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THE EVALUATION OF FORECASTING METHODS AT AN INSTITUTIONAL FOODSERVICE DINING FACILITY

**Kisang Ryu
and
Alfonso Sanchez**

ABSTRACT

The purpose of this study was to identify the most appropriate method of forecasting meal counts for an institutional food service facility. The forecasting methods analyzed included: naïve model 1, 2, and 3; moving average, double moving average, simple exponential smoothing, double exponential smoothing, Holt's, and Winter's methods; and linear and multiple regressions. The accuracy of the forecasting methods was measured using mean absolute deviation, mean squared error, mean percentage error, mean absolute percentage error, root mean squared error, and Theil's U-statistic. The result of this study showed that multiple regression was the most accurate forecasting method, but naïve method 2 was selected as the most appropriate forecasting method because of its simplicity and high level of accuracy.

Introduction

Almost every organization, large or small, uses forecasting to plan events. Forecasting is defined as the prediction of future events based on known past values of relevant variables (Makridakis, Wheelwright, & Hyndman, 1998). Of the four management functions—planning, organizing, leading, and controlling—planning is the foundation of management activities. When managers fail to perform planning activities effectively, products and services may be unacceptable to customers. Accurate forecasting is essential for managers to plan effectively. Inaccurate forecasting may lead to bad decisions that may lead, in turn, to ineffective management in overall operations.

Miller and Shanklin (1988) noted that forecasting is especially critical in food service operations because of the perishable nature of the product. Also, most food items are made or prepared immediately prior to service. Inaccurate forecasting results in over-production or under-production. Over-forecasting leads to leftover or wasted food, and the unused food leads to increased food cost. Even when some of the food can be integrated into another day's menu, it may reduce food quality. Also, it may increase the chance of food contamination through prolonged storage. As a result, leftovers may generate dissatisfaction among customers. Over-forecasting also increases the labor cost because the additional handling of food requires additional labor. Under-forecasting leads to the problem of food that runs out before customer demand is satisfied, which results in more immediate concerns. Under-production leads to increased stress for employees, cooks, and managers who are likely to react to customer dissatisfaction with extra effort to produce a back-up item. Finally, under-forecasting will result in decreased

employee morale and manager confidence. It sometimes can increase cost when customers are compensated by replacing a missing item with menu items of higher cost. More importantly, customers do not receive their menu first choices. This generates unhappy customers, and it may decrease market share. In summary, forecasting in the food service industry affects food production, customer satisfaction, employee morale, manager confidence, inventory, staffing, and financial status (Messersmith & Miller, 1992).

In general, in university food service organizations, managers are in charge of forecasting decisions (Repko & Miller, 1990). They use historical data, including past production information and past customer counts, to forecast customer demand. Forecasting is also affected by many variables, such as semester-to-semester population changes, weather, menu items, special student activities, holidays, food trends, day of the week, and availability of money (Sanchez & Miller, 1995). Based on these data, food service managers frequently employ intuitive guesses and naïve forecasting practices that compare poorly to mathematical forecasting methods (Messersmith & Miller, 1992; Miller, McCahon, & Miller, 1991a; Repko & Miller, 1990).

Many researchers have reported that even simple forecasting mathematical methods outperform intuitive guesses or naïve models (Messersmith & Miller, 1992; Miller, McCahon, & Bloss, 1991). Moreover, simple mathematical models can prove as accurate as more complex ones. Since managers are responsible for many functions and areas, such as managing personnel, production, service, and sanitation, efficient forecasting methods that can be completed with little time or effort should be useful. The development of accurate, simple, and time-saving forecasting methods is highly recommended.

Although managers have recognized the need for better forecasting methods and the use of personal computers, many managers in institutional food service operations still estimate future customer demand based on their own judgment or naïve models. According to Messersmith and Miller (1992), even simple quantitative techniques, such as naïve methods, outperform the intuitive assessments of experts. However, Miller, McCahon, and Bloss (1991) discovered that manually-generated naïve models produced less accurate forecasts than did computerized mathematical models. Efficient computerized mathematical forecasting methods will help institutional food service management control or even reduce costs while increasing customer satisfaction.

The purpose of this study was to identify the most appropriate forecasting method for an existing institutional food service facility at Texas Tech University. The specific purpose of this study was to identify (1) the best quantitative method, based on level of accuracy, to forecast meal counts for the 2001 spring semester and (2) the most appropriate forecasting method, based on level of accuracy and ease of use in practice.

