9-1985

# Customer and Food Item Selection Forecasting in a Hospital Cafeteria

M. Sue Davis

Abstract

CUSTOMER AND FOOD ITEM SELECTION FORECASTING
IN A HOSPITAL CAFETERIA

By

M. Sue Davis

For many years various types of forecast models have reportedly been used in hospital foodservice systems to estimate the patient census level or meal demand for menu items. None of these reports have dealt with the application of forecast models in a hospital cafeteria setting. The purpose of this study was to test selected forecast models in a hospital setting to determine the one that most accurately predicted the number of customers utilizing the cafeteria on a particular day, and the number of servings of a specific food item that was utilized at selected meals. Historical data was used to fit three Forecast models--Simple Moving Average, Exponential Smoothing and Adaptive Exponential Smoothing--for actual use. When results of these models were evaluated, an Analysis of Variance test showed no significant difference between forecasting accuracy. Because it is a less complex model to use, Simple Moving Average was chosen to forecast for actual entree demand. Graphing forecasts from Simple Moving Average against actual demand resulted in very similar curves indicating that managers, with no forecasting system or a system having a high degree of error, might benefit from the use of any of the models evaluated.

Loma Linda University

--------

# CUSTOMER AND FOOD ITEM SELECTION FORECASTING IN A HOSPITAL CAFETERIA

by

M. Sue Davis

--------

A Manuscript submitted in Partial Fulfillment
of the Requirements for the Degree Master of Science
in Food Administration

--------

September 1985

Each person whose signature appears below certifies that this manuscript in his/her opinion is adequate, in scope and quality, in lieu of a thesis for the degree Master of Science.

Bertrum C. Connell ________________________________, Chairman

Bertrum C. Connell, Associate Professor of Nutrition & Dietetics

Kathleen Zolber ________________________________

Kathleen Zolber, Professor of Nutrition

Kenneth I. Burke ________________________________

Kenneth I. Burke, Professor of Nutrition

Gerald Shavlik ________________________________

Gerald Shavlik, Assistant Professor of BioStatistics and Epidemiology

# CUSTOMER AND FOOD ITEM SELECTION FORECASTING IN A HOSPITAL CAFETERIA

## INTRODUCTION

Forecasting in a foodservice system is used to estimate the census level or meal demand for menu items. A dependable forecasting system will have a low incidence of over- and underproduction of menu items. Overproduction of food items may cause several problems. When reheated, food quality and palatability may be decreased. Finding a use for leftover food may be difficult. Overproduction can result in food waste and loss of productive labor time in preparation and processing and increased labor costs.

Underproduction also has its set of problems. It increases scheduled labor costs because of last-minute preparation of menu items and can put unnecessary stress on employees and lead to dissatisfaction. In addition, food quality may decrease if preparation is hurried. Customer dissatisfaction can occur if meals are delayed or menu items are unavailable.

Managers of foodservice operations have been concerned for years with the problem of determining the type and amount of foods to prepare for their clientele. Early research of this problem dealt with food preference and acceptability (1-7). Others studied the effect of repetitive eating of a limited number of food items (8-10).

Very little research has been reported on forecasting production demands in hospital Nutritional Services Departments. Literature in this area stresses the need for accurate, timely information in order to enhance the efficiency and effectiveness of the dietetic management system (11-13). Those who have applied forecasting methods in a hospital setting have done so in relation to patient menu item demand (13-17) or to a combination of patient and cafeteria populations (12).

Dougherty (18) states that the introduction of select menus in health care brought with it an increase in the complexity of forecasting, without a similar change in forecast methods. Even where menu tallies are used, forecasting is complicated by the fact that patient food usage may only account for approximately 50 percent of the production in most health care facilities; as much as 50 percent of the population demand is for a service area (i.e., cafeteria) for which no tally is available.

Teaching hospital populations are composed of numerous individuals in addition to patients. These include medical personnel, students, visitors, and community members of which many utilize the hospital cafeteria for one or more meals each day. Due to the many differing variables this amorphus population represents, methods of forecasting for patient menu item demand are not transferable to the cafeteria setting.

The purpose of this research was to evaluate selected forecast models in a hospital setting to determine the one that most accurately predicted the number of customers utilizing the cafeteria on a particular day, and the number of servings of a specific food item that was utilized at selected meals.

