Nutritional Sciences 9(3), August, 2006, pp.201-211

Suggesting Forecasting Methods for Dietitians at University Foodservice Operations

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The purpose of this study was to provide dietitians with the guidance in forecasting meal counts for a university/college foodservice facility. The forecasting methods to be analyzed were the following: naïve model 1, 2, and 3; moving average, double moving average, simple exponential smoothing, double exponential smoothing, Holt's, and Winters' methods, and simple linear regression. The accuracy of the forecasting methods was measured using mean squared error and Theil's U- statistic. This study showed how to project meal counts using 10 forecasting methods for dietitians. The results of this study showed that WES was the most accurate forecasting method, followed by naïve 2 and naïve 3 models. However, naïvemodel 2 and 3 were recommended for using by dietitians in university/college dining facilities because of the accuracy and ease of use. In addition, the 2000 spring semester data were better than the 2000 fall semester data to forecast 2001spring semester data.

Key words: Forecasting, Meal counts, University foodservice, Forecasting methods, Accuracy, Ease of use

Received April 07, 2006; Revised July 9, 2006; Accepted July 31, 2006

INTRODUCTION

Forecasting especially plays a crucial role in college and university foodservice operations because of the perishable nature of food products and their non-profit nature. Also, food menu items are prepared immediately prior to service to customers.[1] There is no room for inventory, storage, or holding of the finished product beyond demand levels. Forecasting in the college and university foodservice industry affects food production, customer satisfaction, employee morale, manager confidence, inventory, staffing, sanitation, and financial status.[2-3] Inaccurate forecasting resultsin over-production or under-production. Finally, inaccuracy in forecasting leads to increased costs and decreased customer satisfaction.

In general, college and university foodservice organizations require foodservice managers or dietitians to keep tight control of costs. In the college and university foodservice industry, the task of forecasting is usually done by dietitians or foodservice managers.[4] Having a good forecast of meal counts helps dietitians to plan and control. They use historical data, including past production information and past customer counts, to forecast customer demand. Based on the historical data and variables, dietitians frequently employ intuitive guesses and naïve methods compared to mathematical forecasting methods.[2,5-9] Mathematical methods and computers have been neglected because both had reputations of being difficult to understand. However, increased utilization of personal computers facilitates the use of computers for forecasting. Research has also indicated that forecasting is an important tool for dietitians of foodservice operations and that continuing training is necessary in the college and university foodservice industry.[4] For instance, Jang et al. suggested that educational training of forecasting needs for the purpose of helping them acquire a knowledge related to self-development and duty for dietitians.[4] Simple quantitative techniques, such as naïve methods, might outperform the intuitive assessments of experts.[2] However, manually generated naïve models generally produce less accurate forecasts compared to computerized mathematical models.[3,5] Efficiently computerized mathematical forecasting methods will help institutional foodservice management control or even reduce costs in addition to increased customer satisfaction.

Despite the importance of forecasting[4], it has gained little attention by practitioners and researchers within university foodservice operations. Thus, this study aimed to fill this research gap by introducing forecasting models that can be used for a university foodservice

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facility. The purpose of this study was to provide dietitians with the guideline to forecast meal counts for a university or college foodservice operation. This study compared different forecasting models with two data sets: the 2000 spring semester data and the 2000 fall semester data. Both data sets were used to forecast meal counts for the 2001 spring semester. The specific purposes of this study were to: (1) draw the attention of forecasting withinthe university/college foodservice operation; (2) identify the most accurate forecasting method to project meal counts for the 2001 spring semester; (3) suggest the most appropriate forecasting technique for dietitians; and (4) discover whether the 2000 spring semester data is better than the 2000fall semester data to forecast meal counts for the 2001 spring semester.

REVIEW OF LITERATURE

The Importance of Forecasting in College and University Operations

Forecasting plays an important managerial function in college and universityorganizations. Accurate forecasting not only helps foodservice managers or dietitians (hereafter, dietitians) control food costs, labor costs, and inventory costs, but also improves customer satisfaction.[2-4,7-8]

Controlling Food Costs

Dietitians in the college/ university foodservice industry should keep tight controls of costs. Having a good forecast of customer demand will help managers to control or even reduce costs.[2-4,7-8] Particularly, over-estimation of customer demand leads to overproduction and results in extra costs. The problem with over-forecasting is the cost of unused prepared foods in addition to labor costs. Re-handling and discarding menu items are also hidden costs of over-forecasting.

Improving Customer Satisfaction

Customer satisfaction is affected by forecasting.[2-4,7-8] When forecasts are not accurate, under-forecasting might occur. This under- forecasting leads to underproduction. This makes customers unhappy because they do not receive their food choices. The cost of under-forecasting may seem to be minor, but the cost of losing customers is critical. The result of under-production might be more harmful than over-production because under-production results in losing market share by decreasing customer satisfaction.

