ABSTRACT

This paper discusses the financial modelling and rate-setting used at a large government computer center. The discussion includes how to build a workable financial model and the selection of data sources for the forecasting process. Several SAS/ETS® procedures were used to predict workload growth for a six months period, and the results were tracked against actual usage. Guidelines and recommendations for forecasters based on this study are included.

THE PARKLAWN COMPUTER CENTER

The Parklawn Computer Center (PCC) was established to fulfill the automatic data processing needs of the United States Public Health Service and its constituent agencies. Among the many organizations serviced are the regional offices of the Department of Health and Human Services (DHHS); the Office of the Assistant Secretary for Health; the Alcohol, Drug Abuse, and Mental Health Administration; the Food and Drug Administration; the Health Resources and Services Administration; the Consumer Products Safety Commission; the National Institute for Occupational and Safety Health of the Center for Disease Control; and, components of the Social Security Administration. A small amount of processing is also done for the Internal Revenue Service, United States Information Agency, Department of Agriculture, Commodities Futures Trading Exchange, and others.

Although PCC does not sell services in the manner of commercial service bureaus, marketing to any interested parties, use of PCC services and facilities is on a cost-recovery, fee-for-service basis. An environment in which users are charged for resources consumed supports the goal of providing the best possible data processing at the least possible cost.

PCC maintains a central computer facility consisting of one IBM 3090 Model 200 and two 3081 Model K central processing units, telecommunications equipment supporting a nationwide network of COMTEN front-end processors, data storage equipment (reel tape, cartridge tape, 3350 and 3380 disk drives, mass storage devices, and associated controllers), card reading and punching equipment, and output devices including impact printers, laser beam electrostatic printers, plotters, and microfiche processors. The 3090-200 has a Vector Facility attached.

BUILDING A FINANCIAL MODEL

PCC has been performing annual revenue forecasting since its inception in 1968. The fee-for-service nature of the Center has always required an intelligent estimate of future revenue and costs. We felt that it would be unfair to our users, and a poor management practice, to adopt a method which would simply zero-balance expenses and revenue on a monthly basis—an approach used in some government computer centers in the 1970's. By setting rates on a yearly basis, the users would be able to plan and budget in a reasonable manner. The rates for the next fiscal year, which starts in October, are set in July or August.

The goal of the revenue setting process is to slightly overestimate the required income, allowing small rebates several times a year to bring us into a zero balance. Management has never been confident enough in any forecasting process to attempt to totally zero-balance through the rate-setting process. If there was any error which caused an underrecovery, we would be forced to go out and "beg" for money to cover our bills.

The approach we use is, of course, applicable to any computer center, whether profit or not-for-profit. The accuracy of revenue forecasting is equally important regardless of your goals.

PCC bills its users for all data processing services that they receive. Bills for jobs and teleprocessing sessions are created on a nightly basis, and merged with one-time service charges at the end of the month. Users can obtain a daily printout of their charges, and are given a consolidated hard-copy on a monthly basis.
As part of the end-of-month processing, a file is generated that summarizes all revenue for each of the forty-eight categories for which we bill. The summary dataset, which will be referred to as the Revenue Series in this paper, consists simply of one record per month. For simplicity and use in other aspects of the Center's financial management systems, the charges are also grouped into larger Service Categories. A Service Category is defined as a major area for grouping similar DP services so that costs and revenues can be analyzed.

The advantage of using the Revenue Series is that it is relatively easy to obtain and work with. Almost any computer center which generates costs for users would have this data available. Our online file has all revenue from 1980 to the present, yet only uses several 3380 tracks. A more complex file may yield additional insights, but this combines a great deal of information in a compact form.

