Journal of Leisure Research
2003, Vol. 35, No. 4, pp. 441-454

An Evaluation of Alternative Forecasting Methods to Recreation Visitation

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This study examines the advantages and disadvantages of basic, intermediate, and advanced methods for visitor use forecasting where seasonality and limited data are characteristics of the estimation problem. The monthly use rates at the Milwaukee County Zoo, Wisconsin are used to illustrate the seasonal time series techniques. Forecasting methods include the Naïve 1, Naïve 2, single moving average (SMA) with the classical decomposition procedure, single exponential smoothing (SES), double exponential smoothing (DES), Winter's, and the seasonal autoregressive integrated moving average (SARIMA). The variation in visitor rates over the years makes the visitation trend for the Milwaukee County Zoo appealing in this empirical application. The series ranges from January 1981 through December 1999, a total of 228 months. The last 12, 24, or 60 months of those data are excluded from the original analysis, and used to evaluate the various methods. SARIMA and SMA with the classical decomposition procedure are found to be roughly equivalent in performance, as judged by modified mean absolute percentage error (MAPE) and modified root mean square percentage error (RMSPE) values of a longer estimation period with shorter period ahead forecasts. This study also finds that the SMA with classical decomposition method is more accurate than other techniques when a shorter estimation period with longer period ahead forecasts are included. While this study may not speak to all users of leisure related data, it serves as a comparative reference for those who seek guidance in deciding among a set of forecasting tools.

KEYWORDS: *Mean absolute percentage error, Root mean square percentage error*

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We thank Dr. Christos Siderelis for many insightful suggestions, which improved the manuscript dramatically. We also thank the editor, associate editor, and two referees for their helpful comments.

Introduction

Recreation scientists have used a variety of forecasting techniques during the past decades (Archer, 1994; Uysal & Crompton, 1985). Cummings and Busser (1994) note that the formulation, interpretation, and evaluation of forecasts are critical skills for recreation and park managers.

Quantitative forecasting methods may be classified into two categories: causal methods (e.g., regression and structural models) and time series methods (e.g., basic, intermediate, and advanced extrapolative methods). Causal methods establish methodologies for identifying relationships between dependent and independent variables and attempt to incorporate the interdependencies of various variables in the real world. However, the most common difficulty of applying the causal methods is identifying the independent variables that affect the forecast variables. Thus, the reliability of final forecast outputs depends on the quality of other variables (Uysal & Crompton, 1985).

Time series quantitative methods offer many advantages. Box, Jenkins, and Reinsel (1994) point out that "the use at time t of available observations from a time series to forecast its value at some future time $t + 1$ can provide a basis for (1) economic and business planning, (2) production planning, (3) inventory and production control, and (4) control and optimization of industrial processes" (p. 2). Time series methods offer concepts and techniques that facilitate specification, estimation, and evaluation; often yielding more accurate forecasting results than causal quantitative approaches (Witt & Witt, 1995). The most important assumption of the time series methods is that the observations made at different time points are statistically dependent. Accurate forecasts made using suitable time series methods and based on appropriate data from the recreation industry may yield benefits in destination marketing and the scheduling of resources (Cummings & Busser, 1994).

Study Purpose

The overall purpose of this study is to assess various means of visitation forecasting. We specifically focus on the methodological issues surrounding forecasts of recreation use with seasonal patterns. We begin by providing an overview of forecasting methods. We follow this with an empirical application to visitation data at the Milwaukee County Zoo. According to Moore (1989), "seasonality refers to movements in a time series during a particular time of year that recur similarly each year" (p. 49).

The research question is, what are the advantages and disadvantages of basic, intermediate, and advanced methods for visitor use forecasting where seasonality and limited data are characteristics of the estimation problem?

Specifications of Forecasting Models: A Review

Basic Extrapolative Methods

Naïve 1. The naïve 1 forecasting method simply states that the forecast value for this period (t) is equal to the observed value for the last period

($t-1$) (Makridakis, Wheelwright, & Hyndman, 1998) (Appendix A, Equation 1).

Naïve 2. The naïve 2 forecast for period t is obtained by multiplying the current visitor numbers with the growth rate between the previous visitation in time period, $t-1$, and the current visitation figures in time period, t (Makridakis et al., 1998; Newbold & Bos, 1994) (Appendix A, Equation 2).

