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Short Interval Forecasting of Emergency Phone Call (911) Work Loads

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EXECUTIVE SUMMARY

There has been an increasing emphasis over the last 5 to 10 years to improve productivity in the Service Sector of the U.S. economy. Much of the improvement obtained by these managers has come about through better scheduling of the work force in these organizations. Effective scheduling of this personnel requires good estimates of demand, which may exhibit substantial variations between days for certain times of the year. The Indianapolis Police Department (IPD) Communications area is one such organization that exhibits varying workloads and is interested in improving staff scheduling of dispatch operators.

This article explores the use of six different forecasting techniques for predicting daily emergency call workloads for the IPD's communications area. Historical call volume data are used to estimate the model parameters. A hold-out sample of five months compares forecasts and actual daily call levels. The forecast system utilizes a rolling horizon approach, where daily forecasts are made for the coming month from the end of the prior month. The forecast origin is then advanced to the end of the month, where the current month's actual call data are added to the historical database, new parameters are estimated, and then the next month's daily estimates are generated. Error measures of residual standard deviation, mean absolute percent error, and bias are used to measure performance. Statistical analyses are conducted to evaluate if significant differences in performance are present among the six models.

The research presented in this article indicates that there are clearly significant differences in performance for the six models analyzed. These models were tailored to the specific structure and this work suggests that the short interval forecasting problems faced by many service organizations has several structural differences compared to the typical manufacturing firm in a made-to-stock environment. The results also suggests two other points. First, simple modeling approaches can perform well in complex environments that are present in many service organizations. Second, special tailoring of the forecasting model is necessary for many service firms. Historical data patterns for these organizations tend to be more complex than just trend and seasonal elements, which are normally tracked in smoothing models. These are important conclusions for both managers of operating systems and staff analysts supporting these operating systems. The design of an appropriate forecasting system to support effective staff planning must consider the nature, scope, and complexity of these environments.

INTRODUCTION

The last few years has seen increased emphasis in improving productivity in the service sector of the U.S. economy. Much of this improvement has come through better scheduling of the work force providing the service. Improved predictions of future work

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loads over a short interval, such as a day, are a necessary input to the short interval scheduling process of the work force.

The Indianapolis Police Department's Communications Department is one such service unit needing good forecasts of future work loads. The effective utilization of communication operators requires knowledge of incoming emergency calls (911 exchange) and the coordination of police patrol activities. With increasing labor costs and limited municipal budgets, the appropriate scheduling of staff to meet incoming emergency calls requires good forecasts of demand, in which call levels are influenced by many complex behavioral factors.

The Indianapolis Police Department (IPD) operates a communication center in their downtown headquarters. IPD employs over one hundred communication operators, who must be scheduled in such a manner that adequate staff is present 24 hours a day, 7 days a week. In general, emergency phone calls initiate the operator's work load. An operator answers a call, collects the information, reviews the current patrol car assignment and dispatches an available officer/car to service the call.

Forecasts for daily work loads are needed for routine staff scheduling, with work schedules based upon a 28 day work cycle. In particular, vacation, bonus days, and personal days are exceptions the shift supervisors must work into the schedule. Bonus days are earned extra days off when an operator works a holiday such as Christmas day. In a year, an operator will normally have 25–35 planned days-off owing to vacations, bonus, and personal.

During the summer of 1981, IPD was interested in implementing a forecasting system that would provide supervisors with the ability to anticipate different work loads in advance and thus staff accordingly. In the past, little formal planning had taken place, resulting in excess staff on some days or substantial overtime usage on others. Budget pressures to control costs and still provide effective service motivated a close look at the communication area's operation. IPD decided to develop a formal planning system to improve operations [11]. One important element of this system was a good forecasting procedure.