Methodology

This study evaluated different forecasting models using meal count data from a dining center at Texas Tech University. Data from the 2000 fall semester were collected and used to forecast the meal counts of the 2001 spring semester. Then, actual data for the

2001 spring semester were used to determine level of accuracy. Data of the 2000 fall semester were adjusted to eliminate abnormal data (to be explained later in this paper). The forecasting models used in the analyses included naïve model 1, 2, and 3; moving average, double moving average, simple exponential smoothing, double exponential smoothing, Holt's, and Winter's models; and simple linear and multiple regressions. The most appropriate forecasting method in this dining center was determined on the basis of accuracy and ease of use. In this research, several common accuracy methods were used: mean absolute deviation (MAD), mean squared error (MSE), mean percentage error (MPE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). Forecasting methods were also compared against the results of the naïve model using Theil's U-statistic. A ranking was assigned to each forecasting method.

Data Collection and Adjustment of Data

The data for this study were collected and recorded on a daily basis at a Texas Tech University dining facility during the 2000 fall semester and the 2001 spring semester. The data contain breakfast, lunch, and dinner meal counts, though the research analyzed only the meal counts for dinner meals. The data used included meal counts from Monday through Saturday, since the dining facility was closed for dinner on Sundays. All the data was saved into an Excel® spreadsheet

There were several steps for the adjustment of data. First, actual data for a semester consisted of 17 weeks of meal counts. The weeks that had more than two days of missing data in a week due to closure of the dining center were deleted from the database. Therefore, it was decided to reduce the database to 13 weeks of data to have meal counts of complete weeks.

Second, since the forecasting models being developed were intended for normal situations, the database was analyzed to detect abnormalities in the data. In this research, abnormalities in the data were considered when there were either extremely high or low values of data based on the day of the week due to special circumstances. Data with special circumstances were then adjusted by day of the week. There were some extremely high and low figures in the data due to several factors, such as weather, special sports games, special holidays, and special school events. For instance, when there was a home football game, the number of meal counts was very high compared to those on normal days. In contrast, when there were away football games, the number of meal counts was very low. Thus, those figures were adjusted by the average of meal counts based on the day basis. For instance, the meal count was 179 on Wednesday, December 6, in the 2000 fall semester. This was a very low meal count compared to the mean value of meal counts of 266 on Wednesdays for the semester. Thus, the figure 179 was replaced by 266.

Finally, the adjustment for the effect of changes in population was considered. When there are changes in population, the forecasting error is increased. In the case of TTU, the number of meal contracts varies from semester to semester. Makridakis, Wheelwright, and Hyndman (1998) suggest that the standard approach is to employ an equivalent value. The data are then comparable and forecasts will not be affected by this variation.

In this case, the data could be adjusted by the number of meal contracts based on the semester period. Because the purpose of this research was to forecast the 2001 spring semester, the number of meal contracts bought in the 2001 spring semester was considered standard. So the first step was to adjust the meal counts for the 2000 fall semester to obtain the percentage of meal counts. The proportion of meal contracts in the 2000 fall semester was adjusted based on the number of meal contracts for the 2001 spring semester. As the number of meal contracts during the 2000 fall semester was 476, all data of the 2000 fall semester were divided by 476 to obtain the proportion of meal contracts being used. The number of meal contracts for the 2001 spring semester was 422. The 2000 fall semester data were adjusted as follows:

$$\text{Adjusted 2000 fall semester data} = (\text{2000 fall semester data} / 476) \times 422$$

Forecasting Methods

Naïve 1. Naïve methods are forecasting techniques obtained with a minimal amount of effort and data manipulation and are based on the most recent information available (Shim, 2000). The naïve 1 method uses data from the previous day to forecast the current day (one day of lag):

$$F_{t+1} = Y_t \quad (1)$$

where:

F_{t+1} = the forecast value for the next period

Y_t = the actual value at period t

To start the forecast using naïve 1, the last day of the 2000 fall semester was used to forecast the first day of the 2001 spring semester.

Naïve 2. The naïve 2 method considered weekly seasonality by using data from the previous week to forecast the current week (one week of lag):

$$F_{t+1} = Y_{t-5} \quad (2)$$

Here, Y_{t-5} is the actual data one week before the current week. To forecast the first week of the 2001 spring semester, the last week of the 2000 fall semester was used.

Naïve 3. In the naïve 3 method, the data of the same week for the 2000 fall semester was used to forecast the corresponding week of the 2001 spring semester (one semester of lag):

$$F_{t+1} = Y_{t-77} \quad (3)$$

Here, Y_{t-77} is the actual data one semester before the current semester.

Moving Average Method. The moving average method involves calculating the average of the observations and then employing that average as the predictor for the next period (Jarrett, 1991). The moving average method is highly dependent on n , the number of terms selected for constructing the average (Levine, Berenson, & Stephan, 1999). The equation is as follows:

$$F_{t+1} = (Y_t + Y_{t-1} + Y_{t-2} + \dots + Y_{t-n+1}) / n \quad (4)$$

where:

F_{t+1} = the forecast value for the next period

Y_t = the actual value at period t

n = the number of terms in the moving average

The optimal n value can be determined by interactive models that provide the smallest error. In some methods, the general approach has been to use MSE. In this study, forecasts with different n values (ranging from $n = 2$ to $n = 7$) were determined, with ranges to select the optimal n .