Controlling Labor Costs

Controlling costs through effective labor scheduling can be a challenge. To staff correctly, a dietitian must have an accurate forecast of both how many customers can be expected during the meal periods and when the customers will be there during the meal periods. Labor scheduling is the act of balancing customer demand, employee work requests, and profitability.[10] Having too few employees can lead to poor customer service, overworked employees, and the loss of market share. On the other hand, having too many employees reduces operating margins. Labor costs are a large portion of the total costs under a dietitian's control in the foodservice industry.

Controlling Inventory Costs

Controlling inventory requires significant cost control.[11] Inventory accumulation is based on the forecast of expected demand. Inaccurate forecasting generates some problems. Having too much inventory requires too much of an investment, ties up assets, and creates space constraints in the distribution centers. On the other hand, if the operation reduces inventory to more manageable levels, it sometimes experiences shortages of certain menu items, which disappoint customers and cause a loss in market share. Consequently, inventory reduction by accurate forecasting is critical to controlling operating costs.

Accuracy of Forecasting Methods

Accuracy is the criterion which determines the best forecasting method, so that 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.[3,5,7-9,12] The formula is given as follows:

$$e_t = Y_t - F_t \tag{1}$$

where e_t = forecast error in time period t; Y_t = actual value in time period t; F_t = forecast value in time period t.

Some research has suggested using *MSE* and U-statisticto evaluate accuracy, if all errors are of relatively the same magnitude.[13]

Mean Squared Error (MSE)

The mean squared error (MSE) is one generally accepted technique for evaluating the exponential smoothing methods as well as other methods.[13)] The equation is as follows:

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

where Y_t = actual value in time period t; F_t = forecast value in time period t; n = 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.

U-Statistic

Theil's U-statistic allows a relative comparison of the forecasting approaches with naïve methods.[13-14)] Naïve models are used as the basis for making comparisons against which the performance of more sophisticated methods are judged. A modified U-statistic based on the root mean square error (RMSE) was employed in this study. The U-statistic is computed as the ratio of RMSE from a forecasting method to the RMSE of the naïve method.[14)] The formula is as follows:

$$RMSE=\frac{1}{n}\sum_{t=1}^{n}\sqrt{(Y_t-F_t)} \quad (3)$$

where F_t is forecast for period t, Y_t actual demand that occurred in period t, and n number of forecast observations in the estimation period.

U = RMSE of the forecasting method / RMSE of the naïve method	(4)

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-static, the better the forecasting technique used is, compared to the naïve method. The closer the U-statistic is to 0, the better the method.

METHODOLOGY

This study evaluated different forecasting models using meal count data from a dining center at a Midwestern University. Data from two semesters the 2000 spring semester and the 2000 fall semester were collected and were used to forecast the meal counts of the 2001 spring semester. Then actual data of the 2001 spring semester were used to test accuracy. There were several steps for the adjustment of data. First, data for a semester consisted of 17 weeks of meal counts. The weeks that had more than two sets of missing data in a week due to closure of the dining center were deleted in order to exclude from the database of incomplete weeks. Second, since the forecasting models being developed were intended for typical situations, the database was analyzed to detect abnormalities in the data. In this research, abnormalities in the data were considered when there was either extremely high or low value of data based on the day of the week due to special circumstances. Then data with special circumstances were adjusted by days of the week. Finally, the adjustment for the effect of changes in population was considered.

1. Forecasting Methods

After data was adjusted and compiled into a spreadsheet, forecasting the 2001 spring semester was implemented using 10 different forecasting methods with the 2000 spring semester data and the 2000 fall semester data, respectively. Computations were done using Microsoft Excel®.

Naïve Methods

In this research, three naïve models were used as follows: naïve 1 (the simplest naïve model with one day of lag), naïve 2 (the naïve model including weekly seasonality with one week of lag), and naïve 3 (the naïve model including weekly seasonality with one semester of lag).

Naïve 1. The naïve 1 method uses data from the previous day to forecast the current day (one day of lag).

$$F_{t+1} = Y_t \quad (5)$$

where

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

Y_t = actual value at period t

To start the forecast using naïve model 1, the last day of the 2000 spring semester or the 2000 fall semester was used to forecast the first day of the 2001 spring semester. For instance, using the 2000 fall semester to forecast the 2001 spring semester, the meal count of the last day (126) was used to forecast the first day (Monday) of the 2001 spring semester (see Table 1). To forecast the second day (Tuesday) of the 2001 spring semester, the actual meal count of Monday was needed. In this case, the actual meal count was 230, and was used for the forecast for Tuesday. Note that this model does not allow forecasting two days in advance.

$$F_{78+1} = Y_{78}$$
$$F_{79} = Y_{78} = 126$$

As the actual meal count for the first Monday of the 2001 spring semester was 230, the forecasting error for Monday was 104 (e= 230-126) (see Table 1).