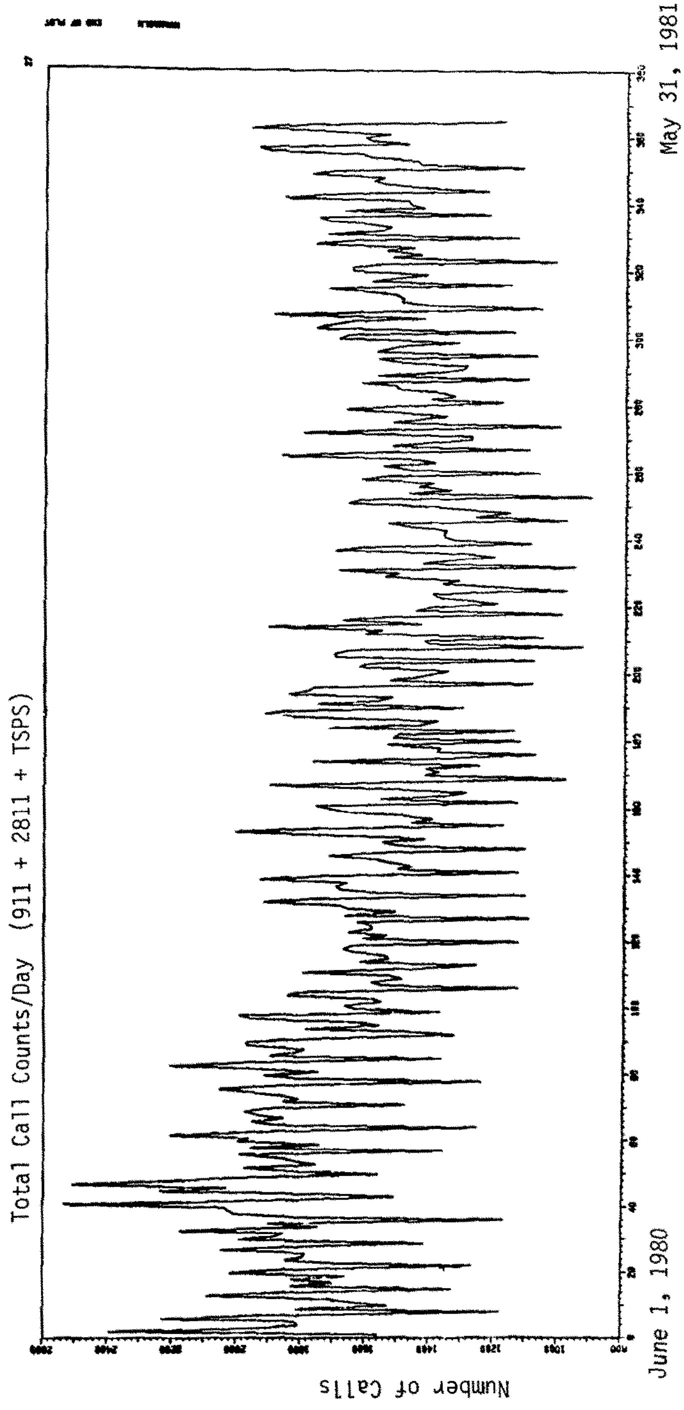
This article explores the use of six different forecasting techniques for predicting daily emergency call work loads for the Indianapolis Police Department (IPD). Historical call volume data are used to estimate the model parameters. A hold-out sample of five months compares forecasts and actual daily call levels. The forecast system utilizes a rolling horizon approach, where daily forecasts are made for the coming month (m) from the end of the prior month ($m - 1$). The forecast origin is then advanced to the end of month m, month m's actual call data are added to the historical database, new parameters are estimated, and then the next month's ($m - 1$) daily estimates are generated.

First, a description of historical IPD emergency call data is presented. Then industry practice and relevant research are reviewed. Six forecasting models are suggested for predicting daily call volumes. The six approaches are then compared using the performance criteria of residual standard deviation, mean absolute percent error (MAPE), and average residual error (bias). The conclusion indicates the implications of this study to the short interval forecasting problem faced by many service organizations.