Double Moving Average Method. Hanke and Reitsch (1998) recommended the use of the double moving average method to forecast time series data that have a linear trend. Forecasting with a double moving average requires determining two averages. The first moving average is determined in similar manner to the one in the simple moving average. After the first moving average is computed, a second moving average is calculated. Five equations are used in the double moving average:

$$\begin{aligned} M_t &= F_{t+1} = (Y_t + Y_{t-1} + Y_{t-2} + \dots + Y_{t-n+1}) / n \\ M'_t &= (M_t + M_{t-1} + M_{t-2} + \dots + M_{t-n+1}) / n \\ a_t &= 2M_t - M'_t \\ b_t &= \frac{2}{n-1} (M_t - M'_t) \\ F_{t+p} &= a_t + b_t p \end{aligned} \quad (5)$$

where:

n = the number of periods in the double moving average

Y_t = the actual series value at time period t

p = the number of periods ahead to be forecast

Simple Exponential Smoothing Method. The exponential smoothing method is a technique that uses a weighted moving average of past data as the basis for a forecast. The procedure gives heaviest weight to more recent observations and smaller weights to observations in the more distant past (Hanke, Wichern, & Reitsch, 2001). The equation for the simple exponential smoothing method is:

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_{t-1} \quad (6)$$

where:

F_{t+1} = the new smoothed value or the forecast value for the next period

α = the smoothing constant ($0 < \alpha < 1$)

Y_t = the new observation or actual value of the series in period t

F_t = the old smoothed value or forecast for period t

The accuracy of the simple exponential smoothing method strongly depends on the optimal value of alpha (α) (Hanke et al., 2001). A traditional optimization method based on the lowest MSE was used to determine the optimal alpha value.

Since the exponential smoothing methods assume the continuation of a random historical pattern for the future, it is useful to develop a technique to determine when the basic pattern has changed. A tracking signal was used to monitor changes in the pattern. As long as a forecast fell within a range of permissible deviations of the forecast from actual values, no change in alpha was necessary (Hanke et al., 2001). But if a forecast fell outside the range, the system indicated the possibility of updating alpha value. In this

study, the researcher uses limits set at ± 2 standard deviations of the forecast ($\pm 2\sqrt{MSE}$) that gives a 95% chance that the actual observation will fall within the limits. That is, as long as the forecasting errors are within the range of acceptable deviations of the forecast between $+2\sqrt{MSE}$ and $-2\sqrt{MSE}$, no change in alpha is necessary.

Double Exponential Smoothing Method. The double exponential smoothing model is recommended to forecast time series data that have a linear trend (Hanke & Reitsch, 1998). Five equations are employed:

$$\begin{aligned} A_t &= \alpha Y_t + (1 - \alpha) A_{t-1} \\ A'_t &= \alpha A_t + (1 - \alpha) A'_{t-1} \\ a_t &= 2A_t - A'_t \\ b_t &= \alpha (A_t - A'_t) / (1 - \alpha) \\ F_{t+p} &= a + b_t p \end{aligned} \quad (7)$$

where:

A_t = the exponentially smoothed value of Y_t at time t

A'_t = the double exponentially smoothed value of Y_t at time t

F_{t+1} = the new smoothed value or the forecast value for the next period

α = the smoothing constant ($0 < \alpha < 1$)

Y_t = the new observation or actual value of series in period t

F_t = the old smoothed value or forecast for period t

As in the simple exponential smoothing, the accuracy of the forecasting method strongly depends on the optimal value of alpha. The method generating the lowest MSE value was selected as the optimal alpha. Also, a tracking system was developed to monitor the change of patterns.

Holt's Method. A technique frequently used to handle a linear trend is Holt's method. It smoothes the trend by using different (alpha and beta) smoothing constants (Hanke & Reitsch, 1998). Three equations are used:

$$\begin{aligned} L_t &= \alpha Y_t + (1 - \alpha) (L_{t-1} + T_{t-1}) \\ T_t &= \beta (L_t - L_{t-1}) + (1 - \beta) T_{t-1} \\ F_{t+p} &= L_t + pT_t \end{aligned} \quad (8)$$

where:

L_t = the new smoothed value

α = the smoothing constant for the data ($0 < \alpha < 1$)

Y_t = the new observation or actual value of series in period t

β = the smoothing constant for trend estimate ($0 < \alpha < 1$)

T_t = the trend estimate

p = the periods to be forecast into the future

F_{t+p} = the forecast for p periods into the future

The initial values for the smoothed series and the trend must be set in order to start the forecasts (Hanke et al., 2001). In this research, the first estimate of the smoothed series was assigned a value equal to the first observation. The trend was then estimated to equal zero. Accuracy of Holt's exponential smoothing method requires optimal values of alpha (α) and beta (β). The optimal alpha and beta values were selected on the basis of minimizing the MSE. As in simple and double exponential smoothing methods, this method also required a tracking signal to monitor pattern changes.

