limited screen availability for their movies because the number of movies release was more than the available number of screens. Major distributors released a number of movies during the peak seasons, especially summer and Christmas (Swami et al., 1999; Einav, 2007; Eliashberg et al., 2009). With no price competition, distributors constantly compete for suitable release timing. Thus, strong seasonal effects in demand will be encountered throughout the movie's run. If the new movies expected to receive a high demand from potential audiences, then they are released on high demand weekend (Einav, 2001; Einav, 2007). Past literature also revealed the significant of release timing in determining the movie performance (Litman, 1983; Zhang and Skiena, 2009; Brewer et al., 2009; Gong et al., 2011). Therefore, our work intends to forecast the movie demand in the evaluation period by using seasonal exponential smoothing models and attempts to compare their forecasting performance to better support movie distributors' decisions.

The main objective of this paper is to gain an understanding of the usefulness of the newly proposed total and split exponential smoothing method. The method was developed for daily sales forecasting and generated accurate forecasts, particularly for early lead times (Taylor 2007). Then, it was applied to a publishing company's monthly sales series (Taylor, 2011). In this paper, we use this method to the monthly box office taken from the website. In addition, we evaluate the forecasting performance of this method and compare against other seasonal exponential smoothing methods. Unlike past studies, we concerned the performance of these methods in capturing seasonality of historical movie sales. There is no inclusion of any explanatory variables. The excellent performance of exponential smoothing in empirical studies led to its popular application in the industry (Gardner, 1985; Gardner 2006). Compared to other methods, exponential smoothing obtained a high level of satisfaction among the sales forecasting practitioners (McCarthy et al., 2006). In movie demand forecasting, various approaches were implemented and their accuracy has been proven. However, there is the limited application of exponential smoothing models in the motion picture industry. Exponential smoothing models are expected to be capable of capturing 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 section. The third section gives the descriptive of the study including the background of the monthly movie sales data and methodology used in this study. All the results will be reported in the fourth section. The final section will present the conclusion and recommendations for future research.

## FORECASTING MODELS

### Exponential Smoothing Methods

Exponential smoothing methods generate forecasts by addressing the forecast components of the level, trend, seasonality and cycle. The smoothing coefficients for each of these components are determined statistically and are applied to smooth previous period information (Gardner, 2006). Forecasts generated by exponential smoothing are weighted averages of past observations, with the weight decaying, as the observations get older. It put more weight on recent observations (Hyndman and Athanasopoulos, 2014). The exponential smoothing methods act as benchmarks to compare the performance of the total and split exponential smoothing method. Previous studies have proven the existence of seasonality in movie demand (see, Litman, 1983; Litman and Kohl, 1989; Einav, 2007; Gong et al., 2011; Kim et al., 2015), so we included only seasonal methods in the forecast comparison. The symbols and notations of the formulations were presented in the Appendix.

### 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, on a monthly basis, the forecast for all future first-month values of the year is equal to the last observed first month of the year. The formulation is written as:

$$\hat{X}_t\ (\mathrm{m}) = X_{t-p+m} \tag{1}$$

*Seasonal (no trend) exponential smoothing*

There are two variations to this method: additive and multiplicative seasonality formulations. The notation "N-A" indicates no trend and additive seasonality. Given that

| | | |
|---|---|---|
| Level: | $S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)S_{t-1}$ | (2) |
| Seasonal: | $I_t = \Upsilon(X_t - S_t) + (1-\Upsilon)I_{t-p}$ | (3) |
| Forecast: | $\hat{X}_t\,(m) = S_t + I_{t-p+m}$ | (4) |

Notation "N-M" represented exponential smoothing with no trend and multiplicative seasonality. Given that:

| | | |
|---|---|---|
| Level: | $S_t = \alpha(X_t/I_{t-p}) + (1-\alpha)S_{t-1}$ | (5) |
| Seasonal: | $I_t = \Upsilon(X_t/S_t) + (1-\Upsilon)I_{t-p}$ | (6) |
| Forecast: | $\hat{X}_t\,(m) = S_t I_{t-p+m}$ | (7) |