IPD EMERGENCY CALL DATA

Daily emergency call volumes at IPD are not constant over time. Figure 1 presents a one year plot of daily calls, indicating calls ranging from less than 1000 to over 2000 per

FIGURE 1
Daily Call Activity



day. A closer review of the data indicates two other elements present. First, the number of calls tend to be higher during the summer months and lower during the winter, indicating a seasonal pattern based upon time of year. Second, there is a seven-day cycle in the data that relates to the day of the week.

The impact of the monthly and daily patterns are highlighted more clearly in Figures 2 and 3 for the same period as shown in Figure 1. Figure 2 presents the average daily call rate within each month, illustrating the dramatic differences in volume between the peak of July and the valley of January. In general, the summer months have greater work loads because of greater population activity during the warmer weather. This results in more crime, disturbances, and accidents. Figure 3 indicates the change in call rates due to different days of the week. Monday through Thursday experience similar levels. Friday and Saturday experience greater calls rates, while Sunday has a much lower work load.

Not as obvious from Figures 1 to 3 is the presence of certain days during the year that have unique emergency call levels. For example, the Indianapolis 500 race, Labor Day, New Year's Eve, and Halloween are times when call levels increase substantially. On the other hand, Christmas and Thanksgiving tend to have a lower number of emergency calls, reducing the need for staff in the communications area.

As one can see, the daily work load patterns present at IPD are controlled by many factors. Such an environment creates a unique challenge that must be addressed in a structured manner. In the next section a review of relevant forecast literature is conducted for this problem.