Winter's Method. Winter's method provides a useful way to explain the seasonality when time series data have a seasonal pattern (Hanke & Reitsch, 1998). The formula of this method includes four equations:

$$\begin{aligned} A_t &= \alpha Y_t / S_{t-L} + (1 - \alpha)(A_{t-1})(A_{t-1} + T_{t-1}) \\ T_t &= \beta (A_t - A_{t-1}) + (1 - \beta) T_{t-1} \\ S_t &= \gamma Y_t / A_t + (1 - \gamma) S_{t-L} \\ F_{t+p} &= (A_t + pT_t) S_{t-L+p} \end{aligned} \quad (9)$$

where:

A_t = the new smoothed value

α = the smoothing constant

Y_t = the new observation or actual value of series in period t

β = the smoothing constant for the trend estimate

T_t = the trend estimate

γ = the smoothing constant for the seasonality estimate

S_t = the seasonal estimate

p = the periods to be forecast into the future

L = the length of seasonality

F_{t+p} = the forecast for periods into the future

To start the forecasts, the initial values of the smoothed series L_t , the trend T_t , and the seasonality indices S_t must be given. In this research, the first six new smoothed values were considered the same as the first six observations, and the first six trend estimates were set as zero. The first six seasonality indices were assigned the value one. The accuracy of Winter's method strongly depends on the optimal values of alpha (α), beta (β), and gamma (γ). The optimal α , β , and γ were determined by minimizing a measure of forecast error of MSE. Also, like other exponential smoothing methods, a tracking signal was needed to monitor the change of patterns.

Linear Regression. Jarrett (1991) noted that one purpose of regression is to estimate the nature of the relationship between a dependent variable and an independent variable. A simple regression model can be expressed in the form of a straight line with the following formula:

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (10)$$

Here, $\beta_0 + \beta_1 X$ is the mean response with X . The deviation ε is assumed to be independent and normally distributed with a mean of zero and standard deviation σ . β_0 , β_1 , and σ are the unknown constants.

Multiple Regression. Multiple regression is used to estimate the nature of the relationship between a dependent variable and several independent variables. The relationship between two variables allows forecasting the dependent variable from knowledge of the independent variables. It allows us to apply several independent variables instead of just one (Hanke et al., 2001). Symbolically, the equation for multiple regression is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon \quad (11)$$

Here, Y represents the dependent variable as in the simple regression, and X_1, X_2, \dots, X_k represent the independent variables. β_k s and σ are the unknown constants. The calculations in the multiple regression analysis were executed by using the SAS® software program.

Measuring Forecasting Error

There is no consensus among researchers as to which measure is best for determining the most appropriate forecasting method (Levine et al., 1999). Accuracy is the criterion that determines the best forecasting method; thus, accuracy is the most important concern in evaluating the quality of a forecast. The goal of the forecasts is to minimize error. Forecast error is the difference between an actual value and its forecast value (Hanke & Reitsch, 1998).

Some of the common indicators used to evaluate accuracy are mean absolute deviation, mean squared error, mean absolute percentage error, mean percentage error, root mean squared error, and U-statistic. Regardless of the measure being used, the lowest value generated indicates the most accurate forecasting model.

Mean absolute deviation. A common method for measuring overall forecast error is the mean absolute deviation (MAD). Heizer and Render (2001) noted that this value is computed by dividing the sum of the absolute values of the individual forecast errors by the sample size (the number of forecast periods). The equation is:

$$MAD = \frac{1}{n} \sum_{t=1}^n |Y_t - F_t| \quad (12)$$

where:

Y_t = the actual value in time period t

F_t = the forecast value in time period t

n = the number of periods

If a method fits the past time series data perfectly, the MAD is zero, whereas if a method fits the past time series data poorly, the MAD is large. Thus, when two or more forecasting methods are compared, the one with the minimum MAD can be selected as most accurate.

Mean square error. Jarrett (1991) stated that the mean square error (MSE) is a generally accepted technique for evaluating exponential smoothing—and other—methods. The equation is:

$$MSE = \frac{1}{n} \sum_{t=1}^n (Y_t - F_t)^2 \quad (13)$$

where:

Y_t = the actual value in time period t

F_t = the forecast value in time period t

n = the number of periods

This measure defines error as the sum of squares of the forecast errors when divided by the number of periods of data.