Single moving average (SMA) with decomposition. Based on adding the previous observations together and dividing by the number of observations, the single moving average method uses the resulting average figures to forecast future values. One assumption of the SMA method is that all selected previous data points have the same weight on the forecast value (Kendall, Stuart, & Ord, 1983; Makridakis et al., 1998). The major aim of the decomposition procedure is to distinguish the trend, cyclical, seasonal, and irregular factors (Baxter, 1994; Makridakis et al., 1998). A multiplicative relationship among the components is assumed by this method (Appendix A, Equation 3).

Single exponential smoothing (SES). The single exponential smoothing method (Appendix A, Equation 4) allows forecasters to determine the influence of a recent observation on the forecast values. The SES equation states that the forecast for the current period (t), is equal to the forecast for the previous period ($t-1$) plus a smoothing constant (α) multiplied by the error that the forecasting model produced for the previous period ($t-1$). The previous values are weighted by the smoothing constant, which must take a value between zero and one, and is set by the forecaster (Gardner, 1985; Makridakis et al., 1998).

Intermediate Extrapolative Methods

Double exponential smoothing (DES): Brown's method. The double exponential smoothing method is capable of capturing increases or decreases in linear trends, and is called Brown's method (Brown, 1963) (Appendix A, Equations 5a-5e).

Winter's method. Winter's three parameter linear and seasonal exponential smoothing model is capable of reducing forecast errors (Winters, 1960; Makridakis et al., 1998) (Appendix A, Equations 6a-6d).

Advanced Time Series Forecasting Methods

The Box-Jenkins (1970) univariate method is more sophisticated than other techniques used. A time series that shows the same statistical properties in different time windows is said to be stationary. To be precise, both the mean and variance are constant in a (second-order) stationary time series. The correlations between values with the same time separations do not change over time. The autocorrelations of a stationary time series typically drop close to zero after a few lags in time. A non-stationary time series does not possess autocorrelations. However, if they are estimated as if the series are stationary, they do not approach zero even after many lags. The behavior of the estimated autocorrelations is used to distinguish between stationary and non-stationary series.

The mathematical statement of an autoregressive moving average (ARMA) model reveals how the variable V_t is related to its past values $\{V_{t-1}, V_{t-2}, V_{t-3}, \ldots\}$. The ARMA models are stationary and can be used in a straightforward manner to construct forecasts for stationary time series. Also, they construct forecasts for some non-stationary time series. For instance, if the first differences of the time series under study are stationary, an ARMA model may be fitted to them and used to forecast the differences. These forecasted differences may then be accumulated to produce forecasts for the values of the original series. When the d'th (d = times of differencing) differences of a time series have an ARMA structure, the time series is said to have an autoregressive integrated moving average (ARIMA) structure. An ARIMA model is a refined curve fitting device using the present and past values of a dependent variable to forecast future values. When the observations of a time series are statistically dependent on each other, the ARIMA is a suitable choice.

Once the analyst identifies the time series model, the parameter estimates are obtained with a statistical package. Regarding the adequacy of the forecasting model, two modeling aspects are studied: (1) the lack of serial correlations in the errors, and (2) the statistical significance of the parameter estimates. Correlations in the errors are detected by the Q statistic, and the statistical significance of each parameter estimate is verified through the use of a t-test.

Seasonality: seasonal autoregressive integrated moving average (SARIMA). The difference between the non-seasonal and seasonal time series is that the non-seasonal relationships are described as those between observations for successive time periods (V_t and V_{t-1}), whereas seasonal relationships are between observations for the same month in successive years (V_t and V_{t-12}). The seasonal autoregressive integrated moving average (SARIMA) model examines the year-to-year relationships for each month (Appendix A, Equation 7). Readers are referred to Box, Jenkins, and Reinsel (1994) for more information about the calculation and limitations of the SARIMA method.

Evaluation of Forecasting Models

The magnitude of the forecasting error allows the analyst to evaluate the performance of the forecasting procedures across time periods in the series (Appendix B, Equation 8). Several criteria could be used to measure the accuracy of the forecasting estimates. The most common of the measures is mean absolute percentage error (MAPE), which has been widely used in previous forecasting studies (Martin & Witt, 1989; Wong, 1997). Other common measures are the root mean square percent error (RMSPE), mean error (ME), and mean percent error (MPE). Some error measures can be problematic. For example, mean error (ME) and mean percent errors (MPE) may give misleading measures due to the cancellation of positive and negative errors (Makridakis & Hibon, 1979; Makridakis et al., 1998). Especially when it is used for a longer predicted period, the level of inaccuracy will increase.