The simplest model used in the annual rate-setting process, using linear regression and averaging for most components, consists of equations which cover all the forty-eight basic revenue sources for which we bill. For each category, the Average Monthly Revenue (AMR) can be calculated:

\[ \text{AMR} = \text{Number} \times \text{Base} \times \text{Rate} \times \text{Discount} \times \text{Growth} \]

where Number is items in the category, such as jobs or sessions; Base is the item being measured, such as Disk I/Os or minutes of connect time; Rate is the current or proposed charge per unit; Discount is the effect on the revenue brought about by jobs run at discount, such as overnight or low priority work; and, Growth is the expected annual rate of increase in this category.

For example, the revenue estimate for batch CPU charges is:

- N=average number of jobs per month
- B=average CPU seconds per job
- R=CPU rate per second
- D=% of CPU time processed at discount rates
- G=Annual growth rate for batch jobs

Traditionally, the N variable was a mean value derived from the April-June billing data. The current value of B can be calculated by dividing the AMR by (N*Current rate). The Discount component, D, is obtained from the system measurement database, in PCC's case, MICS*. G was the annual change in N, often modified to take into account outside factors that affected users' processing such as major federal budget cuts, new CPUs, new software offerings, etc. Thus, the summary of the equations would yield the revenue for a typical month midway in our fiscal year.

A more useful form of the model is one that can be used to predict the revenue for each month of the year. Among other features, the monthly model assuages the concern among senior management that usually occurs in January or February when the monthly averages have not yet been reached. The easiest expansion requires only:
\[ AMR(i) = N \times B \times R \times D \times S \times G^{(1/12)} \times i \]

for \( i = 1 \) to \( 12 \)

with the annual growth rate, \( G \), being calculated on a monthly basis, and a new term \( S \), reflecting the monthly seasonal component of change. The purpose of our forecasting is to generate a useful form of this model.

**DATA SOURCES**

One of the more complex issues in forecasting is choosing the types and ranges of data necessary to obtain useful predictions. One can spend endless time and energy gathering more and more complex data with often little benefit. One of our objectives was to work with series that are easily obtained and evaluate the results.

Only three areas are evaluated in this paper: batch, TSO, and Model204 an inverted database management system. These three areas encompass most of the difficulties faced by forecasters.

Two series were extracted from the Revenue Series, the monthly summary of billing data. First, the Count Series, consisting simply of one observation per month with batch job counts, and TSO and Model204 sessions. Variable names are BATJOB, TSOSESS, and M24SESS, respectively.

The second data series, referred to as the Financial Series, was developed in an attempt to universalize financial and historical revenue information across a number of years. This series is used to search for "pure" growth by eliminating the effects of rate changes and machine upgrades. PCC has historically reduced rates nearly every fiscal year, often in the range of twenty-five percent. We have also made CPU changes and upgrades, and had major customer arrivals and departures.

This data, in conjunction with the changes in data processing that occur over any extended length of time, invalidate some fields in the Revenue Series for use in forecasting. For instance, predicting TSO usage and growth based on total TSO revenue would be false when if crossed a fiscal year boundary where a rate change occurred.

We have also found that the characteristics of both batch jobs and teleprocessing sessions change when new CPU resources are put in place. This was illustrated when we switched from an overloaded 3033 CPU to a 3081 in 1984--TSO sessions stayed approximately the same length, at 22 minutes per session, but the CPU time used per session doubled. This makes forecasts over long periods of time based solely on the Count Series misleading.

The Financial Series is a subset of the Revenue Series. However, it deals with revenue at the Service Category level rather than at the billing item level. If we could accurately predict large blocks of the financial model, such as TSO or Batch revenue, the model could be greatly simplified. Even though many of the 48 equations in the complete model are relatively constant, it is still burdensome to work with.

Therefore, the Financial Series contains only identifying information and variables for total batch revenue (BATREV82), TSO revenue (TSOREV82) and Model204 revenue (M24REV82) with each monthly dollar revenue adjusted to be constant with the Fiscal Year 1982 data.

Three adjustments are potentially required for each month's revenue figure: rate changes, CPU processing power, and special situation or intervention factors.