Mean absolute percentage error. The mean absolute percentage error (MAPE) is the mean or average of the sum of all of the percentage errors for a given data set taken without regard to sign. It is one measure of accuracy commonly used in quantitative methods of forecasting (Makridakis et al., 1998). The equation is:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|Y_t - F_t|}{Y_t} \quad (14)$$

where:

Y_t = the actual value in time period t

F_t = the forecast value in time period t

n = the number of forecast observations in the estimation period

Mean percentage error. The mean percentage error (MPE) is the average of all of the percentage errors for a given data set. This average allows positive and negative percentage errors to cancel one another. Because of this, it is sometimes used as a measure of bias in the application of a forecasting method (Makridakis et al., 1998; Hanke & Reitsch, 1998). The equation for MPE is:

$$MPE = \frac{1}{n} \sum_{t=1}^n \frac{(Y_t - F_t)}{Y_t} \quad (15)$$

where:

Y_t = the actual value in time period t

F_t = the forecast value in time period t

n = the number of forecast observations in the estimation period

Root mean square error. Root mean square error (RMSE) is the square root of MSE. This measures error in terms of units that are equal to the original values (Jarrett, 1991). Symbolically, the equation is:

$$RMSE = \frac{1}{n} \sum_{t=1}^n \sqrt{(Y_t - F_t)^2} \quad (16)$$

where:

F_t = the forecast for period t

Y_t = the actual demand that occurred in period t

n = the number of forecast observations in the estimation period

U-statistic. Theil's U-statistic allows a relative comparison of the forecasting approaches with naïve methods (Theil, 1971). Naïve models are used as the basis for making comparisons against which the performance of more sophisticated methods is judged. A modified U-statistic based on RMSE was developed. The U-statistic is computed as the ratio of the RMSE from a forecasting method to the RMSE of the naïve method (Pindyck & Rubinfeld, 1981; Maddala, 1977). The formula is:

$$U = \text{RMSE of the forecasting method} / \text{RMSE of the naïve method} \quad (17)$$

The ranges of the U-statistic can be expressed as follows:

U = 1: the naïve approach is as good as the forecasting technique being evaluated.

U < 1: the forecasting technique being used is better than the naïve approach.

U > 1: there is no reason to use a formal forecasting method, since using a naïve method will generate better results.

The smaller the U-statistic, the better the forecasting technique used is, compared to the naïve method. The closer the U-statistic is to 0, the better the method. When the value of the U-statistic is 0.55 or less than this value, the forecasting method is very good.

Evaluation of Forecasting Methods

In this study, the most appropriate forecasting method was selected on the basis of both level of accuracy and ease of use. After the 2001 spring semester forecasts were completed using various forecasting methods, the accuracy of the forecasting methods was assessed using mean absolute deviation (MAD), mean squared error (MSE), mean percentage error (MPE), mean absolute percentage error (MAPE), root mean squared error (RMSE), and Theil's U-statistic. Since there is no standard, universally accepted model for determining forecast accuracy, consideration had to be given to which model to adopt.

Makridakis et al. (1998) mentioned the usefulness of MSE and U-statistic as measures of the accuracy of the forecasting methods. Some research also has suggested using MSE and U-statistic, if all errors are of relatively the same magnitude (Pindyck & Rubinfeld, 1981; Maddala, 1977). In this research, therefore, MSE and Theil's U-statistic were selected as the most important models in assessing forecast accuracy, even though MAD, MPE, MAPE, and RMSE for each forecasting method were also tested and evaluated.

In the case of institutional food service operations, special consideration as to each method's ease of use was required, since the person in charge of forecasting usually has little time and—in some instances—little knowledge of how to implement the forecasts. The ease of the use of the forecasting methods is sometimes far more important in practice than the accuracy of the forecasting method.

A ranking of the forecasting methods was used, based on ease of use. The naïve methods 1, 2, and 3 were considered the simplest models, and they ranked first. The simple moving average and the simple exponential smoothing methods were ranked second, with the double moving average and the double exponential smoothing methods ranked third. Holt's method and the linear regression were ranked fourth, Winter's method fifth, and multiple regression was ranked sixth because it was considered the most complicated (Georgoff & Murdick, 1986; Hanke & Reitsch, 2001; Wheelwright & Makridakis, 1985).

Results and Discussion

The purpose of this research was to identify an appropriate forecasting method for a dining facility at Texas Tech University. The meal counts of the 2001 spring semester were used to assess the accuracy of different forecasting methods. The meal counts of the 2000 fall semester were used as a base in order to forecast the meal counts of the 2001 spring semester. The most appropriate forecasting method was selected based on accuracy and ease of use.

Accuracy of the Forecasting Methods

In this study, six accuracy models—mean absolute deviation, mean squared error, mean percentage error, mean absolute percentage error, root mean squared error, and Theil's U-statistic (U-statistic)—were adopted to assess the accuracy of forecasting methods. The smaller the forecast error, the more accurate the forecasting method.