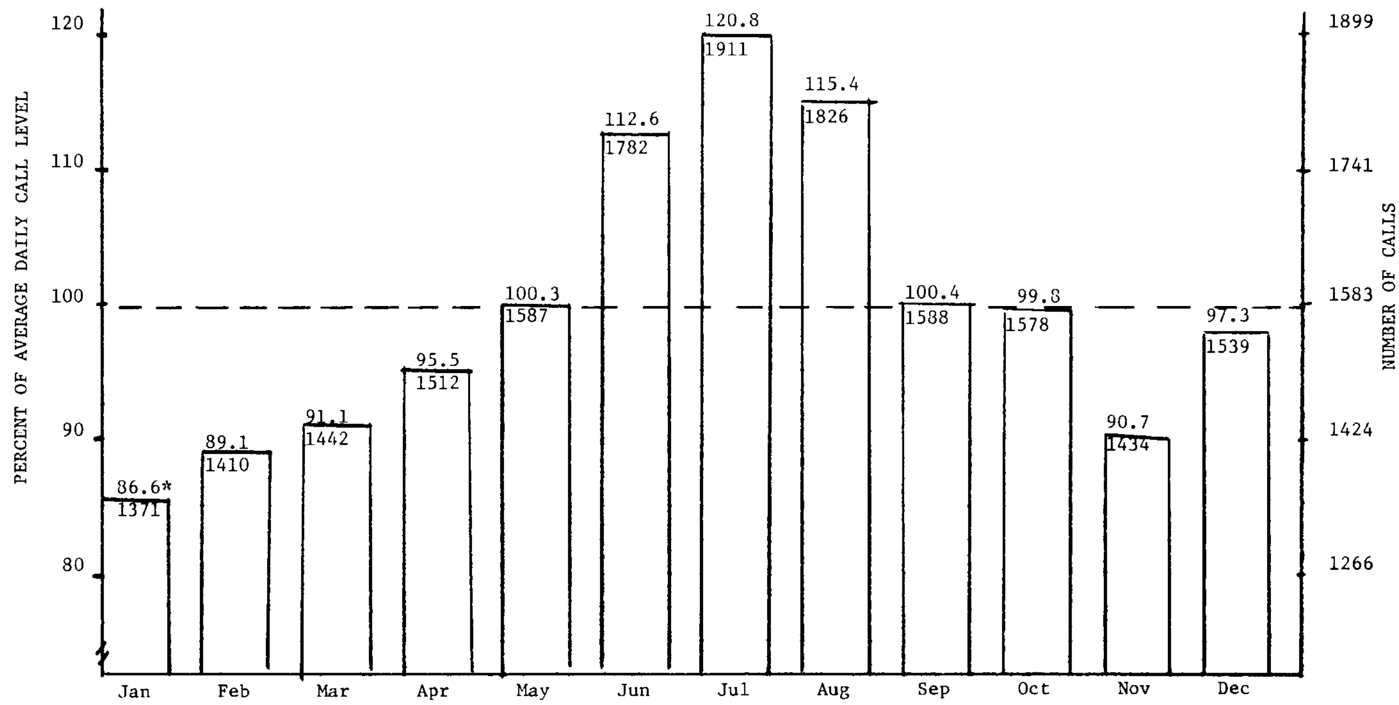
LITERATURE REVIEW

A review of recent literature shows little published research has appeared concerning the subject area of daily forecasting of telephone calls. Two implemented systems were identified, however, which provide some useful information on two approaches to forecasting in practice. Buffa, Cosgrove and Luce [7] present a daily forecasting model using a Box-Jenkins univariate time series approach. It incorporates historical call levels as far back as one year to predict a corresponding day one year later. The daily forecasted calls are converted into hourly estimates by using historical percentages of within-day call levels. This system was implemented by GTE for telephone operator scheduling.

The author also visited with staff from Indiana Bell to discuss their approach to forecasting daily telephone call activity. They utilize a proprietary system called "FMS/FRPS" provided by McDonnell Douglas Automation Company (McAuto). Telephone exchange centers are connected to St. Louis, where quarter hour telephone call history is maintained and used for forecasting. Only limited information was available on the system's internal logic, but an overview of the system was identified. Each user exchange routinely (weekly) estimates daily call traffic, based on past year work loads and judgement. Using these daily total estimates, half hour or quarter hour estimates are developed from historical within-day averages. These estimates become the basis for the determination of operator requirements within the exchange.

Two other articles were identified that focused on the forecasting function within the communication industry. Thompson and Tiao [16] developed forecasts for monthly inward and outward station movement using the Box-Jenkins univariate methodology. These forecasts would be used for staff determination for equipment installation and removal. Brubacher and Hiscock [6] utilized multivariate Box-Jenkins to predict monthly