*Seasonality trend exponential smoothing*

Two methods are under the category of additive and multiplicative seasonality formulations. Unlike previous exponential smoothing methods, these methods involved three different parameters, α, β, and ϒ to smooth the level, trend, and seasonality respectively. Additive formulation with notation of "A-A" represented an additive trend and additive seasonality. Given that:

| | | |
|---|---|---|
| Levels: | $S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)(S_{t-1} + T_{t-1})$ | (8) |
| Trend: | $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$ | (9) |
| Seasonal: | $I_t = \Upsilon(X_t - S_t) + (1-\Upsilon)I_{t-p}$ | (10) |
| Forecast: | $\hat{X}_t\,(m) = S_t + mT_t + I_{t-p+m}$ | (11) |

Multiplicative formulations with notation "A-M" represented additive trend and multiplicative seasonality. Given that:

| | | |
|---|---|---|
| Level: | $S_t = \alpha(X_t/I_{t-p}) + (1-\alpha)(S_{t-1} + T_{t-1})$ | (12) |
| Trend: | $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$ | (13) |
| Seasonal: | $I_t = \Upsilon(X_t/S_t) + (1-\Upsilon)I_{t-p}$ | (14) |
| Forecast: | $\hat{X}_t\,(m) = (S_t + mT_t)I_{t-p+m}$ | (15) |

*Seasonal damped trend exponential smoothing*

Other than smoothed the level, trend, and seasonality, there is an additional damping parameter, to damp the trend in the forecast function. It has three smoothing parameters (α, β, and ϒ) and a damping parameter (ϕ). Notation "DA-A" showed a damped additive trend with additive seasonality. Given that:

| | | |
|---|---|---|
| Level: | $S_t = \alpha(X_t - I_{t-p}) + (1-\alpha)(S_{t-1} + \phi T_{t-1})$ | (16) |
| Trend: | $T_t = \beta(S_t - S_{t-1}) + (1-\beta)\phi T_{t-1}$ | (17) |
| Seasonal: | $I_t = \Upsilon(X_t - S_t) + (1-\Upsilon)I_{t-p}$ | (18) |
| Forecast: | $\hat{X}_t\,(m) = S_t + \sum_{i=1}^{m} \phi^i\, T_t + I_{t-p+m}$ | (19) |

Notation "DA-M" showed damped additive trend with multiplicative seasonality. Given that:

| | | |
|---|---|---|
| Level: | $S_t = \alpha(X_t/I_{t-p}) + (1-\alpha)(S_{t-1} + \phi T_{t-1})$ | (20) |
| Trend: | $T_t = \beta(S_t - S_{t-1}) + (1-\beta)\phi T_{t-1}$ | (21) |
| Seasonal: | $I_t = \Upsilon(X_t/S_t) + (1-\Upsilon)I_{t-p}$ | (22) |
| Forecast: | $\hat{X}_t\,(m) = (S_t + \sum_{i=1}^{m} \phi^i\, T_t)I_{t-p+m}$ | (23) |

**Total and Split Exponential Smoothing**

We applied this new exponential smoothing method to monthly movie sales. For a series of monthly observations, $y_t$, the method involves smoothing the total yearly sales, $Y_t$, and the split, $L_t$, of the yearly sales across the months of the year (Taylor, 2011). The method has the following formulation:

$$Y_t = \alpha \sum_{i=0}^{11} y_{t-i} + (1-\alpha)\, Y_{t-1} \quad (24)$$

$$L_t = \frac{\Upsilon y_t}{\sum_{i=0}^{11} y_{t-i}} + (1-\Upsilon)\, L_{t-12} \quad (25)$$

where $\alpha$ and $\Upsilon$ are smoothing parameters. The forecasts are given by:

$$\hat{y}_t\,(m) = Y_t L_{t+m-12} \text{ for } m = 1 \text{ to } 12 \quad (26)$$

$$\hat{y}_t\,(m) = Y_t L_{t+m-24} \text{ for } m = 13 \text{ to } 18 \quad (27)$$

Taylor (2007) stated that the method is a combination of the ratio-to-moving average seasonal adjustment procedure and Holt-Winters exponential smoothing with no trend and multiplicative seasonality (N-M exponential smoothing). The smoothed total yearly sales substituted the Holt-Winters smoothing of the level while the total and split method is substituting simple averages by exponentially weighted moving averages in the ratio-to-moving average seasonal adjustment approach (Taylor, 2007).