Table 1. Naïve 1 forecast using the 2000 fall semester data as a base

Year	Week	Day	t	Y_t	F_t	e_t
2000	13	Monday	73	209		
		Tuesday	74	250		
		Wednesday	75	240		
		Thursday	76	244		
		Friday	77	145		
		Saturday	78	126		
2001	1	Monday	79	230	126	104
		Tuesday	80	296	230	66
		Wednesday	81	245	296	-51
		Thursday	82	297	245	52
		Friday	83	167	297	-30
		Saturday	84	169	167	3

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

$$F_{t+1} = Y_{t-5} \quad (6)$$

Here Y_{t-5} is the actual data one week before the current week. Equation 6 makes forecasts based on data that are one week old. To forecast the first week of the 2001 spring semester, the last week of the 2000 spring semester or the 2000 fall semester has to be used. For instance, when the 2000 fall semester data were used for forecasting, the number of meal counts of the last week of the 2000 fall semester corresponded to the forecast of the first week of the 2001 spring semester (see Table 2). Since the meal count for the last Monday of the 2000 fall semester was 209, the forecast for the first Monday of the 2001 spring semester would be 209.

$$F_{78+1} = Y_{78-5}$$
$$F_{79} = Y_{73} = 209$$

As the actual meal count for the first Monday of the 2001 spring semester was 230, the forecasting error for Monday was 21 (e = 230-209) (see Table 2).

Table 2. Naïve 2 forecast using the 2000 fall semester data as a base

Year	Week	Day	t	Y_t	F_t	e_t
2000	13	Monday	73	209		
		Tuesday	74	250		
		Wednesday	75	240		
		Thursday	76	244		
		Friday	77	145		
		Saturday	78	126		
2001	1	Monday	79	230	209	21
		Tuesday	80		250	
		Wednesday	81		240	
		Thursday	82		244	
		Friday	83		145	
		Saturday	84		126	

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).

$$F_{t+1} = Y_{t-77} \quad (7)$$

Here Y_{t-77} is the actual data one semester before the current semester. For instance, the meal count of the first Monday for the 2000 fall semester was used to forecast the first Monday of the 2001 spring semester.

$$F_{78+1} = Y_{78-77}$$
$$F_{79} = Y_1 = 258$$

As the actual meal count for the first Monday of the 2001 spring semester was 230, the forecasting error for Monday was -28 (e = 230 - 258) (see Table 3).

Table 3. Naïve 3 forecast using the 2000 fall semester data as a base

Year	Week	Day	t	Y_t	F_t	e_t
2000	13	Monday	1	258		
		Tuesday	2	257		
		Wednesday	3	277		
		Thursday	4	245		
		Friday	5	171		
		Saturday	6	109		
2001	1	Monday	79	230	258	-28
		Tuesday	80		257	
		Wednesday	81		277	
		Thursday	82		245	
		Friday	83		171	
		Saturday	84		109	

Simple Moving Average Method

The moving average is concerned with more recent observations. As each new observation becomes available, a new mean is calculated by adding the newest value and dropping the oldest one.[13] The moving average method for smoothing a time-series is highly dependent on *n*, the number of terms selected for constructing the average. In this study, forecasts with different *n* were determined, with ranges from $n = 2$ to $n = 7$ in order to select the optimal *n*. For instance, when a 3-day moving average (n = 3) was considered, the forecast for the first Monday of the 2001spring semester was calculated based on equation 8.

$$F_{78+1} = (Y_{78} + Y_{77} + Y_{78-3+1})/ 3$$
$$F_{79} = (Y_{78} + Y_{77} + Y_{76}) / 3 = (126 + 145 + 244) / 3 = 172 \quad (8)$$

Table 4. Forecasting with simple moving average method ($n = 3$) using the 2000 fall semester data as a base

Year	Week	Day	t	Y_t	F_t	e_t
2000	13	Monday	73	209		
		Tuesday	74	250		
		Wednesday	75	240		
		Thursday	76	244		
		Friday	77	145		
		Saturday	78	126		
2001	1	Monday	79	230	172	58
		Tuesday	80	296	167	129
		Wednesday	81	245		
		Thursday	82	297		
		Friday	83	167		
		Saturday	84	169		

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

As the actual meal count for the first Monday of the 2001 spring semester was 230, the forecasting error was 58 ($e = 230-172$) (see Table 4). The determination of the optimal n was included in Results section.

Double Moving Average Method

The use of the double moving average method should be used to forecast time series data that have a linear trend.[12] Forecasting with a double moving average requires determining two averages. The first moving average is determined similarly to the one in the simple moving average. After the first moving average is computed, a second moving average is calculated. For instance, the forecast for the first Tuesday of the 2001 spring semester was calculated using equations 9 to 13 with 2000 fall semester data and $n = 3$.

The first moving average was computed using equation 9.

$$M_{78} = Y_{78} + Y_{77} + Y_{76} = (126 + 145 + 244) / 3 = 172$$
$$M_{77} = Y_{77} + Y_{76} + Y_{75} = (145 + 244 + 240) / 3 = 210 \quad (9)$$
$$M_{76} = Y_{76} + Y_{75} + Y_{74} = (244 + 240 + 250) / 3 = 245$$

Equation 10 was used to calculate the second moving average.

$$M'_{78} = (M_{79} + M_{78} + M_{77}) / 3 = (172 + 210 + 245) / 3 = 209 \quad (10)$$

Equation 11 was used to develop a forecast by getting the difference between moving averages.

$$a_{78} = 2\,M_{78} - M'_{78} = 2\,(172) - 209 = 135 \quad (11)$$

Equation 12 was used as an additional adjustment factor.

$$b_{78} = 2 / (3-1)\,(M_{78} - M'_{78}) = (1)\,(172-209) = -37 \quad (12)$$

Finally, the forecast for one period ahead ($p = 1$) with double moving average was obtained using equation 13.

$$F_{78+1} = a_{78} + b_{78} * p = 135 + (-37)\,(1) = 98 \quad (13)$$

Observe that you need (2n - 1) days of data in order to start using this method.