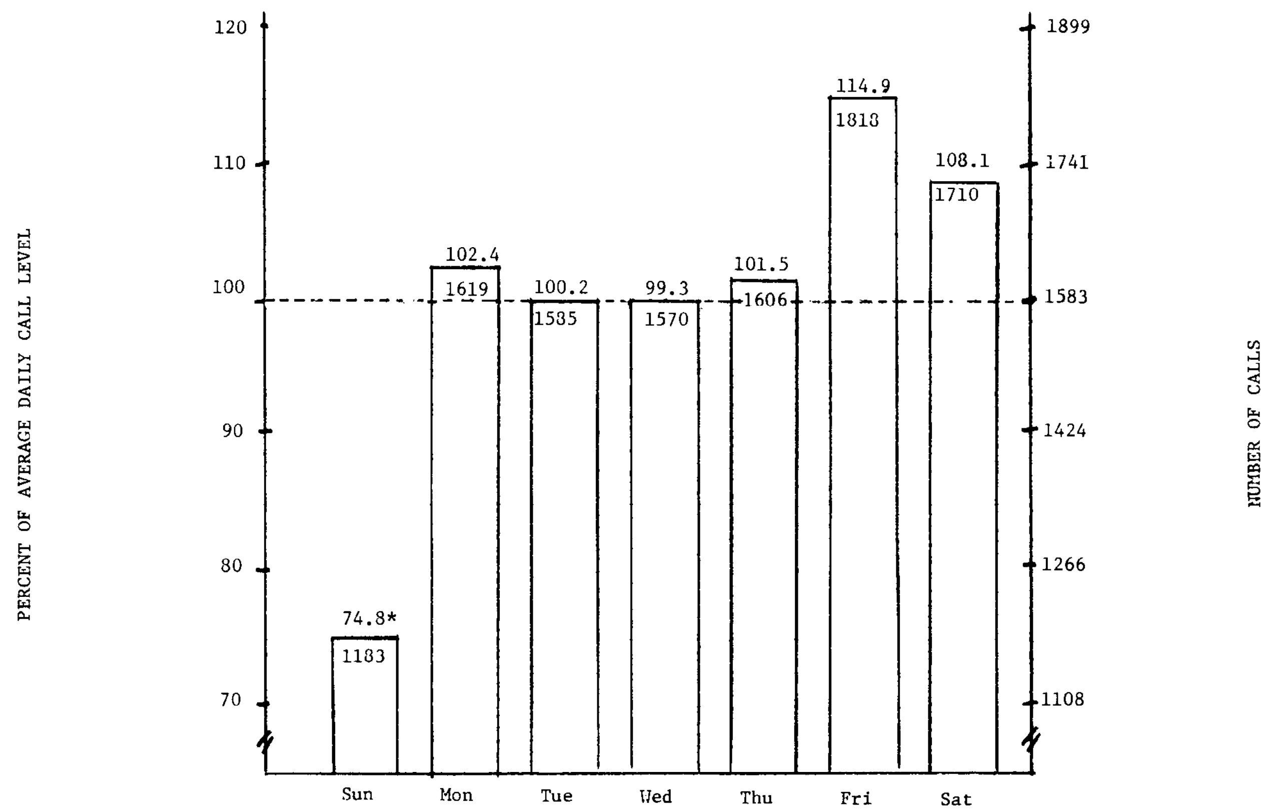
FIGURE 2
Daily Call Level by Month



Note: Above line indicates percent of daily average (1583), below line indicates average calls (911 + 2811 + TSPS) by month

FIGURE 3

Daily Call Level by Weekday



Note: Above line indicates percent of daily average (1583) below line average daily call (911 + 2811 + TSPS) by day of week usage rates of public telephones in Ontario and Quebec, when prices change. These forecasts provide estimates of revenues from public phone installations.

Some relevant research has been conducted in the banking industry, which exhibits three similar demand elements identified in the IPD data. First, banks, like many service organizations, are faced with demand patterns that are not equally spaced over time. Boyd and Mabert [4] demonstrate that demand can vary by date within a month for the check processing area within a commercial bank. Since months are not of equal length, some confounding can occur if one uses a lag of 30 when month lengths of 28, 29 or 31 days are present. Boyd and Mabert demonstrate the use of a zero/one multiple regression model to solve the issue. Second, multiple cycles can exist in the time series, where both between-month and between-day seasonal variations are present. Therefore, tracking these patterns for changes and recognizing when a significant shift has occurred becomes a more difficult process. Finally, special events, like holidays, influence work loads. Often these events do not cycle over regular intervals and their influence may last a single day or as long as a week. Mabert and Hill [12] illustrate how one could include the single day special events into an ARIMA model through the use of dummy variables. Berry, Mabert, and Marcus [1] show that special factors can be incorporated with an exponential smoothing model [17] to predict daily branch bank traffic levels.

In viewing the work done to date on daily forecasting, a number of approaches ranging from simply using last year's call rates to more complex Box-Jenkins models have been identified. Six models will now be described that represent a cross section of sophistication. These will provide the basis for a comparative analysis not reported in prior research.

FORECASTING MODELS

Six forecasting models were identified for forecasting daily call levels from a time origin t. The first model represents a naive approach, while the remaining five model structures are designed to capture the daily, monthly, and special event patterns in the data. The six models are

Model #1: One Year Lag (OYL)

$$F_{t+n} = C_{t+n-364} \tag{1}$$

where: F_{t+n} = forecasted number of calls on day $t + n$ in the future
C_t = actual calls on day t
t = forecast time origin

Model #1 looks back 364 days and uses the actual call levels on that day and uses last year's level as a forecast. The use of 364 allows the different days of the week to be matched against similar days one year ago.