Mean Absolute Percentage Error (MAPE)

The original mean absolute percentage error (MAPE) is shown in Appendix B, Equation 9. As a rule, the lower the MAPE percentage errors, the more accurate the forecast. Lewis's (1982) interpretation of MAPE results is a means to judge the accuracy of the forecast—less than 10% is a highly accurate forecast, 11% to 20% is a good forecast, 21% to 50% is a reasonable forecast, and 51% or more is an inaccurate forecast.

Root Mean Square Percentage Error (RMSPE)

This approach is capable of comparing the actual rates of change in time series data and computes the average forecast error in percent. The original root mean square percentage error (RMSPE) is displayed in Appendix B, Equation 10.

Case Study

The Milwaukee County Zoo in Wisconsin is located on 200 wooded acres and houses its collection of approximately 2,500 animals, representing 300 species of mammals, birds, reptiles, fish and invertebrates. Data from the Milwaukee County Zoo visitation records were used to demonstrate the various forecasting methods. In 1999, there were more than 1.3 million visits to the Milwaukee County Zoo. What made the visitation trend for the Milwaukee County Zoo appealing for study were the variations in visitor rates over the years. Attendance records were based on the zoo's ticket receipts, which made zoo visitation data highly reliable. The reliability, availability of explanatory variables, and the length of forecasting time periods influenced the selection of the forecasting methods.

The time series ranged from January 1981 through December 1999, a total of 228 months. Attendance exhibited a consistent seasonal pattern, peaking in the months of June to August with a slightly decreasing trend (Figure 1). The zoo data were transformed to remove the seasonal structure from the original data. In addition to data transformation, both the first differencing and the 12-month differencing procedures were employed to obtain a stationary, non-seasonal time series.

Data from January 1981 to December 1998 were used to predict the visitation figures for the following 12 months (January 1999 to December 1999). Next, for a 24 month forecast, visitation data from January 1981 to December 1997 were used to forecast the periods between January 1998 to December 1999 visitation. Data from January 1981 to December 1994 were used to predict the visitation for the following 60 months (January 1995 to December 1999).

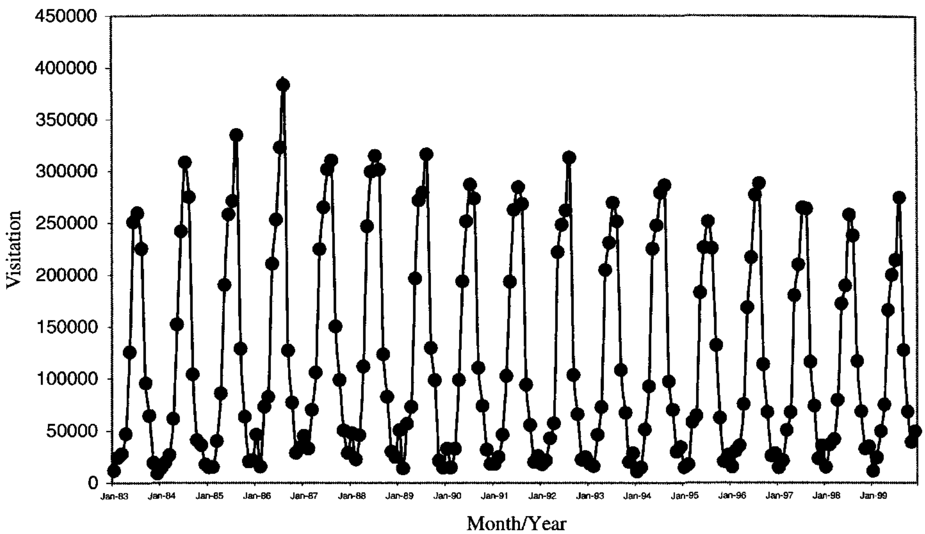

Figure 1. Monthly visitation to the Milwaukee Zoo (January, 1981 to December, 1999).