Naïve 1 model considers the last actual datum available as the forecast for the next day. As the number of meal counts at the dining center studied changes according to the day of the week, this method did not obtain good accuracy. The meal counts in the 2000 fall semester generally decrease from Monday to Saturday ($M > T > W > Th > F > Sa$). Naïve 1 model had the worst level of accuracy ($MSE = 4993$; $U\text{-statistic} = 2.83$), as shown in Table 1.

Table 1
Summary of forecast accuracy

	MAD	MSE	MPE	MAPE	RMSE	U-statistic
Naïve 1	52	4993	-6.63%	25.93%	70.66	2.83
Naïve 2	20	625	-2.04%	9.82%	25.00	1.00
Naïve 3	23	908	-0.25%	11.76%	30.13	1.21
MA ($n=7$)	45	2845	-8.66%	25.03%	53.34	2.13
DMA ($n=6$)	46	2967	-8.27%	25.66%	54.47	2.18
SES ($\alpha = .022$)	46	3054	-11.23%	26.39%	55.26	2.21
DES ($\alpha = .008$)	46	3000	-10.26%	26.17%	54.77	2.19
HES ($\alpha = .002$; $\beta = .095$)	47	2861	-7.6%	25.77%	53.49	2.14
WES ($\alpha = .11$; $\beta = .04$; $\gamma = .17$)	17	431	-2.69%	8.59%	20.76	0.83
LR	52	3210	0.19%	26.44%	56.66	2.27
MR	16	382	-1.31%	7.85%	19.54	0.78

MA = moving average; DMA = double moving average; SES = simple exponential smoothing; DES = double exponential smoothing; HES = Holt's method; WES = Winter's method; LR = linear regression; MR = multiple regression; MAD = mean absolute deviation; MSE = mean squared error; MPE = mean percentage error; MAPE = mean absolute percentage error; RMSE = root mean squared error; U-statistic = Theil's U-statistic. The minimal errors are in bold.

Naïve 2 model considers seasonality by using the last week of data to forecast the next week. It has a lag of one week. Since the data in this research considered weekly seasonality, naïve 2 had small errors. This method had the third smallest MSE (625), as shown in Table 1. Naïve 2 was used as the reference for the U-statistic, so the value of U-statistic was 1.

Naïve 3 model was a modified version of naïve 2. Like naïve 2, it considers seasonality but has a lag of one semester. That is, the first week of data of the fall 2000 semester base is used to forecast the first week of the 2001 spring semester. Naïve 3 had good accuracy and ranked fourth (MSE = 908; U-statistic = 1.21), as shown in Table 1. Even though this method obtained good accuracy, it was not as good as naïve 2.

Moving average (MA) is one of the simplest mathematical models. However, it does not perform well when the time series contains seasonality. Several moving average models with different n values were tested and the model with $n = 7$ produced the smallest MSE (2845), as shown in Table 2. MA was ranked fifth in accuracy (U-statistic = 2.13), as shown in Table 1. Since the value of U-statistic is larger than 1, this method does not outperform the naïve 2 model and should not be used for this application. However, MA ($n = 7$) was the most accurate method among the forecasting methods that were not designed for seasonal data.

Table 2
Results of MSE with different n values using moving average

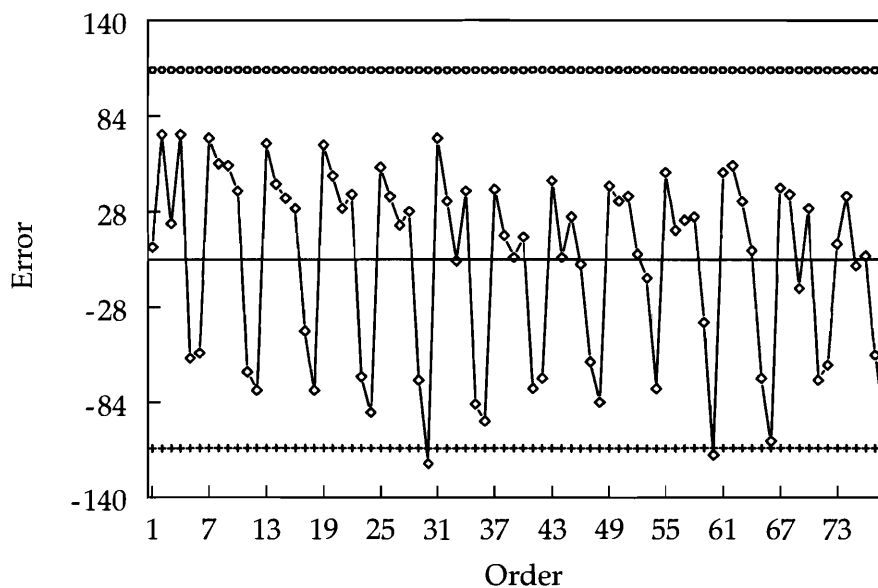
	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$
MSE	5450	5013	4902	4141	2966	2845	3334

MSE: mean squared error. The minimal error is in bold.