## METHOD

### Selection of Forecast Models

Three forecasting models were chosen for testing in this research: a) Simple Moving Average (SMA) (19), b) Exponential Smoothing (ES) (19), and c) Adaptive Exponential Smoothing (AES) (19,20). Criteria for selection included: 1) low cost of design and operation, 2) a relatively high degree of accuracy, 3) limited amounts of historical data necessary for priming the models, and 4) ease of computation.

Chambers, Mullick and Smith (21) discuss these criteria in relation to Moving Average and Exponential Smoothing. Time required to develop each computer program was one day. Cost of forecasting with a computer was $0.005 for each model. The accuracy rating of the Moving Average model was stated to be poor to good while Exponential Smoothing was fair to very good. Historical data required for both models was a minimum of two years since seasons were present. Due to the simplicity of these models, calculation is possible without a computer. Use of a computer, however, minimizes both calculation time and cost.

Harris (22) reported testing five models: (1) Simple Moving Average, (2) Moving Average Regression, (3) First Order Exponential Smoothing, (4) Double Exponential Smoothing, and (5) Adaptive Exponential Smoothing. Selection of the best model was based on accuracy, ease of computation and amount of historical data required. In view of these criteria, the First Order Exponential Smoothing was considered best. All models substantially improved on the intuitive forecasts which were then being used in the department.

Cullen, et.al. (16) reported that for the two-echelon system, Adaptive Exponential Smoothing was preferable to Modified Box-Jenkins Model 7 because it is a simpler model and results in comparable average costs.

Kirby (23) compared three methods of forecasting—Moving Average, Exponential Smoothing, and Least Squares—on actual and synthetic data. Kirby indicated that noise (short irregular cycles in the data trends) caused poor performance with Least Squares thus real comparisons were between Moving Average and Exponential Smoothing.

Lusk (24) summed up the forecast model decision process by stating that forecasts should be generated by simple, less costly models and these forecasts compared to management's specifications of the standard error above which the forecast fails to provide relevant planning and control information. If it does not fall in this area, management must decide how much it is willing to pay for more sophisticated models which produce greater accuracy.

**Limitations**

In planning the methodology for this study, several limitations were determined. Forecasts of customers utilizing the cafeteria Sunday through Saturday would be calculated. Entree demand would be evaluated from the same restricted time frame. Data used to pretest the forecast models would be limited to a two year time span prior to the period to be forecasted. One week, out of the four-week menu cycle, would be used for further evaluation of the best forecast model through forecasting of actual entree demand.

**Data Collection**

For several years, the Nutritional Services Department at this medical center has maintained records on the number of customer transactions occurring in the cafeteria each day. These customer transactions are felt to be an accurate reflection of the total number of actual customers utilizing the cafeteria. Although some transactions may include multiple meals paid for by one individual, other transactions may reflect an individual's second or third trip back for purchase(s) of additional items such as beverage, dessert, etc. Using this source of data, Customer Summary forms were completed for the two years prior to the period to be forecasted.

Entree Summary sheets were used to record usage of the two entrees served at the noon meal for one randomly chosen week of the four-week menu cycle. This data was drawn from the three rotations of the menu cycle immediately following Year Two's historical data.

"Total number of servings used on trayline" for patients was subtracted from "total number of servings the recipe made" to yield the number of servings available for sale in the cafeteria. By subtracting the number of servings left over when the hot deck in the cafeteria closed or prorating the number of servings which could have been sold, based on exact time that entree was used up, the number of entree servings used in the cafeteria was calculated.

The number of servings of each entree used in the cafeteria were divided by the total number of customers utilizing the cafeteria that particular day to yield the entree demand percentage. Information from three rotations of the menu cycle were used to obtain an average entree demand percentage.

Development of Computer Programs

Since computers constitute a fast, accurate generation of information, they are useful for processing data such as that dealt with in this research. Programs were written for each of the forecast models as well as for the calculation of forecast errors, Mean Absolute Deviation (MAD) and Bias. In addition, a program to calculate the cost of errors (cost factor) was developed.

Forecast error is the numeric difference between forecasted and actual demand. Mean Absolute Deviation (MAD) is an average of the absolute deviations. Errors are measured in magnitude without regard to sign. Mean Absolute Deviation expresses the extent but not the direction of error. Bias, on the other hand, indicates the directional tendency of the forecast errors. The direction of error (Bias) versus magnitude of error (MAD) is considered when discussing criticalness of forecasting errors.