## RESEARCH METHODOLOGY

**Description of the Study**

Monthly movie sales in the United States from Box Office Mojo (www.boxofficemojo.com) will be utilised in this paper. This data was collected from January 1982 to December 2017, with a total of 432 observations. The first 80% of observations of the series (in-sample) were used to estimate the parameters. The final 20% of the observations used as post-sample forecast evaluation (as shown in Figure 2). We considered forecast horizons of 18 months.

Figure 1 presented the time series plot. The plot showed some of the features in the data. The data showed a slight increasing trend in the long-term horizon. 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 and Kohl, 1989; Einav, 2007; Gong et al., 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. Therefore, we only involved seasonal exponential smoothing models in the paper.

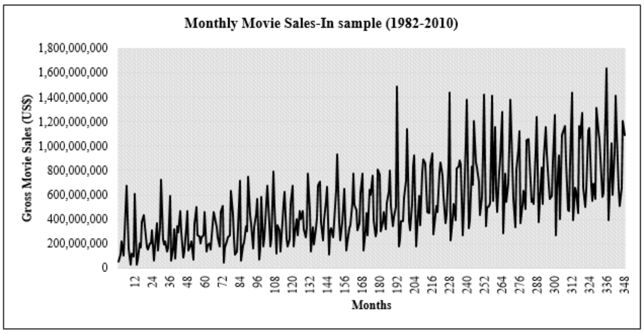


Figure 1 Time series plot for in-sample from the year 1982 to 2010

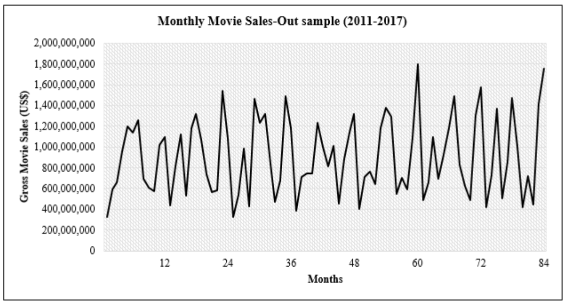


Figure 2 Time series plot for out-sample from the year 2011 to 2017

### Forecasting Methods and Parameters Description

Seasonal methods were very sensitive to the method used to obtain the initial values. In this paper, the initial values of all exponential smoothing methods were generated utilising simple averages of the early observations in the series. Demand cannot attain negative values. Thus, for all methods, if a forecast produced negative value, that forecast is set to zero.

For all the series, Taylor (2007; 2011) used subjectively chosen parameters, $\alpha$=0.7 and $\Upsilon$=0.1, in total and split exponential smoothing method. We included this together with optimised values for monthly box office data. Empirical studies claimed that it was preferable to optimise the parameters of the exponential smoothing methods by minimising the sum of absolute errors (SAE), rather than the standard use of the sum of squared errors (SSE) (see Gardner and Diaz-Saiz, 2008; Taylor, 2011). Gardner (1999) showed that when the outliers existed in a series, MAD criterion often generates better forecasting accuracy. For all exponential smoothing methods, the optimisation approach by minimising the SSE of estimation samples, as well as minimising the SAE was considered. Taylor (2011) reported the methods using optimised parameters generated better forecasts at the early lead times. It may be due to the parameter optimisation 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.

### Post-sample Forecast Evaluation Criteria

The forecast errors, $e_t$, are the difference between the actual values ($y_t$) and the forecasts ($\hat{y}_t$) produced. Mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and median absolute percentage error (MdAPE) are used to evaluate the forecast performance of various models. The formulae are expressed as followed:

| | | |
|---|---|---|
| Mean Absolute Error (MAE) | $= \text{mean}(\lvert e_t \rvert)$ | (28) |
| Root Mean Square Error (RMSE) | $= \sqrt{\text{mean}(e_t^2)}$ | (29) |
| Mean Absolute Percentage Error (MAPE) | $= \text{mean}(\lvert p_t \rvert)$ | (30) |
| Median Absolute Percentage Error (MdAPE) | $= \text{median}(\lvert p_t \rvert)$ | (31) |

where $p_t$ denotes as percentage error, $p_t = 100e_t/y_t$.