Table 5. Forecasting with double moving average method (n = 3) using the 2000 fall semester data as a bas

Year	Week	Day	t	Meal Counts	M_t	M'_t	Value of a	Value b	F_t
2000	13	Monday	73	209					
		Tuesday	74	250					
		Wednesday	75	240					
		Thursday	76	244	245				
		Friday	77	145	210				
		Saturday	78	126	172	209	135	-37	
2001	1	Monday	79	230					98
		Tuesday	80	296					
		Wednesday	81	245					
		Thursday	82	297					
		Friday	83	167					
		Saturday	84	169					

$M_t = F_{t+1} = (Y_t+Y_{t-1}+Y_{t-2}+\cdots+Y_{t-n+1})/n$; $M'_t = (M_t+M_{t-1}+M_{t-2}+\cdots+M_{t-n+1})/n$

Simple Exponential Smoothing Method

Exponential smoothing approach is easy to use and capable of producing reliable forecasts.[15] The simple exponential smoothing method is based on smoothing past values of a series in an exponential technique. The observations are weighted, with more weight being given to the more recent observations. Equation 14 was used to forecast in the simple exponential smoothing method. An initial value of Ft, the old smoothed value, was needed to start the forecast. There are several approaches to determine the initial value. One approach is to set the first estimate equal to the first observation; that is, $F_1 = Y_1$. Another approach is to use the average of the first five or six observations for the initial smoothed value. In this study, the first approach was employed (see Table 6).

The accuracy of the simple exponential smoothing method strongly depends on the optimal value of alpha (α). A traditional optimization method based on the lowest *MSE* was used to determine the optimal alpha value. Then, the alpha was used in forecasting. For instance, to forecast 2000 fall semester data using α= 0.1, F_1 was assumed to be Y_1, in this case 258 (see Table 6). The forecasts for the next couple of periods were the following:

Table 6. Forecasting with simple exponential smoothing method (α = .1) using the 2000 fall semester data as a base

Year	Week	Day	t	Meal Counts	F_t
2000	1	Monday	1	258	258
		Tuesday	2	257	258
		Wednesday	3	277	257.9
		Thursday	4	245	259.8
		Friday	5	171	
		Saturday	6	109	

$$F_{t+1} = \alpha Y_t + (1-\alpha)\, F_t$$
$$F_{1+1} = \alpha Y_1 + (1-\alpha)\, F_1$$
$$F_2 = (0.1)(258) + (1 - 0.1)(258) = 258 \qquad (14)$$
$$F_3 = (0.1)(257) + (1 - 0.1)(258) = 257.9$$
$$F_4 = (0.1)(277) + (1 - 0.9)(257.9) = 259.8$$

Forecasts based on exponential smoothing methods assume the continuation of non-random historical patterns into the future.[13] When the continuation of the non-random historical pattern is broken, the accuracy of the exponential smoothing method is greatly reduced. Thus, it isimportant to detect changes in non-random historical patterns. 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. But, if a forecast fell outside the range, the system indicated the possibility of updating alpha value. In this study, the researcher used limits set of ± 2 standard deviations of the forecast ($2\sqrt{MSE}$) that gives a 95% chance that the actual observation will fall within the limits (see Figure 1).

Fig. 1 Tracking Signal with Exponential Smoothing Forecasting Error (α= .022)

Double Exponential Smoothing Method

The double exponential smoothing method is recommended for forecasting time series data that have a linear trend.[12] The equations from 15 to 19 were used for the double exponential smoothing. In this research, to start forecasting, the initial values of A_t and A'_t were considered equal to the first observation. Table 7 shows that $Y_1 = A_1 = A'_1 = 258$ was used as the initial value. For instance, the forecast for the first Tuesday of the 2000 spring semester was calculated as follows:

$$A_2 = \alpha Y_2 + (1-\alpha) A_{2-1} = (0.5)(300) + (1-0.5)\,258 = 279 \quad (15)$$

$$A'_2 = \alpha A_2 + (1-\alpha) A'_{2-1} = (0.5)(279) + (1-0.5)\,258 = 268.5 \quad (16)$$

$$a_2 = 2A_2 - A'_2 = 2\,(279) - 268.5 = 289.5 \quad (17)$$

$$b_2 = \alpha (A_2 - A'_2)/(1-\alpha) = 0.5\,(279-268.5)/0.5 = 10.5 \quad (18)$$

$$F_{2+1} = a_2 + b_2 (p) = 289.5 + 10.5\,(1) = 300 \quad (19)$$

Table 7. Forecasting with double exponential smoothing method (α= .5) using the 2000 fall semester data as a base

t	Meal Count	A_t	A'_t	Value of a	Value of b	Forecast a+bp
1	258	258	258	258	0	258
2	300	279	268.5	298.5	10.5	258
3	279					300
4	244					
5	196					
6	178					