MAPE and RMSPE were selected to evaluate the performance of forecasting methods. The seasonal variations of the zoo data sets were adjusted, which means deseasonalized before fitting the various forecasting approaches. The forecasts generated were also modified with the seasonal variations before comparing them with the actual visitations. We modified the equations of MAPE and RMSPE (Appendix B, Equations 11 and 12). Both MAPE and RMSPE were calculated and were dominated by one-step (e.g., predicting sequentially one step at a time) in-sample (e.g., including the estimation period only) forecast errors. The relatively few out-of-sample forecast errors corresponded to different leads (the number of time periods ahead; for example, 1, . . . , n_{pred}), and carried little weight in either calculation.

Forecasting Results

Forecasting result evaluations are displayed in Table 1. SARIMA had the lowest forecasting error (MAPE) and DES had the highest error (MAPE) for the 12-month forecast. SMA with the classical decomposition procedure had the lowest forecasting error (MAPE) and DES had the highest error (MAPE) for the next 24-month and next 60-month forecasts. SMA with the classical decomposition procedure (with MAPE values ranging from 18.26% to 19.5%) and SARIMA (with 19.15% of MAPE value) consistently outperformed all the other techniques in forecasting the zoo's visitation. DES (with MAPE values ranging from 139.34% to 230.89%) consistently performed worst among all the other techniques.

Based on the examination of the RMSPE values in Table 1, the SARIMA model was the best among the seven techniques for a 12-month forecast. The RMSPE values of the Winter's and Naïve 1 methods illustrated that these two methods gave good forecasts. The DES performed the worst. When next 24-month and next 60-month forecasts were estimated, the SMA with the classical decomposition procedure was the best and the DES performed the worst.

TABLE 1
Zoo Forecasting Performance

Model {Estimation Period}: Forecasting Period	Mean Absolute Percentage Error (MAPE)	Root Mean Square Percentage Error (RMSPE)
(1) Naïve 1		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	21.66% (4)	32.26% (3)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	20.53 (3)	28.79 (4)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	21.74 (3)	29.56 (3)
(2) Naïve 2		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	37.03 (5)	58.76 (5)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	42.22 (5)	72.68 (5)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	53.08 (5)	90.03 (5)
(3) Single Moving Average (SMA) with Decomposition		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	19.86 (2)	33.92 (4)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	18.26 (1)	25.72 (1)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	19.50 (1)	26.92 (1)
(4) Single Exponential Smoothing (SES)		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	126.34 (6)	192.18 (6)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	118.57 (6)	170.40 (6)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	117.27 (6)	168.69 (6)
(5) Double Exponential Smoothing (DES)		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	230.89% (7)	232.58% (7)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	141.01 (7)	221.59 (7)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	139.34 (7)	219.75 (7)
(6) Winter's Method		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	20.76 (3)	28.50 (2)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	20.86 (4)	28.11 (3)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	31.79 (4)	43.83 (4)
(7) Seasonal Autoregressive Integrated Moving Average (SARIMA)		
{Jan. 1981-Dec. 1998}: Jan. 1999-Dec. 1999	19.15 (1)	26.93 (1)
{Jan. 1981-Dec. 1997}: Jan. 1998-Dec. 1999	18.38 (2)	26.10 (2)
{Jan. 1981-Dec. 1994}: Jan. 1995-Dec. 1999	20.94 (2)	28.06 (2)

Note. Figures in parenthesis denote rankings. For example, based on the examination of the MAPE and RMSPE values, SARIMA (ranked 1) was the best and DES (ranked 7) performed worst among other models, when next 12 month forecasts were calculated. SMA with the classical decomposition procedure (ranked 1) had the lowest MAPE/RMSPE and DES (ranked 7) had the highest MAPE/RMSPE among all the forecasting methods, when next 24 month and next 60 month forecasts were calculated.

In this study, both the estimation period and forecasting period (as shown in Table 1) were included and estimated in the modified MAPE and RMSPE (see Appendix B) in order to compare the performances of various forecasting methods. SARIMA and SMA with the classical decomposition procedure were roughly equivalent in performance; as judged by MAPE values in terms of a longer estimation period (January 1981 to December,1998) with shorter period ahead forecasts (next 12 month: January to December, 1999). We found that the SMA with the classical decomposition method was more accurate than other forecasting techniques for a shorter estimation period with longer period ahead (in the case of next 24 and 60 month) forecasts.