## RESULTS AND DISCUSSION

For simplicity, we present the results in terms of parameters estimation by minimising SAE. The performance of the methods was broadly similar in terms of parameter estimation by minimising SSE. The tables include total and split exponential smoothing method that had optimised parameters by minimising the SSE for the purpose of comparison. Post-sample results for methods have been applied to 84 months of data. The tables showed the average of the accuracy measures for forecast horizons 1 to 6, 7 to 12, 13 to 18, and for all 18 horizons. The lowest error measures are presented in bold.

Table 1 and 2 present the MAE and RMSE post sample results for all the exponential smoothing methods. Both MAE and RMSE yield different results. Referring to MAE measures (Table 1), total and split exponential smoothing with subjectively chosen parameters outperformed the other exponential smoothing methods followed by seasonal damped trend exponential smoothing (DA-M). It performed well in the first 12 months of the forecast horizon, after that, it was outperformed by seasonal damped trend exponential smoothing (DA-M). However, RMSE results (Table 2) revealed that seasonal damped trend exponential smoothing (DA-M) was the best performing method followed by seasonal trend exponential smoothing (A-M). The total and split exponential smoothing method with subjectively chosen, and optimised parameters by minimising SAE performing well in the earlier lead time and after 12 months of forecast horizon respectively.

Table 1 Post-sample evaluation of methods for 84 monthly observations using mean absolute error (MAE)

| | MAE<br>Forecast lead time | | | |
|---|---|---|---|---|
| | 1-6 | 7-12 | 13-18 | All |
| Seasonal methods | | | | |
| Seasonal naïve | 182,381,535.44 | 182,381,535.44 | 192,354,249.63 | 185,705,773.50 |
| Seasonal (no trend) ES (N-A) | 153,507,125.94 | 152,541,265.09 | 156,340,158.30 | 154,129,516.44 |
| Seasonal trend ES (A-A) | 154,558,171.94 | 153,690,004.45 | 159,974,919.37 | 156,074,365.25 |
| Seasonal damped trend ES (DA-A) | 153,288,828.32 | 152,334,520.37 | 156,534,280.86 | 154,052,543.18 |
| Seasonal (no trend) ES (N-M) | 153,965,033.78 | 152,785,137.64 | 154,727,098.01 | 153,825,756.48 |
| Seasonal trend ES (A-M) | 153,757,129.06 | 152,554,220.36 | 157,526,305.98 | 154,612,551.80 |
| Seasonal damped trend ES (DA-M) | 153,274,937.19 | 152,323,014.54 | **151,358,369.74** | 152,318,773.82 |
| Total and split ES (optimised using SAE) | 152,286,093.72 | 152,708,448.45 | 154,543,716.45 | 153,179,419.54 |
| Total and split ES (optimised using SSE) | 153,407,608.65 | 153,775,863.75 | 155,459,093.44 | 154,214,188.61 |
| Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$) | **151,467,997.16** | **151,681,364.16** | 153,238,241.51 | **152,129,200.94** |

Note: Parameter optimisation by minimising the sum of absolute errors (SAE). The values in bold are the methods with lowest forecasting errors for each lead time.

Table 2 Post-sample comparison of methods for 84 monthly observations using root mean square error (RMSE)

| | RMSE<br>Forecast lead time | | | |
|---|---|---|---|---|
| | 1-6 | 7-12 | 13-18 | All |
| Seasonal methods | | | | |
| Seasonal naïve | 229,659,962.38 | 229,659,962.38 | 247,646,924.97 | 235,655,616.58 |
| Seasonal (no trend) ES (N-A) | 193,908,169.72 | 193,016,470.69 | 202,492,997.56 | 196,472,545.99 |
| Seasonal trend ES (A-A) | 194,375,990.24 | 193,590,665.97 | 204,021,758.40 | 197,329,471.53 |
| Seasonal damped trend ES (DA-A) | 193,413,811.13 | 193,040,016.86 | 201,953,762.89 | 196,135,863.63 |
| Seasonal (no trend) ES (N-M) | 193,574,417.67 | 192,568,337.51 | 202,147,373.93 | 196,096,709.71 |
| Seasonal trend ES (A-M) | 193,228,402.03 | 192,293,559.09 | 203,746,076.98 | 196,422,679.37 |
| Seasonal damped trend ES (DA-M) | **192,530,319.75** | **191,935,728.61** | **198,729,233.56** | **194,398,427.31** |
| Total and split ES (optimised using SAE) | 192,647,490.72 | 193,963,027.50 | 202,626,819.54 | 196,412,445.92 |
| Total and split ES (optimised using SSE) | 193,677,283.68 | 195,062,592.21 | 203,636,924.46 | 197,458,933.45 |
| Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$) | 197,548,652.93 | 196,463,570.72 | 202,080,674.92 | 198,697,632.86 |