The rate change factor is obtained from the ratio of the current rate to the original 1982 rate in the category, adjusted by the percent that the category is part of a major Service Category. For example, if CPU charges are 40% of all batch charges and paper charges are 7%, then a rate reduction in the two categories requires the following adjustment:

\[
\begin{align*}
\text{CPU.RATE82} & = 1 + \frac{\text{NEW.CPURATE}}{\text{PAPER.RATE82}} \\
& \quad \times \left( \frac{\text{NEW.PAPER.RATE}}{\text{PAPER.RATE82}} \right) \\
& \quad \times \left( \frac{1}{\text{NEW.PAPER.RATE}} \right)
\end{align*}
\]

The monthly revenue from batch times BAT82 would yield the effect of rate changes since 1982.

When PCC installs a new CPU, we always set the rates so that a job run on either the old or new CPU will cost the same. Since 1985, IBM has published service unit adjustment values that allow a fairly equal comparison of different CPUs. These values are described in Systems Initialization and Tuning Manual in terms of the number of service units per second produced by each IBM mainframe. For example, an IBM 3033 CPU, the machine in use at PCC in 1982, would generate 262 CPU service units per second. The 3081 Model B increased to 276.3. Our current 3090-200 produces 712.5 service units per second. Note that these values are for EACH engine in a multi-engine mainframe. The factor for CPU adjustment for CPU changes is therefore,

\[
\text{NEW.CPU.SERVICE} = 1 + \frac{\text{NEW.CPU.SERVICE}}{262}
\]

Although the service unit ratio is only measuring CPU changes, it can be applied to all charges (region, I/O, etc.) in the service category because they all tend to increase proportionately with the installation of a faster CPU.
The final adjustment factor in the search for underlying growth is an intervention variable that can be used to account for major changes in workload processing. For example, in 1984 the General Services Administration moved all their Model204 database processing to a newly acquired CPU at their own computer center. They were approximately 25% of the Model204 workload in August 1984, their last month of processing at PCC. If we do not factor this into our equation, it will appear that there is a workload drop, although the change is not actually reflective of the long-term trends that we are seeking. The corollary to this situation, a major new customer added to the system, would also need to be handled as an intervention situation so that unrealistic forecasts are not produced.

The final equation for each month in the Financial Series for batch is

\[
\text{BATREV}_{02} = \text{monthly revenue} \times \text{BAT}_{02} \times \text{CPU}_{02} \times \text{INT}_{02}
\]

Similar calculations for the teleprocessing systems provide constant dollar series based on 1982 usage.

Figure 2 shows the relationship between PCC's unadjusted revenue and the Financial Series over the last several years for batch and TSO.

The importance for forecasters of understanding data sources is apparent when viewing the different patterns of growth for the Count and Financial Series (Figure 3).

A study was conducted in 1985 to see if the Number and Growth variables in the annual financial model could be replaced with monthly predicted values from the SAS system Econometric and Time Series (SAS/ETS) procedures. This might serve to improve the annual forecasts and would increase the model's usefulness by allowing it to be used as a monthly predictor of revenue, the second form of the financial model discussed earlier. The 1985 study only dealt with variables in the Count Series.

A second study was set up in July 1987 for inclusion in this paper. For this study, we wanted to update the data and methods analyzed in 1985 and expand the processing to look at the Financial Series. We also investigated the X11 and ARIMA procedures for the Financial Series.

1985 STUDY OF PREDICTIVE METHODS

This study analyzed various series of data for batch jobs and Model204 and TSO sessions, and tests PROC FORECAST models for their accuracy in predicting growth. In terms of the financial model discussed earlier, this would provide values for the variable N, items in a category, on a monthly basis.

Eight different forecasting runs were made on each of the above series of data:

3 forms of STEPAR, a Stepwise Autoregressive method using constant, linear, and quadratic trend models;
4 forms of EXPO, an Exponential Smoothing Method using a quadratic trend model with Weights of .05, .10, .15, and .20

1 form of WINTERS, a method using updating equations and seasonal adjustments

Details of the each of the above methods can be found in the SAS/ETS User's Guide.