Discussion

Managers at the zoo may use the findings in Table 2 to select an appropriate forecasting method based on an agency's budget constraint, data availability, human resources, and time. Naïve methods are easy to learn and involve a spreadsheet. Although the single moving average (SMA) with a decomposition procedure is complicated, it performs better than other basic and intermediate extrapolative methods. Overall, the levels of ease in learning various forecasting approaches vary from moderate to difficult.

TABLE 2
Check List of Selecting an Appropriate Method for the Milwaukee County Zoo

Method/Criteria	Estimation Technique	Accuracy	Ease of Learning
(1) Naïve 1	Visual or spreadsheet	Reasonable to good	Easy
(2) Naïve 2	Spreadsheet	Reasonable	Easy
(3) Single Moving Average (SMA) with Decomposition	Spreadsheet	Reasonable to good	Moderate to difficult
(4) Single Exponential Smoothing (SES)	Spreadsheet or statistical packages (e.g., MiniTab, SAS, etc.)	Inaccurate	Moderate to difficult
(5) Double Exponential Smoothing (DES)	Spreadsheet or statistical packages (e.g., MiniTab, SAS, etc.)	Inaccurate	Moderate to difficult
(6) Winter's Method	Spreadsheet or statistical packages (e.g., MiniTab, SAS, etc.)	Reasonable to good	Moderate to difficult
(7) Seasonal Autoregressive Integrated Moving Average (SARIMA)	Statistical packages (e.g., STATA, SAS, etc.)	Good	Difficult

SES and DES methods are inferior, whereas the accuracy of a Winter's method ranges from reasonable to good. To use a SARIMA model, a great understanding of the Box-Jenkins univariate approach, knowledge of the structure of an autoregressive (AR) and moving average (MA) models, and applications of differencing approaches are required. An experienced forecaster is necessary to contribute to the model's specification, estimation, and evaluation. For example, the Milwaukee County Zoo manager may consider using SMA with the decomposition procedure, SARIMA and Winter's methods to produce reasonable and good forecasts.

Merits and Limits of Forecasting Methods for Recreation Attractions

The advantages of the Naïve methods are that they are easy to use and with capability to generate forecasts by short previous observations when longer historical series data are not available. For example, based on the structure of Naïve methods, Naïve 1 only needs one previous observation (A_{t-1}) in order to generate the next forecasting value (F_t) and Naïve 2 needs at least two previous observations (A_{t-1}, A_{t-2}) to produce the next prediction, F_t. Naïve methods have been seen as playing a "benchmark" role in the literature (Makridakis et al., 1998). Forecasters may use the Naïve methods to determine how much improvement other more sophisticated forecasting methods have made and to decide whether other sophisticated methods are worthwhile when there are time and budgets constraints.

Using the decomposition procedure, several components—seasonal variations, secular trends, and irregular fluctuations—can be identified. Indeed, this mathematical process enables forecasters to apply the moving average procedures to produce more accurate forecasting results, when a data series exhibits seasonality. To be deseasonalized, the time series data are divided by the seasonal indices that are computed through the decomposition procedure. Then, a moving average method will be applied to the deseasonalized data to obtain the forecasts. Generally, while using the moving average method, each of the values entering the averaging process receives an equal weight.

The main difference between the exponential smoothing methods and moving average method is that the exponential smoothing methods treat the averaged observations progressively. More specifically, more recent observations get higher weights while less recent data receive less weight. Different exponential smoothing methods have different ways of treating trends and seasonality in the data. The parameter of the single exponential smoothing is fixed, and the method is better for horizontal trend data sets. When there is seasonality in the data, Winter's method may be appropriate. It uses a third parameter to compute seasonal indices (Makridakis et al., 1998).

A main limitation of the SARIMA method is that longer histories are required than other forecasting methods to yield reliable results. An advantage shared by the single and double exponential smoothing methods and the SARIMA method is that all three produce prediction intervals (Table 3).