Note: Parameter optimisation by minimising the sum of absolute errors (SAE). The values in bold are the methods with lowest forecasting errors for each lead time.

Table 3 and 4 displayed the MAPE and MdAPE post sample results of all the 10 exponential smoothing models. Both MAPE and MdAPE yield almost the same results. Total and split exponential smoothing method with subjectively chosen parameters outperformed the other exponential smoothing methods as shown in both tables. As presented in MAPE results, it was then followed by seasonal damped trend exponential smoothing method (DA-M) and seasonal (no trend) exponential smoothing (N-M). Total and split exponential smoothing method with optimised parameters by minimising SAE was performing as good as these methods. MdAPE results revealed that total and split exponential smoothing with optimised values (SAE) performing as good as the one with subjectively chosen parameters.

Table 3 Post-sample comparison of methods for 84 monthly observations using mean absolute percentage error (MAPE), %

| | MAPE, % Forecast lead time | | | |
|---|---|---|---|---|
| | 1-6 | 7-12 | 13-18 | All |
| Seasonal methods | | | | |
| Seasonal naïve | 21.57 | 21.57 | 22.64 | 21.93 |
| Seasonal (no trend) ES (N-A) | 18.26 | 18.38 | 18.53 | 18.39 |
| Seasonal trend ES (A-A) | 18.74 | 19.11 | 19.84 | 19.23 |
| Seasonal damped trend ES (DA-A) | 18.27 | 18.41 | 18.62 | 18.44 |
| Seasonal (no trend) ES (N-M) | 18.05 | 18.09 | 18.00 | 18.05 |
| Seasonal trend ES (A-M) | 18.58 | 18.55 | 19.33 | 18.82 |
| Seasonal damped trend ES (DA-M) | 18.08 | 18.08 | **17.71** | 17.95 |
| Total and split ES (optimised using SAE) | 18.10 | 18.21 | 18.12 | 18.14 |
| Total and split ES (optimised using SSE) | 18.31 | 18.35 | 18.24 | 18.30 |
| Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$) | **17.92** | **17.87** | 17.76 | **17.85** |

Note: Parameter optimisation by minimising the sum of absolute errors(SAE). The values in bold are the methods with lowest forecasting errors for each lead time.

Table 4 Post-sample comparison of methods for 84 monthly observations using median absolute percentage error (MdAPE), %

| | MdAPE, % Forecast lead time | | | |
|---|---|---|---|---|
| | 1-6 | 7-12 | 13-18 | All |
| Seasonal methods | | | | |
| Seasonal naïve | 17.04 | 17.04 | 18.91 | 17.66 |
| Seasonal (no trend) ES (N-A) | 14.74 | 14.81 | 15.68 | 15.08 |
| Seasonal trend ES (A-A) | 14.67 | 15.03 | 17.30 | 15.67 |
| Seasonal damped trend ES (DA-A) | 14.73 | 14.82 | 16.15 | 15.23 |
| Seasonal (no trend) ES (N-M) | 15.17 | 15.12 | 13.60 | 14.63 |
| Seasonal trend ES (A-M) | 14.78 | 14.43 | 15.08 | 14.76 |
| Seasonal damped trend ES (DA-M) | 15.06 | 15.03 | 13.66 | 14.59 |
| Total and split ES (optimised using SAE) | 14.31 | 14.49 | 14.90 | 14.57 |
| Total and split ES (optimised using SSE) | 14.86 | 14.63 | 15.16 | 14.88 |
| Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$) | **13.91** | **13.90** | **13.01** | **13.61** |

Note: Parameter optimisation by minimising the sum of absolute errors (SAE). The values in bold are the methods with lowest forecasting errors for each lead time.