Model #2: Zero/One Regression (ZOR)

$$F_{tdmh} = B_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n \tag{2}$$

where: F_{tdmh} = forecast for day d in month m with special event h present from time origin t.
X_i = zero/one variable for event i [month (m), weekday (d) and special day (h)]

This regression model is similar to the one reported by Boyd and Mabert [4] in use at Chemical Bank. Equation (2) is reestimated every month as the most recent month's call activity data become available.

Model #3: Multiplicative/Additive (MA)

$$F_{tdmh} = C_t \cdot I_d \cdot I_m + S_h \quad (3)$$

where: C_t = daily average for the last 365 days from origin t.
I_d = seasonal index for week day d (d = 1, 2, . . . , 7).
I_m = seasonal index for month m (m = 1, 2, . . . , 12).
S_h = impact of special day h.

Equation (3) represents a multiplicative forecasting model using indices for day and month patterns, with an additive special-day factor present. This model, like ZOR, is updated when a new month's data become available. The model's coefficients are estimated using the Hooke-Jeeves pattern search procedure [9].

Model #4: Zero/One with adjustment (ZORA)

$$F'_{tdmh} = B_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n + DELTA_{m-1} \quad (4)$$

where: F'_{tdmh} = the adjusted forecast for day d in month m with special event h present from time origin t.
$DELTA_{m-1}$ = the adjustment to F based upon the average of month m − 1 residual value, given by

$$\frac{(C_k - F_k)}{K}$$

C_k = actual number of calls on day k
K = number of days in month m − 1
F_k = the base forecast for day k using model ZOR, without any error adjustment.

The ZORA model follows the same procedure as ZOR. However, future forecasts are adjusted by $DELTA_{m-1}$, which represents a tracking signal on the prior month's average errors with ZOR as the base forecasting model. If ZOR has consistently underestimated the daily estimates in month m − 1, then $DELTA_{m-1}$ will be greater than zero and month m's forecasted will be increased. The reverse is also true when overestimating occurs. This model recognizes the presence of possible short-run changes that need to be included in the forecasts.

Model #5: Multiplicative/Additive with Adjustment (MAA)

$$F'_{tdmh} = C_t \cdot I_d \cdot I_m + S_h + DELTA_{m-1} \quad (5)$$

Equation (5) is the combination of the MA model with the $DELTA_{m-1}$ tracking signal logic. The MAA uses the average errors from the base MA model in the prior month to adjust future forecasts (F′). If MA has consistently over- or underestimated month m − 1, then the next month's daily forecasts would be changed in the appropriate direction. As with ZORA, MAA utilizes the base MA model's errors for improvement.

Model #6: ARIMA Intervention (ARIMA)

$$F_{t+n} = C_{t+n-364} + \theta_{28}A_{t+n-28} + S_hY_h \quad (6)$$

where: A_t = errors present on day t ($C_t - F_t$)
θ_{28} = moving average coefficient

Y_h = a zero/one time series that indicates the absence/presence of the impact of event S_h

S_h = impact of special event h

Equation (6) represents the identified intervention model suggested by Box and Tiao [3]. It was developed after analyzing two years of daily call activity using the three-step procedure of Identification, Estimation, and Diagnostic Checking suggested by Box and Jenkins [2]. It is interesting to note that the model suggests yearly patterns (lag of 364 days on C_t) and prior month's levels (lag of 28 days on A_t). In this case the lag of 364 days captures the yearly cycle and weekday pattern in one value. The lag of 28 days on past forecast errors recognizes the presence of short-run shifts overtime.

MODEL ANALYSIS

The historical call data for IPD were partitioned into two segments: preforecast origin and postforecast origin. The preforecast origin data were used to estimate the six models' parameters for predicting the next month. The postforecast origin data represented a hold-out sample allowing for an evaluation of forecast accuracy by looking at the daily errors present.