To determine error costs, Cullen (16) used a cost function which included the food cost of the menu item, a labor-overhead cost component, and a penalty factor to quantify costs associated with over- and under-production. A penalty factor of 1.5 was assigned for overproduction; and a factor of 2.0 for underproduction.

In this research, the cost function was calculated by multiplying the selling price of each food item by the same factors assigned by Cullen. Error costs were then determined by multiplying the absolute deviation of forecasted from actual demand by this cost function.

**Pretesting and Determination of Best Forecast Model**

Pretesting entailed using the historical data collected from Year One to fit the forecast models for actual use on Year Two's historical data. Data in the SMA model were evaluated to determinemine the ideal combination of window length and sequence of days to be used in forecasting. Window length refers to the number of data averaged to obtain the next forecast. In the pretesting stage, window lengths of 3,4,5...14 were used. Data were compared by sequential days (e.g.; Sunday, Monday, Tuesday... Saturday) and by like days (e.g.; Sunday, Sunday, Sunday...etc.)

The ES model was evaluated to determine which alpha value minimized forecast error. In this model, alpha values in 1/100th increments (e.g.; .01,.02,.03 to .99) were used in combination with "like days" as well as "sequential days" grouping of data.

Since the AES model continually modifies its alpha value based upon changes in the underlying demand pattern, the original alpha value used to prime the model is not critical. It was decided that the best alpha value determined through testing of the ES model would be used to initiate this model. All adaptions of the alpha value from this point on were then limited to a (+ or -).05 variation in order to minimize any effect sudden noise might have on the model. The AES model was moved through the data in the two directions mentioned previously, like days and sequential days.

The SMA model requires 14 days of data to prime it for forecasting the longest window length. Because a uniform number of forecasts were desired, all models began forecasting with day 15.

When all the models finished processing Year One's data, forecast errors were evaluated using MAD and Bias. The best combination of data for each model was determined to be the one which minimized MAD or, in the case of a tie, Bias. The second year's data was then processed using the models fitted with only the optimum factors.

Forecast errors for each model were again determined when they had finished processing Year Two's data. Mean Absolute Deviation was used to determine the most accurate model. In addition, an Analysis of Variance test was done to determine whether there was a significant difference between the models being tested.

**Actual Forecasting of Entree Demand**

This step combined all the varied information accumulated throughout the study. In it the best forecast model and factors were further evaluated through use in determining the number of servings of entree that would be utilized at the noon meal in the cafeteria for one week of the four-week menu cycle.

The anticipated number of customers utilizing the cafeteria during the one randomly selected week were forecast using the best forecast model and method as determined previously. The forecast of customer demand was multiplied by the predetermined entree demand percentage to yield the forecast of entree demand. The error was obtained by subtracting the actual demand for the entree from the amount of entree forecast. The absolute value of this error was then multiplied by the entree cost and over/underproduction factor to give the error cost.

The cost of forecast error was calculated on the forecast system presently employeed in the Nutritional Services Department. This system uses a combination of computerized forecasting and intuition and does not forecast for entree demand in the cafeteria as a separate entity from patient demand. The error cost of the present system was compared to that of the best forecast model and method through an Analysis of Variance test.

## RESULTS AND DISCUSSION

### Pretesting and Determination of Best Forecast Model

Simple Moving Average ran several different window lengths through the data in order to determine the ideal combination of window length and sequence of days to be used in future operations. In the pretesting stage, window lengths of 3, 4, 5...14 were used. As seen in Table 1, the lowest MADs were found at a different window length for each day of the week with the data combined as like days.

The ES model was evaluated to determine which alpha value minimized forecast error. In this model, values in 1/100th increments (e.g.; .01,.02,.03... .99) were used in combination with like and sequential days. Findings from testing this model, Table 1, showed that a different alpha was best for each day of the week. Combining data as like