Estimating the parameters by minimising SAE was preferable over SSE. The analysis revealed that exponential smoothing methods with optimised values by minimising SAE provide a better forecasting accuracy than SSE as proven by Gardner (1999). In the paper by Taylor (2011), due to parameter optimisation using one-step ahead errors, the outcome of the optimised values in total and split exponential smoothing only useful for the first few periods, but beyond that, the subjectively chosen values were most accurate. Thus, this study performed optimisation separately for each lead time using in-sample forecast errors corresponding to that lead time. It is expected that the total and split with optimised values will outperform the other exponential smoothing methods. Nevertheless, the results showed that the total and split exponential smoothing with optimised parameter especially by minimising SSE are performing poorly and SAE only performing as good as the one with subjectively chosen parameters.

Table 5 presented the post sample Theil-U value based on RMSE of various exponential smoothing methods. The purpose of using Theil-U measure is 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 seasonal naïve model. The lower the value of Theil-U, the better the model it is. Based on the results, the seasonal damped trend exponential smoothing model (DA-M) dominated the other forecasting methods in terms of Theil-U in post sample period. It is followed by seasonal trend exponential smoothing (A-M). The total and split exponential smoothing method with optimised parameters by minimising SAE performing well in the earlier lead time while the one with subjectively chosen parameters performing better in later lead time.

Table 5 Theil-U values based on Root Mean Squared Error (RMSE)

| | Theil-U Forecast lead time | | | |
|---|---|---|---|---|
| | 1-6 | 7-12 | 13-18 | Mean Theil-U |
| Seasonal methods | | | | |
| Seasonal naïve | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Seasonal (no trend) ES (N-A) | 0.8443 | 0.8404 | 0.8177 | 0.8341 |
| Seasonal trend ES (A-A) | 0.8464 | 0.8429 | 0.8238 | 0.8377 |
| Seasonal damped trend ES (DA-A) | 0.8422 | 0.8405 | 0.8155 | 0.8327 |
| Seasonal (no trend) ES (N-M) | 0.8429 | 0.8385 | 0.8163 | 0.8325 |
| Seasonal trend ES (A-M) | 0.8414 | 0.8373 | 0.8227 | 0.8338 |
| Seasonal damped trend ES (DA-M) | **0.8383** | **0.8357** | **0.8025** | **0.8255** |
| Total and split ES (optimised using SAE) | 0.8388 | 0.8446 | 0.8182 | 0.8339 |
| Total and split ES (optimised using SSE) | 0.8433 | 0.8494 | 0.8223 | 0.8383 |
| Total and split ES ($\alpha = 0.7$, $\Upsilon = 0.1$) | 0.8602 | 0.8555 | 0.8160 | 0.8439 |

Note: Parameter optimisation by minimising the sum of absolute errors(SAE). The values in bold are the methods with lowest Theil-U for each lead time.

Overall, the total and split exponential smoothing with subjectively chosen parameters is the best performing model. Different error measures revealed different results regarding the performance of the newly proposed exponential smoothing method as compared to other seasonal exponential smoothing methods especially RMSE measures. RMSE showed different error measures as compared to other three error measures. It could be due to the high sensitivity of RMSE to outliers. Due to this, RMSE has poor reliability and validity, thus it is advisable not to be used for comparisons (Armstrong, 2001; Willmott and Matsuura, 2005). According to Mentzer and Kahn (1995), the most generally utilised error measure was MAPE with 52%, while utilisation of RMSE only 10% based on the survey of 207 forecasting executives.

## CONCLUSION

We have investigated the forecasting performance of exponential smoothing presented by Taylor (2007) and compared with other exponential smoothing methods using monthly movie sales series. The seasonal exponential smoothing models are being employed in our empirical study. Overall, total and split exponential smoothing method with subjectively chosen parameters achieved the best result in our study. Other methods that produced competitive results are damped trend exponential smoothing (DA-M) and total and split method with optimised parameters by minimising SAE. For total and split exponential smoothing, the results showed that subjectively chosen values performed better than those optimised separately for each lead time corresponding to their lead time. Moreover, parameter estimation by minimising absolute errors provides a better forecasting accuracy as compared to squared errors.