TABLE 3
Advantages and Disadvantages of Listed Seasonal Forecasting Methods

Method	Advantage	Disadvantage
(1) Naïve 1, and (2) Naïve 2	Have capability to generate forecasts by short previous observations.	Use intuitive assumptions but are not based on scientific mathematics theories.
(3) Single Moving Average (SMA) with Decomposition	Is useful for data sets with seasonal patterns.	Uses complicated procedures to deseasonalize data sets.
(4) Single Exponential Smoothing (SES)	Produces prediction intervals.	Is better for horizontal data sets without seasonal patterns.
(5) Double Exponential Smoothing (DES)	Produces prediction intervals and is more flexible than SES.	Is better for linear trend data sets without seasonal patterns.
(6) Winter's Method	Produces prediction intervals and uses a third parameter to compute seasonal indices.	May not be suitable for data sets without seasonal patterns.
(7) Seasonal Autoregressive Integrated Moving Average (SARIMA)	Produces prediction intervals and generates more accurate in-sample forecasting results.	Requires longer histories.

Conclusion

The forecasting methods, described, are readily transferable to recreation use data sets with seasonal patterns. Moreover, the potential applications of forecasting methods to the broad range of recreational settings may include seasonal use at museums, aquariums, outdoor recreational areas, campgrounds, historical sites, trails, and so on.

In another study, the MAPE and RMSPE were calculated for each of seven forecasting techniques [Naïve 1, Naïve 2, single moving average (SMA), single exponential smoothing (SES), Brown's, Holt's, and the autoregressive integrated moving average (ARIMA)] for annual visitation rates (without seasonality) at three selected national parks (Chen, 2000). In the case of three national parks, the ARIMA, Naïve 1, and DES methods are generally superior to Naïve 2, SES, and Holt's methods. The current results for recreation attractions are not similar to national parks. SARIMA and SMA with decomposition are best for the zoo monthly data.

Available visitor information (e.g., activity preferences, distance traveled, etc.) might enhance the explanation of why people decide to visit a particular destination. Analysts are encouraged to add other explanatory variables to investigate the demand changes, including increased oil price in certain years (e.g., increased oil price in 2003), marketing strategic promotion, significant weather factor, and admission fees. As Wilkinson (1988) notes that "in many cases, the absolute accuracy of the forecasting process is not the most important consideration, but . . . the process of preparing alternate forecasts to force considerations of many possibilities is a more important function" (p.4).

State parks, national parks, theme parks, zoological parks, and various recreation agencies may need short- and medium-term forecasts to establish their strategic marketing plans. Such forecasts can provide valuable information for pricing, facility monitoring, seasonal employment, and short-term budgeting. With respect to developing long-run plans and protect the existing natural resources, forecasts can determine future infrastructure needs, new facilities and utilities, and future staffing.

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Appendix A
Equations of Basic, Intermediate, and Advanced Time Series Forecasting Methods

Method/Equations	Definition
Basic Time Series Forecasting Methods	
(1) Naïve 1	
$F_t = A_{t-1}$	F_t = forecast visitation at time t; A_{t-1} = actual visitor number at time $t-1$.
(2) Naïve 2	
$F_t = A_{t-1}\ [1 + (A_{t-1} - A_{t-2})/A_{t-2}]$	F_t = forecast visitation at time t; A_{t-1} = actual visitor number at time $t-1$.
(3) Single Moving Average (SMA) with Decomposition	
$M_{t-1} = F_t = [(A_{t-1} + A_{t-2} + A_{t-3} + \cdots + A_{t-n})/n]$ $A_t = \psi_t^* C_t^* \xi_t^* \Theta_t$	M_{t-1} = moving average at time $t-1$; F_t = forecasted value for next period; A_{t-1} = actual value at period $t-1$; n = number of terms in the moving average. A = actual visitor number in the time series; ψ = the trend factor; C = the cyclical factor; ξ = the seasonal factor; Θ = the irregular factor; t = less than one year time period.
(4) Single Exponential Smoothing (SES)	
$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$	F_t = forecasted value for next period at time t; α = smoothing constant ($0 < \alpha < 1$); A_{t-1} = actual visitor number at time $t-1$.