Table 1. Lowest Mean Absolute Deviations (MAD) of forecast models when processing historical data from Year One

| | simple moving average | | first order exponential smoothing | | adaptive exponential smoothing | |
|---|---|---|---|---|---|---|
| days of the week | window length | MAD | alpha value | MAD | alpha value | MAD |
| Sundays | 3 | 186.90 | .68 | 173.77 | .68 | 183.12 |
| Mondays | 5 | 368.31 | .36 | 344.68 | .36 | 362.56 |
| Tuesdays | 5 | 277.31 | .63 | 264.58 | .63 | 283.93 |
| Wednesdays | 3 | 212.48 | .53 | 201.46 | .53 | 219.44 |
| Thursdays | 4 | 242.69 | .58 | 231.40 | .58 | 256.48 |
| Fridays | 3 | 236.11 | .59 | 216.59 | .59 | 234.64 |
| Saturdays | 3 | 190.22 | .91 | 169.29 | .91 | 188.73 |
| sequential days | 8 | 518.18 | .99 | 472.38 | .99 | 565.18 |

days also minimized MAD in this model.

Since the AES model continually modifies its alpha value based upon changes in the underlying demand pattern, the original alpha value used to prime the model was not critical and so the best alpha value determined through testing of the ES model was used to initiate it. All adaptions of the alpha value from this point on were then limited to a (+ or -) .05 variation in order to minimize any effect sudden noise might have on the model.

Table 1 also summarizes the results of processing like and sequential days through AES using the alpha values determined to be best through testing of the ES model. Results again showed that a different alpha value for each day of the week coupled with data entered as like days yielded the best fit.

When all the models finished processing Year One's data, the best fit for each model was evident. The second year's data was then processed using the models fitted with the best combination of window length or alpha value and grouping of days. Mean Absolute Deviations determined after processing Year Two's data are summarized in Table 2.

It should be noted that the alpha value used to prime the AES model for use in processing Year Two's data was different from the one used to prime the model for Year One. Instead, the alpha value used to prime Year Two was the "adapted" alpha value used for the last calculation of Year One's data. This provided continuity since the last alpha value used for processing Year One's data was the first alpha value used to process Year Two's data. For this reason, results seen in Table 2 for AES are at different alpha values than seen for the same model in Table 1.

Overall performance of the three forecast models was evaluated by

Table 2. Lowest Mean Absolute Deviations (MAD) of forecast models when processing historical data from Year Two

| | simple moving average | | first order exponential smoothing | | adaptive exponential smoothing | |
|---|---|---|---|---|---|---|
| days of the week | window length | MAD | alpha value | MAD | alpha value | MAD |
| Sundays | 3 | 100.19 | .68 | 100.48 | .39 | 95.75 |
| Mondays | 5 | 373.24 | .36 | 399.13 | .29 | 405.97 |
| Tuesdays | 5 | 287.04 | .63 | 264.46 | .25 | 284.14 |
| Wednesdays | 3 | 314.11 | .53 | 309.21 | .33 | 291.35 |
| Thursdays | 4 | 253.38 | .58 | 267.52 | .30 | 248.18 |
| Fridays | 3 | 280.16 | .59 | 271.16 | .33 | 257.05 |
| Saturdays | 3 | 135.90 | .91 | 140.50 | .37 | 128.75 |

averaging the MADs for all the days in the week and comparing them. It was found that SMA, ES, and AES all had similar average MADs (249.15, 250.35 and 244.46). Because of the similarity, an Analysis of Variance test was done to determine if any significant difference was present. The Analysis of Variance test indicated that there was not a significant difference between models ($P<.6144$).

Since there was not a significant difference between models and the range between highest and lowest average MAD was so small, it was decided that the SMA model would be used to forecast actual entree usage. The SMA model is a much less complex model to understand and may, in the absence of a computer or programmable calculator, be manually calculated.

**Actual Forecasting of Entree Demand**

A holiday was present in the rotation of the menu cycle immediately following the three over which the entree summary was obtained. Therefore, it was decided that this rotation would not be used to evaluate the SMA model against actual demand. Instead, the rotation of the menu cycle following it was used.

To obtain the forecast of entree demand, two factors were used: Forecast of customer demand and the predetermined entree demand percentage. Forecast of customer demand was calculated by processing historical data through the SMA model. Historical data used to prime the model were from the nine weeks prior to the period to be forecast. The forecast of customer demand for each day was multiplied by the entree demand percentage to obtain the forecast of entree demand (Table 3).