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 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 during the exhibition period of the movie (Einav, 2007). The distributors have to compete with each other to get the best release timing, so as to reap high revenue in the opening week. For them, the best release timing is the highest admission of the month. 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 and Shugan, 2005). However, they have to aware of the possibility of similar movies release in the same period. Distributors often change the date of launching in response to such information. To avoid such competition, they will announce the movie's release date early (Einav, 2007).

Before the announcement, they have to make a forecast to see which month will have the highest admission to the cinema based on historical sales. Since there is seasonality in movie demand, it is suggested to use exponential smoothing methods that were known for their simplicity and reliable forecasts in capturing various patterns in time series (Gardner, 1985). The exponential smoothing methods are relatively simple but robust approaches to forecasting (Billah et al., 2006). They are not costly to apply and involve a small amount of data storage (Gardner, 1985; Mentzer and Gomes, 1989). The evidence suggesting that the total and split exponential smoothing with subjective chosen parameters was the best performing model as compared to other seasonal exponential smoothing methods. The forecasts generated do not indicate the sales estimation of the individual movie. They gave a general idea of the expected number of admission every month. Moreover, distributors faced limited space available for their new movies in the theatres (Swami et al., 1999). By deciding the release date early for new movies allowed the distributors to get the optimal number of screens before their competitors do. Other than that, the success of new movies highly depends on marketing activities in this period (Sawhney and Eliashberg, 1996). It allows them to make appropriate decisions concerning the budget allocations for additional marketing activities and screen allocation across movie theatres (Kim et al., 2015) based on demand forecasts.

In comparison to other empirical papers, the results of this study cannot be generalised. Unlike results reported in the previous study (see Taylor, 2011), our study only involve a single data set. Thus, further study should involve more data series to gain robust results on the accuracy of the total and split exponential smoothing. We also aware of the double seasonal total and split exponential smoothing method (see Taylor, 2010). However, double seasonal total and split exponential smoothing method is not applicable as we lack intraday dataset. Another one is exponential smoothing with multiplicative and damped multiplicative trend (see Pegels, 1969; Taylor, 2003). 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 and damped multiplicative trend methods in movie demand forecasting are 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 consumer behaviour. In addition, an event study or addition of dummy variables in the models is recommended to gain optimal results in movie demand forecasting. For total and split exponential smoothing, Taylor (2011) expected that the estimation of parameters by minimising the in-sample errors for each lead time will lead to superior accuracy over the one with subjective chosen parameters. But, the results of this study do not support his view. Thus, it is suggested to use various estimation methods (Hyndman et al., 2002) or a statistical procedure, such as maximum likelihood. Other than parameter estimation, outlier adjustment and seasonal adjustment is recommended to adjust extreme values in the series before going to the forecasting stage. This newly proposed exponential smoothing method can be applied to another area of study, such as volatility and prices to gain more insights into the usefulness of this model when applying to different datasets. Simply to say, there are more to explore regarding this new method.

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## NOTATIONS

| | |
|---|---|
| $\alpha$ | Smoothing parameter for the level of the series |
| $\beta$ | Smoothing parameter for the trend |
| $\Upsilon$ | Smoothing parameter for seasonal indices |
| $\phi$ | Damping parameter |
| $S_t$ | Smoothed level of the series |
| $T_t$ | Smoothed additive trend at the end of period $t$ |
| $I_t$ | Smoothed seasonal index at the end of period $t$ |
| $X_t$ | Observed value of the time series in period $t$ |
| $m$ | Number of periods in the forecast lead-time |
| $p$ | Number of periods in the seasonal cycle |
| $\hat{X}_t (m)$ | Forecast for $m$ periods ahead from origin $t$ |
| $y_t$ | Monthly observations |
| $Y_t$ | Smoothed total yearly sales |
| $L_t$ | Split of the yearly sales across the months of the year |
| $\hat{y}_t (m)$ | Forecast for $m$ periods ahead from origin $t$ |
| $e_t$ | Forecast error |
| $p_t$ | Percentage error |