The six models were used within a rolling horizon framework. Five months of daily forecasts were generated from March to July, 1981 for a total of 153 days. In this study, each day in March was forecasted using the last day in February as the origin. Only data prior to the origin was used in generating the forecasts. Then the forecast origin was moved to the end of March. The March data was then incorporated into the data set to reestimate model parameters. With the estimation complete, daily forecasts for April were predicted. This process was repeated for each of the five months.

The five months of daily forecasts were compared against actual call rates. Three error statistics were utilized to measure performance: the residual standard deviation, mean absolute percent error (MAPE), and monthly bias range.

The results are summarized in Table 1. The OYL model is clearly the poorest, with the largest residual standard deviation and MAPE. ZORA has the lowest errors, closely followed by MAA model. The ARIMA model ranks third out of the six.

Table 2 presents a paired evaluation of the residuals for the six models. Using the error variance of the six models, 'F' values were computed and compared to critical values at 153 degrees of freedom. Clearly the ZORA and MAA provide statistically better performance. ZORA is statistically different for all paired tests at a .01 level of confidence, except for MAA. MAA and ARIMA are significantly different at the .05 level of confidence. It is clear that ZORA, MAA, and ARIMA models are superior performers over OYL, ZOR, and MA.

The resources required to generate forecasts are also important in forecasting. Resource requirements can be broken down into two parts: 1) the time required to forecast, and 2) the user skill requirements to understand and implement a forecasting system. Table 3 presents the computer execution time, measured in CPU seconds, and computer core size requirements for estimating model coefficients, plus forecasting daily call levels for the next month. The ZORA model used the SPSS [14] system to estimate coefficients. This was linked to a FORTRAN program to do the residual adjustment and forecast future days. This approach required less than 9 seconds to estimate and update, with a 50,000 word core requirement. MAA used the Hooke-Jeeves pattern search procedure

TABLE 1
Five Month Daily Summary of IPD Emergency Calls

Model	Residual standard deviation (calls)	MAPE	Monthly Bias Range
#1 One year lag (OYL)	315	16.4%	−313 to +249
#2 Zero/one regression (ZOR)	254	14.9%	−322 to +246
#3 Multiplicative/additive (MA)	253	14.7%	−328 to +240
#4 Zero/one regression (ZORA) with adjustment	189	9.4%	−1 to +364
#5 Multiplicative/additive (MAA) with adjustment	203	10.3%	+18 to +445
#6 ARIMA intervention (ARIMA)	237	12.3%	−221 to +197

Note: Each month's (M) dialy calls were forecasted after updating with prior month's (M − 1) actual call rate experience.

written in FORTRAN [9]. MAA required about a threefold increase in computer time, with only half the core size needed. The ARIMA approach required the greatest core, with CPU time between ZORA and MAA.

Ease of understanding of a forecasting model is always important, since it influences implementation and use. It is difficult to give an objective measure of ZORA, MAA, and ARIMA. If one reviews introductory statistic texts as a possible indication of difficulty, one will not normally find dummy variable regression or ARIMA models discussed. On the other hand, index numbers are often present and require less mathematical sophistication to understand. Therefore, models like MA and MAA will require less user sophistication than ZORA or ARIMA to implement. Of course, many new developments in automating many complex data analysis techniques like Box-Jenkins may reduce this problem of required user sophistication.

TABLE 2
Pair Significance Tests of Six Models

	Model					
Model	OYL	ZOR	MA	ZORA	MAA	ARIMA
OYL	—	1.53	1.55	2.77	2.40	1.76
ZOR	.01	—	1.00	1.80	1.56	1.14
MA	.01	.99	—	1.79	1.55	1.13
ZORA	.01	.01	.01	—	1.15	1.57
MAA	.01	.01	.01	.25	—	1.36
ARIMA	.01	.25	.25	.05	.05	—

Note: Values above the diagonal indicate the computed 'F' values for each paired residual variances. Values below the diagonal indicate the α probability of the paired variance test not being significantly different at 153 degrees of freedom.