In the final phase of evaluation, each of the forecasts of entree demand were compared to the actual entree demand and the cost of forecast error calculated. As seen in Table 4, total error cost when using

Table 3. Calculation of entree demand forecast

| | window length | customer demand forecast | X | entree demand percentage | = | entree demand forecast |
|---|---|---|---|---|---|---|
| Sunday | | | | | | |
| entree one | 7 | 1123 | | 11.31 | | 127 |
| entree two | 7 | 1123 | | 7.87 | | 88 |
| Monday | | | | | | |
| entree one | 7 | 2121 | | 28.15 | | 597 |
| entree two | 7 | 2121 | | 15.12 | | 321 |
| Tuesday | | | | | | |
| entree one | 4 | 2266 | | 2.29 | | 52 |
| entree two | 4 | 2266 | | 15.42 | | 349 |
| Wednesday | | | | | | |
| entree one | 7 | 2339 | | 16.19 | | 379 |
| entree two | 7 | 2339 | | 8.98 | | 210 |
| Thursday | | | | | | |
| entree one | 5 | 2665 | | 8.67 | | 231 |
| entree two | 5 | 2665 | | 17.28 | | 461 |
| Friday | | | | | | |
| entree one | 7 | 1948 | | 9.15 | | 184 |
| entree two | 7 | 1948 | | 27.13 | | 529 |
| Saturday | | | | | | |
| entree one | 9 | 1024 | | 18.40 | | 188 |
| entree two | 9 | 1024 | | 20.79 | | 213 |

Table 4. Error cost when using Simple Moving Average to forecast entree demand

| 1 entree demand forecast | 2 actual entree demand | (1-2) forecast minus demand | X | 3 over-/under-production factor | X | 4 selling price | = | 5 cost factor |
|---|---|---|---|---|---|---|---|---|
| 127 | 152 | -25 | | 2.0 | | $0.80 | | $ 40.00 |
| 88 | 89 | -1 | | 2.0 | | 0.90 | | 1.80 |
| 597 | 444 | 153 | | 1.5 | | 0.85 | | 195.08 |
| 321 | 323 | -2 | | 2.0 | | 0.90 | | 3.60 |
| 52 | 25 | 27 | | 1.5 | | 0.85 | | 34.43 |
| 349 | 451 | -102 | | 2.0 | | 0.90 | | 183.60 |
| 379 | 339 | 40 | | 1.5 | | 0.85 | | 51.00 |
| 210 | 335 | -125 | | 2.0 | | 0.80 | | 200.00 |
| 231 | 119 | 112 | | 1.5 | | 0.85 | | 142.80 |
| 461 | 372 | 89 | | 1.5 | | 0.80 | | 106.80 |
| 184 | 242 | -58 | | 2.0 | | 0.85 | | 98.60 |
| 529 | 401 | 128 | | 1.5 | | 0.80 | | 153.60 |
| 188 | 60 | 128 | | 1.5 | | 0.90 | | 172.80 |
| 213 | 180 | 33 | | 1.5 | | 0.45 | | 22.28 |
| | total | | | | | | | $1,406.38 |

the SMA model to forecast was $1,406.38.

The cost of forecast error when using the forecast model presently employed in the Nutritional Services Department was then compared to the error cost found when using the SMA model to forecast. To evaluate the system presently in use at the medical center, the figures obtained for "Recipe issued for" on the Entree Summary sheet minus the "Total number of servings used on trayline" were considered to be the forecast of entree demand. These figures were compared with actual entree demand and the error cost calculated in exactly the same way as described above for the SMA model. Error cost for the present system, as seen in Table 5, was $1,453.60.

An Analysis of Variance test was used to determine whether there was a significant difference between the two forecasting systems. At a mean of 280.64 for the SMA model and 265.86 for the current forecast system, results showed no significant difference between the error costs of the two models ($P < .8099$).

**Forecast Models and the Demand Pattern**

Observation of forecast results for the three models, SMA, ES, and AES seemed to indicate a less stable demand pattern for sequential days of the week than for like days. This was reflected in the higher MAD that forecasting for sequential days showed under each model. A more stable demand pattern usually facilitates a more accurate forecast because of the lack of extreme fluctuation in the pattern which the forecast model may be slow to respond to.