Two groups of data were selected from the Count Series. First, an Extended Group with five plus years of data; second, a Short series, consisting of only the preceding 36 months.

The purpose of the Extended versus Short data groups was to test whether the longer or shorter term data provide better predictive methods, and to search for the minimum series required for good forecasting.

The output of each forecasting run was entered in a master data set and was updated with the actual values from PCC's Revenue Series. The series were ranked according to the absolute value of the difference of the forecast and actual data.

Rankings were also made to check the ability of the predictive method for various future lengths (3, 6, 9, 12, 15, and 18 months). This was done to test for the short-term versus long-term predictive methods. PCC is primarily interested in 12 and 15 month predictions, since this matches the annual rate-setting cycles. Seasonal time dependencies were also checked to see if it made any difference in the time of year that forecasts were made.
Previous experience had shown that time of year is very important in linear regression models. Ending the series in December, for example, can result in very misleading forecasts because of the November-December seasonal drop in work.

This straightforward study led us to several conclusions:

- The shorter series provided more accurate predictions than the longer series. No forecasting system works when a system is saturated. Because our 30D33 was overloaded the Extended series was picking up flat growth patterns that were being imposed by capacity, not reflective of true growth or usage patterns.
- The EREO method with a weight of .10, provided the best batch predictions. This method weights recent data more heavily than other methods, and thus picked up the decline in the number of batch jobs during 1984-1985 as users shifted their work to interactive and database systems. The reasons for the accuracy of this method will be discussed later.
- The Winters method, with second degree polynomial equations, provided the best forecasts for TSO and Model 204 sessions.
- The STEPAR methods all gave the same results, eliminating the need for inclusion of all three methods in future explorations.
- No method was found to be significantly better as a short-term versus long-term predictor.
- Unlike linear regression, it made no difference at which time of year the prediction was made.

The best methods predicted the 15 month workload within about 6 percent. This is more accurate than estimates in the past billing projection process.

1987 STUDY OF PREDICTIVE METHODS

For the 1987 study, we wanted to update and validate the data from the 1985 study. We also were hoping that the Financial Series, with its constant dollar variables, would help us better understand the long term growth patterns of the Center. We were already aware of many of the problems of relying on simple counts of jobs or sessions because they do not reflect the underlying shifts in data processing.

The study was divided into two parts. First, analysis of the traditional variables from the Count Series: batch jobs, Model1204 and TSO sessions. Second, analysis of the batch, Model204, and TSO revenue expressed in terms of 1982 dollars.

Based on the information in the 1985 study, only one series of data, from October 1984 to July 1987, was used for the Count series forecasts. Runs were made on the single series of data using Winters Trend 2, STEPAR Trend 3, and four forms of EREO.

For analyzing the new Financial Series, an Extended Group with five plus years of data, and a Short series, consisting of data started in October 1984 was used. (The short series was expanded to 36 months for XII runs, the minimum data length PROC XII will accept.) Runs were made on both the Extended and Short series of data using the same forecasting methods as the Count series, plus PROC XII.
The output of each forecasting run was entered in a master data set and was updated with the actual values from PCC's Revenue Series. The forecasts were ranked according to the sum of the percentage differences between forecast and actual values of the data. Thus, we could see the cumulative sum of errors.