A_t = exponentially smoothed value of Y_t at time t;
$A_t = \alpha Y_t + (1-\alpha) A_{t-1}$; $A'_t = \alpha A_t + (1-\alpha) A'_{t-1}$; $a_t = 2A_t - A'_t$; $b_t = \alpha (A_t - A'_t)/(1-\alpha)$

As in the simple exponential smoothing, the accuracy of the forecasting method highly depends on the optimal value of alpha. The one 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

Holt's method smoothes the trend and slope directly by using different smoothing constants, alpha (α) and beta (β).[12] The equations from 20 to 22 were used to forecast using the Holt's method. The initial values for the smoothed series and the trend must be set to start the forecasts.[16] There are several methods used to determine the initial values to use in the forecast. In this study, the first estimate of the smoothed series was to set equal to the first observation. Then, the trend was estimated to equal zero. The first observation, 258, corresponded to the first estimate of the smoothed series ($Y_t = L_t = 258$). Also $T_t = 0$ wasused as the initial value (see Table 8). For example, the forecast for the first Tuesday of the 2000 spring semester was calculated as follows:

$$L_2 = Y_2 + (1-\alpha)(L_{2-1} + T_{2-1}) = 0.1 * 300 + (1-0.1)(258 + 0) = 262 \quad (20)$$

$$T_2 = \beta (L_2 - L_{2-1}) + (1-\alpha) T_{2-1} = (0.1)(262-258) + (1-0.1)(0) = 0.4 \quad (21)$$

$$F_{2+1} = L_2 + (1)\,T_2 = 262 + 0.4 = 262.4 \quad (22)$$

Table 8. Forecasting with Holt's method (α= .1 and β= .1) using the 2000 fall semester data as a base

T	Meal Counts	Lt	Tt	Ft
1	258	258	0	258
2	300	262	0.4	258
3	279			262.4
4	244			
5	196			
6	178			

L_t = new smoothed value; T_t = trend estimate; $L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$;
$T_t = \beta (L_t - L_{t-1}) + (1-\beta)\,T_{t-1}$; $F_{t+p} = L_t + pT_t$

Accuracy of Holt's exponential smoothing method requires optimal values of alpha (α) and beta (β). The optimal and values were selected on the basis of minimizing the *MSE.*

Winter's Method

Winter's method not only considers trend but also considers seasonality.[13] This seasonality estimation is provided as a seasonal index. Equations from 23 to 26 were used to forecast with Winter's method. To start the forecasts, the initial values of the smoothed series L_t, the trend T_t, and the seasonal indices S_t must be given. In this research, the first estimate of the smoothed series was set equal to the first observation. Then, the trend was estimated to be equal to zero and the seasonal indices wereset to 1.0. First 6 new smoothed values were considered the same as the first 6 observations. Then, the first 6 trend estimates were set as zero. The first six seasonality indices were assigned as the value, one (see Table 9). For example, the forecast for the second Monday of the 2000 spring semester was calculated as follows:

$$L_7 = \alpha * Y_7 / S_{7-6} + (1-\alpha)(L_{7-1} + T_{7-1}) = 0.19 * 284/1 + (1-0.19)(178+0) = 198 \quad (23)$$

$$T_7 = \beta(L_7 - L_{7-1}) + (1-\beta) * T_{7-1} = 0.01 * (198-178) + (1-0.01) * 0 = 0.2 \quad (24)$$

$$S_7 = \gamma * Y_7 / L_7 + (1-\gamma) * S_{7-6} = 0.19 * 284/198 + (1-0.19) * 1 = 1.08 \quad (25)$$

$$F_{7+1} = (L_7 + p * T_7) * S_{7-6+p} = (198 + 1 * 0.2) * S_2 = 198.8 \quad (26)$$

The accuracy of Winter's method 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.

Simple Linear Regression

Simple linear regression isused to estimate the nature of the relationship between a dependent variable and an independent variable. It involves predicting the variable Y based on knowledge of the variable X. Two regression models were used to forecast the 2001 spring semester. In the first case, data from the 2000 spring semester were used in the regression analysis. The regression model required information about meal counts (Y) and about the time (X) of the data. A confidence level of 95% wasused in the analysis. The resulting model was significant ($F_{(1,76)} = 7.84$, $p = 0.0065$). The coefficient of determination (R^2) was .094, indicating that the model explained 9.4 percent of the variance. The estimate of the β coefficient (β_1) was -0.767 with t-value = -2.80 and p-value = .0065. Finally, the forecasting model was $Y_t = 245.01-0.767$ X. This model was used to forecast the 2001 spring semester. Similarly, data from the 2000 spring semester were used in the same way to create a forecasting model. The forecasting model was $Y_t = 226.32-0.214$ X. Then, this model was used to forecast the 2001 spring semester.