Even though grouping of data by like days appears to yield a more stable demand pattern, the number of past periods used to prime the SMA model varied for each day of the week. That is, a different window

Table 5. Error cost when using the medical center's current system to forecast entree demand

| 1<br>entree demand forecast | 2<br>actual entree demand | (1-2)<br>forecast minus demand | X | 3<br>over-/under-production factor | X | 4<br>selling price | = | 5<br>cost factor |
|---|---|---|---|---|---|---|---|---|
| 200 | 152 | 48 | | 1.5 | | $0.80 | | $ 57.60 |
| 100 | 89 | 11 | | 1.5 | | 0.90 | | 14.85 |
| 454 | 444 | 10 | | 1.5 | | 0.85 | | 12.75 |
| 391 | 323 | 68 | | 1.5 | | 0.90 | | 91.80 |
| 72 | 25 | 47 | | 1.5 | | 0.85 | | 59.93 |
| 288 | 451 | -163 | | 2.0 | | 0.90 | | 293.40 |
| 604 | 339 | 265 | | 1.5 | | 0.85 | | 337.88 |
| 205 | 335 | -130 | | 2.0 | | 0.80 | | 208.00 |
| 193 | 119 | 74 | | 1.5 | | 0.85 | | 94.35 |
| 300 | 372 | -72 | | 2.0 | | 0.80 | | 115.20 |
| 194 | 242 | -48 | | 2.0 | | 0.85 | | 81.60 |
| 420 | 401 | 19 | | 1.5 | | 0.80 | | 22.80 |
| 51 | 60 | -9 | | 2.0 | | 0.90 | | 16.20 |
| 250 | 180 | 70 | | 1.5 | | 0.45 | | 47.25 |
| | total | | | | | | | $1,453.60 |

length appeared best for each day of the week when MADs were evaluated. This seems to indicate that a variation in the demand pattern is also present with data grouped as like days but to a lesser degree than with data grouped as sequential days. This variation is minimized by determining a different best window length for each day. The truth of this is substantiated by looking at the window lengths which minimized MAD at the end of Year One and the best window lengths found, upon reevaluation, at the end of Year Two. Only a change in the overall demand pattern for the year could have resulted in a new best window length.

### Identification and Use of Entree Demand Percentage

The methodology for this study indicated that entree demand be averaged over three rotations of the menu cycle to obtain the entree demand percentage. This is the method that was used and reported in the Results section. Upon further evaluation in this research, it was found that an averaging of two, rather than three, weeks yielded a more accurate forecast.

Another factor which may have interferred with forecast accuracy was the timing of the week to be evaluated in relation to the period over which the entree demand was averaged. The rotation of the menu cycle immediately following the three cycles over which the entree summary was obtained included a holiday. Therefore, it was decided that this rotation would not be used to evaluate the SMA model against actual demand. Instead, the rotation of the menu cycle following it was used. Forecast error might have been minimized further if the Entree Summary had been taken from the periods immediately preceding the one to be forecast.