**COUNT SERIES ANALYSIS AND CONCLUSIONS**

Figure 4 summarizes the forecasts for the Count Series and indicates a wide variety of opinion about where the workload would be in January. The starred line shows the actual data values. The unexpected drop off in processing particularly affects the Exponential prediction with weight .20 because of the emphasis this method gives recent observations: forecasts over any kind of "hill" in workload will grossly misassess the future. The following tables list the mean through February of the percentage differences of the forecast and actual workload:

<table>
<thead>
<tr>
<th>METHOD</th>
<th>BATJOBS</th>
<th>TSOSESS</th>
<th>M24SESS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winters</td>
<td>-6.0%</td>
<td>0.2%</td>
<td>5.6%</td>
</tr>
<tr>
<td>Expo, W5</td>
<td>-5.6%</td>
<td>2.3%</td>
<td>4.2%</td>
</tr>
<tr>
<td>Stepar, W10</td>
<td>-4.3%</td>
<td>3.6%</td>
<td>7.5%</td>
</tr>
<tr>
<td>Expo, W15</td>
<td>2.0%</td>
<td>4.1%</td>
<td>19.2%</td>
</tr>
<tr>
<td>Expo, W20</td>
<td>7.6%</td>
<td>15.3%</td>
<td>22.4%</td>
</tr>
</tbody>
</table>

Both Batch and TSO are fairly well predicted over the six months. Mode1204 usage suffered a drop in sessions that was totally at odds with the preceding three years. The graph of Mode1204 indicates that this may be a seasonal drop, but certainly a significantly larger one than in previous years.

**FINANCIAL SERIES ANALYSIS AND CONCLUSIONS**

The graphs in Figure 5 show the forecasts and the results of the Financial Series runs. As with the Count series, the forecasts again offer a wide variety of opinion about the direction of the workload. The following tables list the mean through February of the percentage differences of the forecast and actual. The S of S indicates whether the five year (Ext) or three year (Short) series was used for the forecast.

<table>
<thead>
<tr>
<th>METHOD</th>
<th>BATREV82</th>
<th>TSOREV82</th>
<th>M24REV82</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expo, W20, E</td>
<td>-0.8%</td>
<td>16.0%</td>
<td>44.7%</td>
</tr>
<tr>
<td>Expo, W20, S</td>
<td>-0.5%</td>
<td>16.6%</td>
<td>44.9%</td>
</tr>
<tr>
<td>ARIMA, E</td>
<td>-0.3%</td>
<td>-6.8%</td>
<td>---</td>
</tr>
<tr>
<td>Expo, W15, E</td>
<td>5.1%</td>
<td>11.7%</td>
<td>40.2%</td>
</tr>
<tr>
<td>Expo, W15, S</td>
<td>6.2%</td>
<td>13.4%</td>
<td>40.7%</td>
</tr>
<tr>
<td>Expo, W10, E</td>
<td>11.2%</td>
<td>6.2%</td>
<td>35.2%</td>
</tr>
<tr>
<td>Expo, W10, S</td>
<td>12.0%</td>
<td>-0.1%</td>
<td>23.1%</td>
</tr>
<tr>
<td>Winters, E</td>
<td>14.8%</td>
<td>0.2%</td>
<td>25.5%</td>
</tr>
<tr>
<td>Winters, S</td>
<td>14.9%</td>
<td>5.2%</td>
<td>16.5%</td>
</tr>
<tr>
<td>Stepar, E</td>
<td>16.1%</td>
<td>2.4%</td>
<td>25.3%</td>
</tr>
<tr>
<td>Stepar, S</td>
<td>16.6%</td>
<td>13.4%</td>
<td>26.0%</td>
</tr>
<tr>
<td>X11, E</td>
<td>16.9%</td>
<td>6.6%</td>
<td>25.1%</td>
</tr>
<tr>
<td>X11, S</td>
<td>17.8%</td>
<td>1.4%</td>
<td>21.8%</td>
</tr>
<tr>
<td>X11, S</td>
<td>24.8%</td>
<td>7.9%</td>
<td>13.6%</td>
</tr>
</tbody>
</table>

Analysis of the graphs and tables suggest the following conclusions:

- TSO and Batch are predicted fairly well in a period of unexpected change from the past.

- There is minimal differences between the short and long series as input data except for X11, which will be dealt with separately. This is probably because neither series included a period of extreme overload which was seen in the 1985 study in the extended series.