Table 9. Forecasting with Winter's method (α= .19, β= .01, and γ= .19) using the 2000 fall semester data as a base

T	Yt	Lt	Tt	St	Ft
1	258	258	0	1	
2	300	300	0	1	
3	279	279	0	1	
4	244	244	0	1	
5	196	196	0	1	
6	178	178	0	1	
7	284	198	0.2	1.08	
8					198.8

Y_t = new observation or actual value of series in period t; A_t = new smoothed value; T_t = trend estimate; S_t = seasonal estimate; $A_t = \gamma_t/S_{t-L}+(1-\alpha)(A_{t-1})(A_{t-1}+T_{t-1})$; $T_t = \beta(A_t-A_{t-1})+(1-\beta)\ T_{t-1}$; $S_t = \gamma Y_t/A_t+(1-\gamma)\ S_{t-L}$; $F_{t+p} = (A_t+pT_t)\ S_{t-L+p}$

RESULTS AND DISCUSSION

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. For instance, the meal counts in the 2000 spring semester generally decreased from Monday to Saturday (M > T > W > TH > F > Sa). This effect induces a bias in the forecast, creating over-forecasting errors. When the 2000 spring semester was used as a base, naive 1 model had the second worst accuracy (MSE = 5,070; U-statistic = 3), as shown in Table 10. When the 2000 fall semester was used as a base, similar results occurred with this method (MSE= 4,993; U-statistic = 2.83). These results demonstrate that when the 2000 spring semester data was used as a base to forecast the 2001 spring semester, the forecasting errors were larger than those in the corresponding 2000 fall semester data.

Naïve 2 model considers seasonality by using the last week of data to forecast the next week. Since the data

Table 10. Forecast accuracy using the 2000 spring and fall semester data as a base

	2000 Spring Semester			2000 Fall Semester		
	MSE	U-Statisti	Rank Best to Worst	*MSE*	U-Statisti	Rank Best to Worst
Naïve 1	5070	3.00	9	4993	2.83	10
Naïve 2	563	1.00	2	625	1.00	2
Naïve 3	604	1.04	3	908	1.21	3
MA (n=7)	2901	2.27	5	2845	2.13	4
DMA (n=6)	2932	2.28	6	2967	2.18	6
SES (α= .017)	3054	2.33	8	3054	2.21	8
DES (α= .007)	3000	2.35	7	3000	2.19	7
HES (α= .002; β= .088)	2853	2.25	4	2861	2.14	5
WES (α= .19; β= .01; γ= .19)	427	0.87	1	431	0.83	1
LR	6865	3.49	10	3210	2.27	9

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; MSE = mean squared error; U-statistic = Theil's U-statistic. The minimal errors are in bold.

in this research considered weekly seasonality, naïve 2 had smaller errors. When the 2000 spring semester was used as a base, this method had the third smallest *MSE* (563), as shown in Table 10. Because of the small *MSE*, naïve 2 was used as the reference for the U-statistic, so the value of the U-statistic was 1. When the 2000 fall semester was used, similar outcomes occurred with this method (*MSE* = 625). Naïve 2 model was also ranked as the 3rd most accurate method. In naïve 2, the 2000spring semester data was better than the 2000 fall semester data to forecast the 2001 spring semester.

Naïve 3 model was a modified version of naïve 2 because it considered seasonality but had a lag of one semester. That is, the first week of data of the semester base was used to forecast the first week of the 2001 spring semester. When the 2000 spring semesterwas used as a base, naïve 3 had good accuracy and ranked the 4th (*MSE* = 604, U-statistic = 1.04), as shown in Table 10. Even though this method obtained good accuracy, it was not as good as naïve 2. Similarly, using the 2000 fall semester as a base, this method produced small errors (MSE = 908, U-statistic = 1.21), ranking this method in fourth place. These results showed that the 2000 spring semester data produced smaller errors than the 2000 fall semester data as a base to forecast the 2001 spring semester.

Several moving average models (MA) with different n were tested and the model with n = 7 produced the smallest *MSE*(2,845) as shown in Table 11. When the 2000 spring semester was used as a base, MA was one of the least accurate methods (*MSE* = 2,901, U-statistic = 2.27), as shown in Table 10. Since the value of the U-statistic is larger than one, this method does not outperform the naïve 2 model and should not be used for this application. When the 2000 fall semester was used as a base, MA (*n* = 7) was the most accurate method among the forecasting methods that did not consider seasonality pattern. MA (*n* = 7) obtained the smallest errors (*MSE* = 2,845, U-statistic = 2.13). These results showed that the 2000 fall data was better than the 2000 spring data for forecasting the 2001 spring semester.

Several double moving averages with different n were tested, and the optimal model (*n* = 6) was the one with the smallest *MSE*. When the 2000 spring semester was used as a base, DMA produced large errors (*MSE* = 2,932, U-statistic = 2.28), as shown in Table 10. This is due to the fact that DMA did not consider seasonality and the data did not have a linear trend pattern. Similarly, when the 2000 fall semester was used as a base, DMA (*n* = 6) also produced large errors (*MSE* = 2,967, U-statistic =2.18). In the DMA, the 2000 spring semester data was a little bit better than the 2000 fall semester data to forecast the meal counts of the 2001 spring semester.