Double moving average (DMA) is more appropriate when time series data have a linear trend. Several double moving averages with different n values were tested, and the optimal model ($n = 6$) was the one with the smallest errors (MSE = 2967; U-statistic = 2.18). DMA produced large errors, because it did not consider seasonality, and the data did not have a linear trend pattern.

Simple exponential smoothing (SES) is more effective when there is random demand and no seasonal pattern in the data. The SES model requires an optimal alpha value in order to reduce forecasting errors. A simple optimization method that minimizes the MSE was used to determine the optimal alpha value. When optimal alpha (α) was 0.017, SES obtained the minimum error (MSE = 3054; U-statistic = 2.21). In this research, SES ($\alpha = 0.017$) had large errors, as shown in Table 1, because it did not consider seasonality. SES ($\alpha = 0.022$) was the third least accurate. A tracking signal was used to monitor changes in the pattern with SES. Since a forecast fell within a range of acceptable deviations of the forecast and $+2\sqrt{MSE}$ and $-2\sqrt{MSE}$ from actual values, no change in alpha was necessary (see Figure 1).

Figure 1
Tracking signal with exponential smoothing forecasting error ($\alpha = 0.022$)



Double exponential smoothing (DES) is recommended for forecasting time series data that have a linear trend. Similar to SES, the optimal alpha was determined when the value of alpha obtained the minimum MSE. In this research, DES had large errors (MSE = 3000, U-statistic = 2.19) when optimal alpha was 0.007, as shown in Table 1. Because DES does not consider seasonality patterns, this method was not appropriate for the time series data with seasonality.

Holt's exponential smoothing method (HES) is frequently used to handle a linear trend. HES smoothes the trend and slope directly by using different smoothing constants—alpha (α) and beta (β). A simple optimization method that minimizes the MSE was used to determine the optimal alpha and beta values. The smallest error (MSE = 2861, U-statistic = 2.14) was obtained when alpha was 0.002 and beta was 0.088, respectively (see Table 1).

Winter's exponential smoothing method (WES) provides a useful way to consider seasonality when the time-series data have a seasonal pattern. A simple optimization method that minimizes the MSE was used to determine the optimal alpha, beta, and gamma values. The smallest error (MSE = 431, U-statistic = 0.83) was obtained when alpha was 0.19, beta was 0.01, and gamma was 0.19. WES generated the second most accurate forecast because it considered seasonality (see Table 1).

Linear regression (LR) was the method with the second largest error (MSE = 3210, U-statistic = 2.27), as shown in Table 1, perhaps because it included only one variable and it did not capture the change induced by the seasonal pattern. However, it was the most accurate by MPE.

Multiple regression (MR) allows us to apply several independent variables instead of just one variable. In this research, MR (MSE = 382, U-statistic = 0.78) outperformed all the other methods because it fits the time series data with seasonality (see Table 1).

Table 3 presents the overall ranking of forecasting performance using different accuracy approaches. MR outperformed all other forecasting models. WES was the second most accurate forecasting method, followed by naïve 2. That is, only MR and WES were better than the naïve approaches (naïve method 2 and naïve method 3). Since the naïve methods (the simplest methods) generate better results, there is no reason to use the other forecasting methods except MR and WES. Naïve 1 was the least accurate forecasting method, showing the highest total value.

Table 3
Overall ranking of forecasting methods

	MAD	MSE	MPE	MAPE	RMSE	U-statistic	Ranking Total	Overall Rankings *
Naive1	10	11	6	7	11	11	56	11
Naive2	3	3	4	3	3	3	19	3
Naive3	4	4	2	4	4	4	22	4
MA	5	5	9	5	5	5	34	5
DMA	6	7	8	11	7	7	46	7
SES	6	9	11	9	9	9	53	10
DES	6	8	10	8	8	8	48	8
HES	9	6	7	6	6	6	40	6
WES	2	2	5	2	2	2	15	2
LR	10	10	1	10	10	10	51	9
MR	1	1	3	1	1	1	8	1

*The overall rankings were determined based on the scores in ranking total.

MA = moving average; DMA = double moving average; SES = simple exponential smoothing; DES = double exponential smoothing; HES = Holt's method; WES = Winter's method; LR = linear regression; MR = multiple regression; MAD = mean absolute deviation; MSE = mean squared error; MPE = mean percentage error; MAPE = mean absolute percentage error; RMSE = root mean squared error; U-statistic = Theil's U-statistic. The minimal errors are in bold.