**FINANCIAL PROJECTIONS**

VARIABLE=BATREV82

VARIABLE=TSOREV82

VARIABLE=M24REV82

![Figure 5](image-url)
• Model 1204 is a real problem for the Center during this time period. A closer analysis of this series is required to determine if there are major customer changes taking place.

• The exponential smoothing methods of high weight, .15 and .20, pick up the swinging action of the last six months, but are may not particularly good candidates for long-range periods of more normal growth.

In the tables and graphs, it appears that PROC X11 was the major disappointment in analyzing the financial series in terms of the percentage error of forecast to actual. Past experience with X11 at PCC had found that it offered insights into both monthly and even "trading day" aspects of PCC's workload. However, when viewed graphically in Figure 6, the long series, in particular, almost perfectly matches the fluctuations in our workload. The only error in the graphs is that they start at points significantly below the initial values of our series.

The cause of the error lies not in the X11 output, which only produces the estimated seasonal variations for the next twelve months, but in the linear regression model used with the seasonal factors to generate the forecast. This illustrates one of the problems in estimating the growth component in the financial model. Because of the steep changes in batch processing, neither a four-month nor twelve month mean yields a useful value for starting the series. Whether one is in a stable period or not, the output of X11 can be extremely valuable in showing the seasonality of workload.

ARIMA MODELS
A primary reason for integrating the PROC FORECAST extrapolation procedure into the revenue modelling system is that the tradeoff between its ease of use, requiring little judgment on the part of the user, and its ability to produce practical results, increases the accessibility of the system at PCC. We felt that the iterative identification, estimation, and diagnosis strategy of executing PROC ARIMA computations on the variety of time series structures represented by the categories of available data would inhibit the usefulness of the model for rather inconsequential gain. However, the powerful methods implemented in PROC ARIMA to analyze and forecast time series data are of such appeal to the analyst prepared to ensure the validity of the results that the methods should be tried whenever possible.

The ARIMA process can be used on an ad-hoc basis by providing for annual adjusted (non-deseasonalized) data from the Financial Series as input. Though not required, interactive execution is the mode of choice for the particular model-building characteristics of the procedure. For illustrative purposes, let us take the extended time series for the batch revenue variable (BATREV82). The values for the time series come directly from the Financial Series. It is at once apparent from the plot of the sample autocorrelation function that the series is seasonal non-stationary and must be transformed or differenced appropriately for analysis. Closer inspection of this plot and iterative execution of the model identification and parameter estimation stages indicate a multiplicative ARIMA $(0,1,1)(0,1,1)_{12}$. 

Figure 6
Forecasts produced on a monthly year-ahead basis from this model compare quite favorably with the appropriately weighted exponential smoothing method of the PROC FORECAST execution. We now have more confidence in the PROC FORECAST METHOD=EXPO determination as the best overall choice in the studies above since this method essentially fits an integrated moving average process like the ARIMA model described above; and the STEPAR method for handling batch revenue can be (of course!) discounted altogether. But in addition to providing validation for the production system results, it is at this point that we can begin to investigate reasons for the forecast magnitudes. For example, the fact that PROC ARIMA output for batch revenue produces predictions closer to actual values when multi-step forecasting is begun six months before the end of the input data is worth some further amount of investigation. As with PROC X11, one must be careful in estimating series when starting in peaks or valleys. Only experience with your data can overcome this. But more notably, the ARIMA output demonstrates that the MODEL204 revenue time series requires impact analysis which is all but impossible without the flexibility of fitting the transfer function part of the model.

CONCLUSIONS

In summary, the SAS/ETS procedures have been found to be very valuable in understanding the workload and forecasting of revenue at PCC. It is a relatively simple exercise for you to duplicate this type of study either for computer center or other types of forecasting. If you are not a statistician, try and find some help in using PROC ARIMA. A knowledge of time series analysis is necessary to accurately utilize this tool.

REFERENCES


NOTES

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