Table 11. The results of MSE with different *n* using moving average on the 2000 spring semester data

	n=2	n=3	n=4	n=5	n=6	n=7	n=8
MSE	5450	5013	4902	4141	2966	**2901**	3334

n = number of terms in the moving average;
MSE = Mean Squared Error. The minimal error is in bold.

Table 12 shows that when optimal was .017, simple exponential smoothing model (SES) obtained the minimum error (*MSE*= 3,054) using the 2000 spring semester as a base. In this research, SES (α= .017) had large errors (*MSE*= 3,054; U-statistic = 2.33), as shown in Table 10, because it did not consider seasonality. When the 2000 fall semester was used as a base, the optimal α was .022 because the minimum error (*MSE* = 3,054) was obtained with value, .022. SES (α= .022) was the third least accurate (*MSE*= 3,054; U-statistic = 2.21). In the SES, there was no difference between spring and fall semesters based on *MSE* and U-statistic.

Table 12. Optimal alpha (α) with simple exponential smoothing method using the 2000 spring semester data

α	.1	.01	.015	.016	.017	.018	.019	.02	.03	.2	.3
MSE	3285	3134	3058	3055	**3054**	3055	3057	3060	3112	3505	3755

α = smoothing constant (0 < α < 1);
MSE = Mean Squared Error. The optimal alpha is in bold.

In this research, double exponential smoothing (DES) had large errors (*MSE* =3,000; U-statistic = 2.35) using the 2000 spring semester as a base when optimal α was .007 (see Table 10). Because DES does not consider seasonality patterns, this method was not appropriate for the time series data with seasonality. Similarly, when the 2000 fall semester was used as a base, DES was the fourth least accurate (*MSE* = 3,000, U-statistic = 2.19). These results showed that the value of *MSE* and U-statistic were the same in both semesters.

Holt's exponential smoothing method (HES) performed best among those methods that were not designed for seasonal data. When the 2000 spring semester was used as a base, the smallest error was obtained when alpha was .002 and beta was .088 respectively. HES had an error of 2,853 as measured by *MSE*. Even though this method only considered the trend pattern, HES generated better accuracy than did MA, DMA, SES, DES, and LR (see Table 10). When the 2000 fall semester data was used as a base, similar results occurred. HES was the sixth most accurate method (*MSE* = 2,861, U-statistic = 2.14). In this HES method, spring semester data was a little bit better than fall semester data for forecasting the meal counts of the 2001 spring semester.

Winter's exponential smoothing method (WES) provides a useful way to consider seasonality when the time-series data has a seasonal pattern. The smallest *MSE* was obtained when alpha was .19, beta was .01, and gamma was .19 using the 2000 spring semester as a base. WES (*MSE* = 427; U-statistic = 0.76) was the second most accurate because it considered seasonality (see Table 10). Similarly, when the 2000 fall semester was used as a base, WES generated the second most accurate forecast (*MSE* = 431, U-statistic = 0.83) because this method considered seasonality. Just as in the case using the 2000 fall semester as a base, the optimal α, β, and γ were .11, .04, and .17, respectively. These results demonstrated that the 2000 spring data was a little bit better than the 2000 fall data for forecasting the 2001 spring semester.

In real-life situations, identifying the relationship between two variables as in simple linear regression is not frequently appropriate because more than one independent variable is usually necessary to predict a dependent variable accurately. In this research, linear regression (LR) was the method with the largest error when spring semester was used (*MSE* = 6,965 U-statistic = 3.49), as shown in Table 10, perhaps because it only included one variable and did not capture the change induced by the season. When the 2000 fall semester was used as a base, LR was the second least accurate method (MSE = 3,210; U-statistic = 2.27). These results showed that the 2000 fall semester data was much better than the 2000 spring semester data for forecasting the 2001 spring semester.

Table 10 shows WES obtained the smallest value of U-statistic (0.87) among the 11 forecasting methods when the 2000 spring semester data was used. Naïve 2 (U-statistic = 1) was the second most accurate forecasting method followed by naïve 3 (U-statistic = 1.04). The result of U-statistic showed that only WES was better than the naïve approaches (naïve method 2 and naïve method 3). Since using the naïve methods, which are the simplest methods, generates better results, there is no reason to use the other forecasting methods except WES. LR was the least accurate forecasting method (U-statistic = 3.49). Similarly, only WES (0.83) was better than naïve approaches on the basis of U-statistic when the 2000 fall semester data was used. Thus, in terms of U-statistic, only WES was better than naïve models in both semesters.

In conclusion, based on accuracy, the best method was WES, followed by naïve 2 and naïve 3. Naïve 2 and naïve 3 were the second and the third most accurate forecasting method in using both spring and fall semesters to forecast the 2001spring semester. Because of the obvious weekly seasonality pattern, WES, naïve 2, and naïve 3 could produce much better accuracy than other methods that did not consider seasonality pattern in both spring and fall semesters.