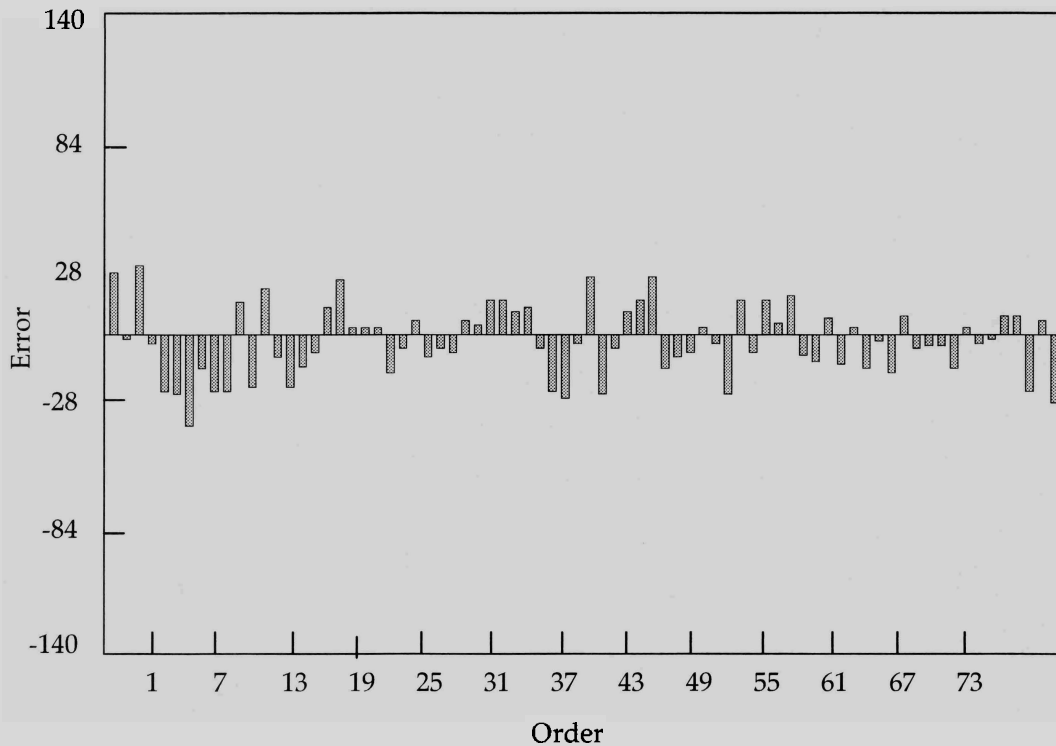
The Most Appropriate Forecasting Method

In this study, the most appropriate forecasting method was selected based on accuracy and simplicity. In terms of accuracy, MR outperformed all the other methods. WES was the second, and naïve 2 was the third most accurate. However, many foodservice managers do not have the time or knowledge to forecast using MR and WES. If the person charged with forecasting is comfortable with MR or WES and has enough time, he or she might appropriately use MR or WES, because both methods produce small errors.

Each forecasting method was ranked based on ease of use. Naïve 1, 2, and 3 were ranked first. Winter's method was ranked fifth, and multiple regression was ranked sixth, because it was considered the most complicated. Naïve 2 was the third most accurate forecasting method and was the simplest to implement and to handle. Only naïve 2 had a high ranking in both accuracy and simplicity. Since naïve 2 was ranked first in simplicity, it could be a good alternative to multiple regression, but only if the increase in forecasting error was not too high. A comparison of the difference in forecasting errors of both methods in terms of the number of meal counts was performed. The increase in error per meal counts by using naïve 2 is presented in Figure 2, which shows that the increase in the error in meal counts is not considerable. Since the increase in the error is not high, one can conclude—at least for this particular case—that both forecasting methods can be used interchangeably. A more complete analysis would include the opportu-

nity cost in dollars. Therefore, naïve 2 was selected as the most appropriate forecasting method for the dining facility studied. When ease of use is an important feature of the forecasting method, this research suggests using the naïve method 2.

Figure 2
Incremental forecasting error by using naïve 2



Conclusions

This study identified the most appropriate forecasting method based on accuracy and simplicity in a dining facility at Texas Tech University. The results showed that multiple regression obtained the best accuracy; however, it was not selected as the most appropriate forecasting method due to its complexity in practice. Appropriate naïve methods are recommended for use by institutional food service managers. Not only were naïve method 2 and 3 the third and fourth most accurate models, they were also the simplest to implement.

Since the analysis was for a specific dining center, the results of this study are not directly applicable to other places and situations. Also, what works well today might not work well in the future because of the dynamics of the industry. Nevertheless, the design of the study may apply to other institutional operations or even other food service industry operations.

Many real-life forecasting situations are more complicated and difficult due to such variables as weather, food menu items, special student activities, holidays, and

availability of funds. Therefore, to obtain better forecasting accuracy, it is recommended that food service managers apply appropriate quantitative methods, such as naïve methods with acceptable judgment, common sense, and experience.

A useful future study might use the data of several dining centers and identify whether the best forecasting method at one dining center is also the best in other dining facilities. More research might also be conducted that applies more sophisticated forecasting techniques, such as Box Jenkins or neural networks.

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