Appendix A
(Continued)

Method/Equations	Definition
Intermediate Time Series Forecasting Methods	
(5) Double Exponential Smoothing (DES) (a) $Y_t = Y_{t-1} + \alpha(A_{t-1} - Y_{t-1})$ (b) $Y_t' = Y_{t-1}' + \alpha(Y_t - Y_{t-1}')$ (c) $C_t = Y_t + (Y_t - Y_t')$ (d) $T_t = [(1 - \alpha)/\alpha]*(Y_t - Y_t')$ (e) $V_{t+h} = C_t + hT_t$	Y_t = single exponential smoothing series at time t; α = smoothing constant ($0 < \alpha < 1$); A_{t-1} = actual visitor number at time $t-1$; Y_t' = double exponential smoothing series at time t; C_t = the intercept of the Y' forecast series at time t; T_t = the slope of the Y' forecast series at time t; V_{t+h} = forecast visitation at time $t + h$; h = the number of time periods ahead.
(6) Winter's Method (a) $V_t = \alpha \dfrac{Y_t}{S_{t-L}} + (1 - \alpha)(V_{t-1} + T_{t-1})$ (b) $T_t = \beta(V_t - V_{t-1}) + (1 - \beta)T_{t-1}$ (c) $S_t = \gamma \dfrac{Y_t}{V_t} + (1 - \gamma)S_{t-L}$ (d) $F_{t+h} = (V_t - hT_t)S_{t-L+h}$	V_t = new smoothed value in period t; α = smoothing constant ($0 < \alpha < 1$); Y_t = new observation or actual value of series in period t; β = smoothing constant for trend estimate ($0 < \beta < 1$); T_t = trend estimate in period t; γ = smoothing constant for seasonality estimate ($0 < \gamma < 1$); S_t = seasonal estimate in period t; h = periods to be forecast into future; L = length of seasonality; F_{t+h} = forecast for h periods into the future.
Advanced Time Series Forecasting Methods	
(7) Seasonal Autoregressive Integrated Moving Average (SARIMA) $\Phi_p(B)\vartheta_P(B^S\nabla(^d\nabla_S^D V_t = \Theta_q(B)\ \Psi_Q(B^S)\varepsilon_t$	V_t = dependent variable (e.g., number of visitors in time t); Φ_p = regression coefficients B = the backshift operator; S = time period (i.e., when analyzing monthly data $S = 12$); ∇_S^D = seasonal differencing operator, where $\nabla_S^D = (1 - B^S)^D$; D = degree of seasonal differencing; Θ_q = coefficient, or called weights; $\vartheta_P(B^S)$ and $\Psi_Q(B^S)$ = polynomials in B^S in degrees of P and Q; ε_t = error with white noise ~ iid $N(0, \sigma^2)$.

Appendix B
Equations of Error Magnitude Measurement

Method/Equations	Definition
(8) Forecast Error $\varepsilon_t = A_t - F_t$	ε = the forecast error; A_t = the actual number of visitors in period t; F_t = the forecast value in time period t.
(9) Original Mean Absolute Percentage Error (MAPE) $\mathrm{MAPE} = \frac{1}{n} * \sum_{t=1}^{n} \left(\frac{\lvert e_t \rvert}{A_t}\right) * 100$	n = number of time periods; e_t = forecast error in time period t; A_t = actual number of visitors in time period t.
(10) Original Root Mean Square Percentage Error (RMSPE) $\mathrm{RMSPE} = \sqrt{\frac{\sum_{t=1}^{n} \left(\frac{e_t}{A_t}\right)^2}{n}} * 100$	n = number of time periods; e_t = forecast error in time period t; A_t = actual number of visitors in time period t.

Modified Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) Used in This Study

(11) $$\mathrm{MAPE} = \frac{1}{n_{\text{est}} + n_{\text{pred}}} \left\{ \sum_{t=1}^{n_{\text{est}}} \frac{\lvert r_t \rvert}{A_t} + \sum_{t=n_{\text{est}}+1}^{n_{\text{pred}}} \frac{\lvert e_t \rvert}{A_t} \right\} * 100$$

Where r_t, $t = 1, \ldots, n_{\text{est}}$ is the one-step in-sample forecast error for time t, $r = 1, \ldots, n_{\text{est}}$, A_t is the actual visitation in time t, and e_t is the $(t - n_{\text{est}})$ − step out-of-sample forecast error for time t, $t = n_{\text{est}} + 1, \ldots, n_{\text{pred}}$.

(12) $$\mathrm{RMSPE} = \sqrt{\frac{\sum_{t=1}^{n_{\text{est}}} \left(\frac{r_t}{A_t}\right)^2 + \sum_{t=n_{\text{est}}+1}^{n_{\text{pred}}} \left(\frac{e_t}{A_t}\right)^2}{n_{\text{est}} + n_{\text{pred}}}} * 100$$