SUMMARY

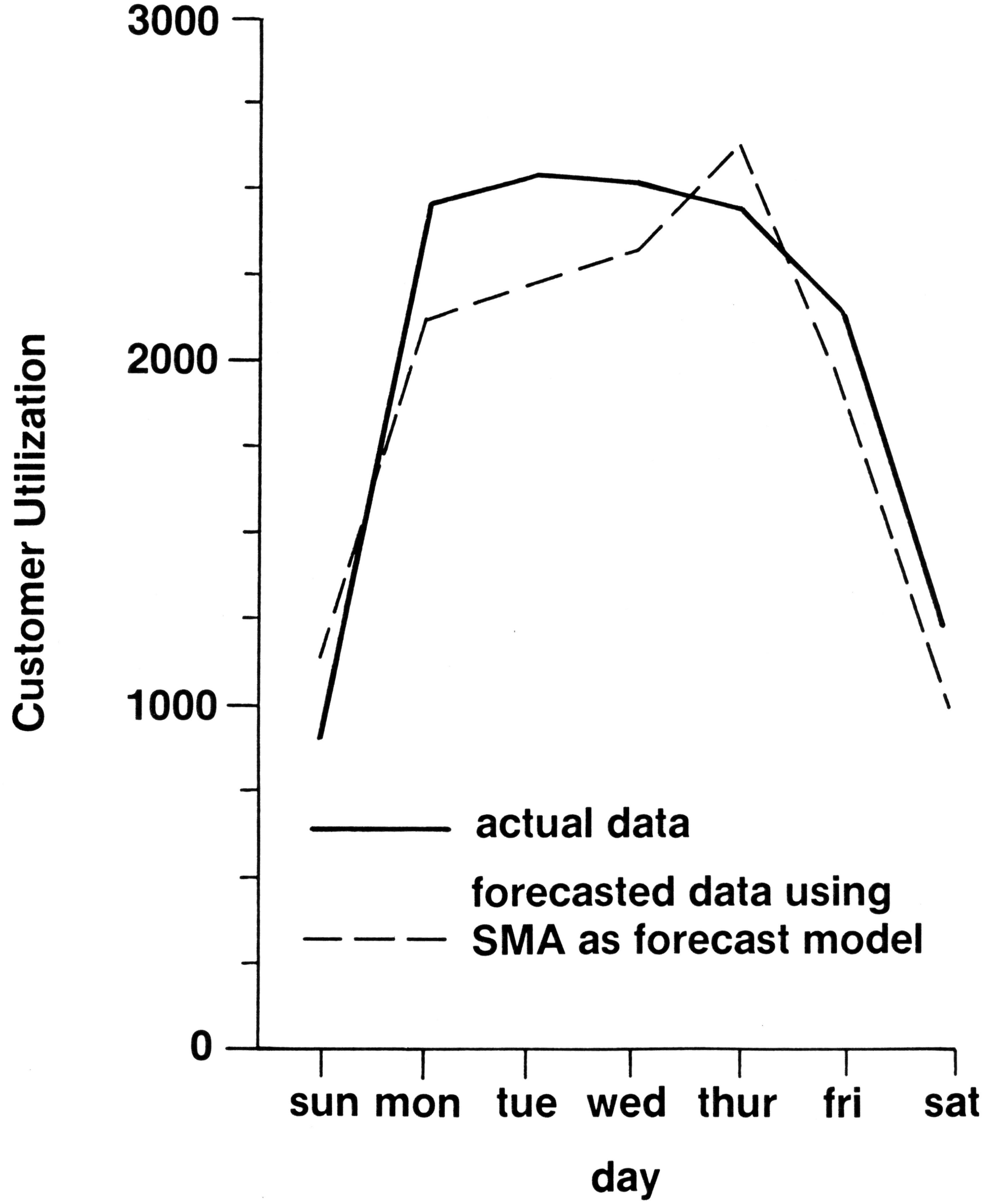
The purpose of this study was to test selected forecast models in a teaching medical center cafeteria. The forecast models were evaluated to determine the one that most accurately predicted the number of cafeteria customers Sunday through Saturday. All three forecast models showed similar results so the simplest model, Simple Moving Average, was chosen for use in predicting the number of servings of entree that would be utilized at the noon meal in the cafeteria for one week of a four-week menu cycle.

The forecast number of entree servings was compared to actual demand and an error cost determined. An error cost was also determined for the forecast system currently in use in this department. When total error costs for the two systems were evaluated using an Analysis of Variance, no significant difference was seen.

When SMAs forecast of customer demand was graphed against actual demand, the resulting curves were very similar (Figure 1). This tends to indicate that the model being evaluated did respond well to changes in the environment. In order to obtain similar results with the model, managers should identify the window length which is best for each day of the week in their establishment. Window lengths should be evaluated independent of each other and for like days only.

The fact that best window length changes over a relatively short period of time based on changes in the overall demand pattern would tend to indicate a need to frequently reassess the window lengths in use. One way of doing this might be to reevaluate the window length after each forecast to determine the best one to use when doing the next forecast. The need to frequently establish new window lengths also tends to sub-

Figure 1. Actual versus forecasted number of customers utilizing cafeteria for one week



3000
2000
1000
0
Customer Utilization
actual data
forecasted data using
SMA as forecast model
sun
mon
tue
wed
thur
fri
sat
day

stantiate that each particular institution must set their own rather than using those determined to be best in this research.

When determining the entree demand percentage, actual demand should be averaged from the two periods just prior to the one being forcast. This percentage should be recalculated each time a forecast is made by discarding the oldest demand and adding in the most recent demand.

Future research in this area might include determination of labor costs involved in using a forecast system such as the one proposed here. Labor cost determination should include time spent obtaining data as well as time spent in actual data processing.

Managers, with no forecasting system for their hospital cafeterias or with a system having a high degree of error, might benefit from the use of any of the models evaluated. Through the future use of a forecast model like the one described here, foodservice managers may generate a more accurate forecast. Food production based on these forecasts might then proceed with less chance of over- or underproduction and may result in increased efficiency and financial gain for the cafeteria.