Most of the forecasting methods using the 2000 spring semester as a base generated better accuracy than did forecasting methods using the 2000 fall semester as a base. In other words, overall, the 2000 spring semester data was better than the 2000 fall semester data to forecast the 2001 spring semester data. This fact implies that same season data can be better than different season data to execute forecasts. It might be that there is a change in the behavior of students between different seasons that affects the students'attendance in dining centers. For instance, female students might skip meals in order to lose weight and fit into swimming suits during the spring semester. Perhaps the nice weather induces students to eat outside.

CONCLUSIONS

This study was attempted to help dietitians acquire knowledge related to forecasting meal countsthrough education for a university or college foodservice industry. The findings of this study showed that Winter's method obtained the best accuracy. However, it may not be considered as the most appropriate forecasting method due to its complexity in practice. In the case of institutional foodservice operations, special consideration is required concerning ease of use of the method since the person in charge of forecasting usually has little time and little knowledge in some instances to implement the forecasts. The easeof use of the forecasting methods is sometimes far more important than the accuracy of the forecasting methods in practice. Thus, appropriate naïve methods are recommended for using by dietitians in university/college dining facilities. Not only were naïve method 2 and 3 the second and third most accurate models, but they were also the simplest models to implement. Some research has noted that naïve models produce less accurate forecasts than do computerized mathematical models.[2,9] In this study, the simplest methods, naïve 2 and naïve 3, outperformed all the forecasting methods implemented except for Winter's method.

In addition, the 2000 spring semester data were better than the 2000 fall semester data to forecast 2001 spring semester data. Previous studiessuggested using spring semester data to forecast spring semester and fall semester data to forecast fall semester.[3] The outcome of this research supports their findings. Even though the 2001 fall semester data was more recent than the2000 spring semester data in forecasting the 2001 spring semester, spring semester data generated better accuracy than did fall semester data.

The forecasting models used in this study were designed to forecast normal demand situations. Thus, forecasting for special demands (extremely high or low) due to many kinds of variables was not considered. Many real-life forecasting situations are more complicated and difficult due to such variables as weather, food menu items, special student activities, holidays, and money availability. Therefore, it is recommended that foodservice dietitians apply appropriate quantitative methods, such as naïve methods, with acceptable judgment, common sense, and experience, in order to obtain better forecasting accuracy.

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. The results of the present study showed that the 2000 spring semester data was better than the 2000 fall semester data for forecasting the 2001 spring semester. This may indicate that same season data is better than different season data in implementing forecasts. Further research may forecast fall semester to identify whether previous fall semester data is better than previous spring semester data.

Literature Cited

1) Miller JL, Shanklin CW. Forecasting menu-item demand in foodservice operations. *J Am Diet Assoc* 88(4):443-449, 1988
2) Messersmith AM, Miller JL. Forecasting in foodservice. John Wiley & Sons, New York, 1991
3) Miller JJ, McCahon CS, Miller JL. Forecasting production demand in school foodservice. *School Food Serv Res Rev* 15(2):117-122, 1991
4) Jang MS, Lee JM, Baek SY. Analysis of training needs with roles in college and university foodservice dietitians. *J Kor Diet Assoc* 11(4):462-472, 2005
5) Miller JJ, McCahon CS, Miller JL. Foodservice forecasting using simple mathematical models. *Hospitality Res J* 15(1):43-58, 1991
6) Miller JJ, McCahon CS, Miller JL. Foodservice forecasting: Differences in selection of simple mathematical models based on short-term and long-term data sets. *Hospitality Res J* 16(2):95-102, 1993
7) Miller JL, Sanchez A, Sanchez N. Forecasting food production: A comparative study of four models. *Nat Assoc Col Uni Foodserv* 18(1):65-71, 1994
8) Repko CJ, Miller JL. Survey of foodservice production forecasting. *J Am Diet Assoc* 90(8):1067-1071, 1990
9) Miller JL, McCahon CS, Bloss BK. Food production forecasting with simple time series models. *Hospitality Res J* 14(3):9-21, 1991
10) Thompson GM. Labor scheduling, part 1, *Cornell Hotel Restaurant Adm Q* 39(5):22-31, 1998
11) Pappas JM. Eat Food, not Profits: How computers can save your restaurant. Van Nostrand Reinhold, New York, 1997
12) Hanke JE, Reitsch AG. Business Forecasting, 6th ed. Prentice Hall, Upper Saddle River, NJ, 1998
13) Ryu K, Jang S, Sanchez A. Forecasting methods and seasonal adjustment for an institutional foodservice facility. *J Foodserv Bus Res* 6(3):17-34, 2003
14) Theil H. Principles of Econometrics. Wiley, New York, 1971
15) Song H, Wong KF, Chon KS. Modeling and forecasting the demand for Hong Kong tourism. *Int J Hospitality Manage* 22:435-451, 2003
16) Hanke JE, Wichern DW, Reitsch AG. Business Forecasting, 7th ed. Prentice Hall, Upper Saddle River, NJ, 2001