TABLE 3
Computer Time Requirements Per Update for Six Models

Forecast Model	Execution CPU Seconds*	Computer Core**
#1 One year lag (OYL)	.5	5,000
#2 Zero/one regression (ZOR)	8.1	50,000
#3 Multiplicative/additive (MA)	23.1	22,000
#4 Zero/one regression with adjustment (ZORA)	8.5	50,000
#5 Multiplicative/additive with adjustment (MAA)	23.4	22,000
#6 ARIMA intervention (ARIMA)	14.6	111,000

* All runs were made on a CDC 6600 at Indiana University.
** Core size is measured in Octal words.

IMPLEMENTATION

IPD implemented the Multiplicative/Additive with Adjustment (MAA) model for forecasting daily call and run activity for communications staffing. At the end of each month, the latest month's data are included in the historical database for parameter estimation. Then daily forecasts are made for a 6-week forecast horizon. The 6-week horizon is used because of the 2–3 day lag between data availability and the time new forecasts are actually generated. Under this approach, the communications department staff scheduler can see what work load estimates are for the current month and the first week of the next month.

The daily work load forecasts are broken down into hourly increments within a day using historical percentages for each day of the week. During the review of this research, a referee suggested that forecasting of hourly calls directly should have been conducted, including the historical daily percentages in the analyses. Four reasons provided the basis for not following this approach. First, a statistical analysis of within-day percentages indicated no differences were present between similar days, Friday to Friday, Sunday to Sunday, etc. Second, forecasting daily volume was more critical to IPD planning. Third, the addition of more complexity to directly forecast hourly volumes was counter to a desire for system simplicity. And fourth, the author noted earlier that using historical within-day percentages was a generally accepted approach followed at GTE and Indiana Bell.

Hourly operator requirements are determined from a simulation model that was written in SLAM [13]. Based on different call and run work load rates, the simulation model duplicated expected service performance with various operator staff levels. Service goals of responding to 90–95% of all communications within ten seconds provides the target to specify the needed staff level.

CONCLUSIONS

This article has presented the short interval forecasting problem within the IPD Communications Department and the comparison of six different time series projection techniques. The time series contained two seasonal patterns (daily and monthly) and four approaches (ZOR, MA, ZORA and MAA) were designed to incorporate them in either an additive or multiplicative model. Due to the presence of unique events in the time series, special factors were introduced into five of the six models investigated. The ZORA and MAA models performed statistically better for the five-month test sample under investigation, with the ARIMA approach placing third out of the six tested.

It is interesting to note that the ARIMA approach did not adequately accommodate the patterns present in the IPD data. The poor performance of ARIMA reported in this study was also noted by Boyd and Mabert [4] when analyzing the daily forecasting problem at Chemical Bank. The evidence to date suggests that the standard time series models (i.e., ARIMA [2] and exponential smoothing [17]) may not be appropriate for the forecasting problem faced by any service organizations.

This study, and prior research in banking [1, 11, 12] and the fast-food industry [13], suggest that the short interval forecasting problem faced by many service organizations has several structural differences compared to the typical manufacturing organization in a make-to-stock environment. The differences are: 1) a forecast interval of one day, 2) a forecast horizon of one to six weeks, 3) the presence of multiple patterns (daily and monthly), and 4) the influence of special events such as holidays. Even though these differences are present, there is still a need for forecasting procedures that are simple, easy to implement, and transparent to the user.

The results of this analysis suggest two points. First, simple modeling approaches, like MAA, can perform well in complex environments. This reinforces some observations made by Groff [8] when comparing exponential smoothing to more sophisticated methods. Second, special tailoring may be necessary for the forecast model for service firms. Historical data patterns for service organizations tend to be more complex than just a trend and seasonal element, normally tracked in smoothing models [17]. This points out the critical fact that good forecasting requires careful analysis and judgement. Blindly applying a set of equations may not produce the best forecasting system.

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