## REFERENCES


(1) Peryam, David R., Polemis, Bernice W., Kamen, Joseph M., Eindhoven, Jan, and Pilgrim, Francis J.: Food Preferences of Men in the United States Armed Forces. Researched by the Quartermaster Food and Container Institute for the Armed Forces, January, 1960.

(2) Pilgrim, Francis J., and Kamen, Joseph M.: Patterns of food preferences through Factor analysis. J. Marketing, 1959.

(3) Kamen, Joseph: Reasons for non-consumption of food in the army. J. Am. Dietet. A. 41(5):437, 1962.

(4) Dickins, Dorothy: Factors related to food preferences. J. Home Econ. 57(6):427, 1965.

(5) Zunich, Michael, and Fults, Anna Carol: Food preferences of children from lower socioeconomic groups--a geographic study. J. Home Econ. 61(1):47, 1969.

(6) Schuck, Cecilia: Food preferences of South Dakota college students. J. Am. Dietet. A. 39(6):595, 1961.

(7) Van De Mark, Mildred S., and Underwood, Virginia Ruth Sherman: Dietary habits and food consumption patterns of teenage families. J. Home Econ. 63(7):540, 1971.

(8) Pilgrim, Frances J., and Schutz, Howard G.: Monotony in food acceptance. Am. Psychol. 10(8):503, 1955.

(9) Siegel, Paul S., and Pilgrim, Francis J.: The effect of monotony on the acceptance of food. Am. J. Psychol. 71(4):756, 1958.

(10) Schuh, Doris D.: Frequency Ratings as a Measure of Patient Attitudes Toward Menu Item Acceptability. Master's Thesis, Department of Nutrition and Dietetics, University of Missouri Medical Center, Columbia, 1966.

(11) Konnersman, Paul M.: Forecasting production demand in the dietary department. Hospitals. 43(18):85, 1969.

(12) Uhrich, Roberta V., and Noort, Albert J.: Production demand forecasting. Hospitals. 45(3):106, February 1, 1971.

(13) Mackle, Margaret, and David, Beatrice Donaldson: Developing a demand forecasting system for a foodservice operation. J. Am. Dietet. A. 68(5):457, 1976.

(14) Tienor, Cynthia, and David, Beatrice Donaldson: A dietary department applies procedure for developing a demand forecasting system. J. Am. Dietet. A. 68(5):460, 1976.

(15) Messersmith, Ann Marie: Design of a Multi-Echelon Menu Item Forecasting System. Unpublished Ph.D. dissertation, University of Missouri-Columbia, 1975.

(16) Cullen, Kathleen O'Connor, Hoover, Loretta W., and Moore, Aimee N.: Menu item forecasting systems in hospital foodservice. J. Am. Dietet. A. 73(6):640, 1978.

(17) Nichols, Dixie Kay: The Development of a Technique to Compile Accurate Patient Demand Statistics for Menu Item Forecasting. Unpublished Master's Thesis, University of Missouri-Columbia, 1973.

(18) Dougherty, D.: Forecasting Production Demand. In Rose, James C.: Handbook for Health Care Food Service Management. Rockville, Maryland: Aspen Systems Corporation, 1984.

(19) Adam, Everette, and Ebert, Ronald: Production and Operations Management, 2nd ed. Engelwood Cliffs, N.J.: Prentice-Hall, Inc., 1982.

(20) Trigg, D.W., and Leach, A.G.: Exponential smoothing with an adaptive response rate. Op. Research Q. 18(1):53, 1967.

(21) Chambers, John S., Mullick, Satinder K., and Smith, Donald D.: How to choose the right forecasting technique. Harvard Business Review. 49(4):55, 1971.

(22) Harris, Ronald J.: Forecasting Patient Tray Census Within a Medical Complex—a Comparative Evaluation of Forecasting Techniques. Unpublished Master's Thesis, University of Missouri-Columbia, 1972.

(23) Kirby, Robert M.: A comparison of short and medium range statistical forecasting methods. Management Science. 13(4):202, 1966.

(24) Lusk, Edward J.: A suggested process for selecting a forecasting model. Hosp. Health Serv. Admin. 25(Special Issue):23, 1980.