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Adaptive Response Rate Exponential Smoothing Forecast in Analyzing IBM's Revenue

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Abstract —*Identification of appropriate forecasting method for time series data is a difficult job for most managers as forecasts are often inaccurate and uncertain.This paper explores several forecasting techniques in analyzing IBM's quarterly sales data for finding an appropriate method. Analysis of forecasts error has been performed for best method identification. Comparisons have been made on the basis of forecast accuracy measures and tracking signal test. It was found that adaptive response rate exponential smoothing (ARRES) technique is the optimal and best predictive technique.*

Keywords and Phrases: ARRES, forecasting, management decision, time series.

JEL Classification: C22; C32; C53.

1. INTRODUCTION

In today's fast-paced business environment, companies are constantly seeking new ideas and innovative means to obtain a competitive edge. The key to success often lies in adequate planning for what lies ahead. One method used to aid companies in such planning efforts is the use of forecasts. Forecasts can be used in virtually all areas within a company and are frequently used in the determination of sales and demand for various products. Used in this capacity, forecasting is employed as a tool that companies use to structure their resources according to their desired needs. In addition to serving as a decision-making tool, forecasts can also be used as a benchmark or goal for which companies may strive to meet.

Forecasts are vital for every business organization and for every significant management decision (Chase et al. 2001; Defusco et al. 2001; Winston et al. 2001). It is clear that forecasts are of tremendous aid to companies and for this reason many companies invest substantial amounts of time and money developing them. While a forecast must deal with the future, we can never observe the future; the raw material for forecasting must lie in the past (Wills

1987; Bowerman and O'Connell 1987). Our implicit assumption is that the underlying variables which influenced demand in the past will continue to influence demand in the future. Thus, by identifying a powerful predictive method, one may be able to prepare a reliable forecast. Forecasts are by no means an exact prediction of the future given the fact that change has and will continue to inevitably characterize the business environment. In this study several methods have been utilized to aid companies like IBM in their forecasting efforts within their own unique environments.

We determined that IBM would be a good candidate for assessing several forecasting techniques due to IBM's loss of an opportunity in the past to dominate the PC market when it severely underestimated sales for what was then a new product, while Compaq and Microsoft were able to capitalize on the PC market (Stevenson 2002). This paper explores many forecasting methods and applies them to IBM sales data. This paper illustrates the reasons, process, advantages and pitfalls of most basic forecasting models. The objective of this paper is to analyze various time series forecasting techniques to accurately model quarterly net sales. The forecast technique that is determined to be the optimal will then be used to forecast the sales for the next four quarters.

2. IBM'S TIME SERIES DATA

The time series is a time-ordered sequence of data taken at regular intervals over time (Stevenson 2002). Forecasting techniques that are based on time series data follow that past or historical performance is an indicator of future performance. To begin the data analysis it is helpful to plot the data to be analyzed to identify any patterns. In this study we used IBM's quarterly sales data from 1994 to 2002 shown in figure 1.

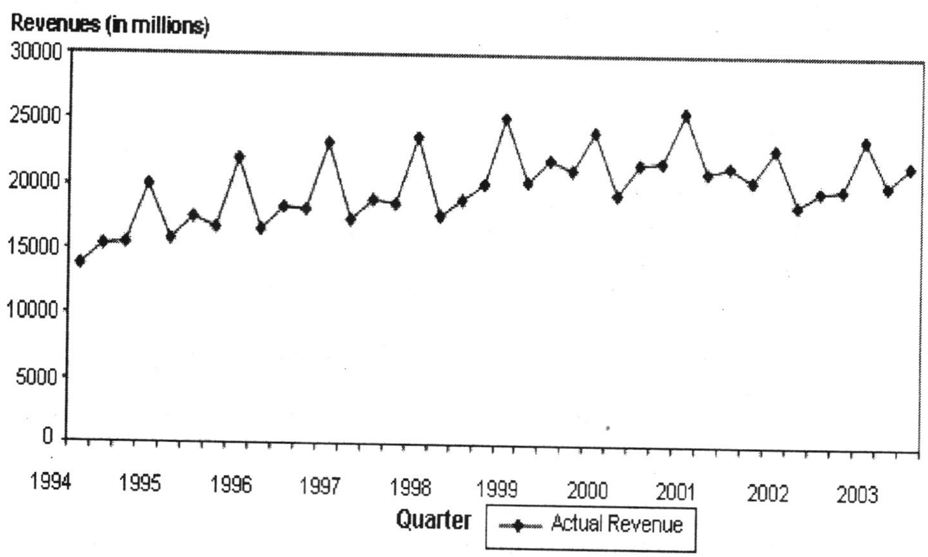

Figure 1. IBM total quarterly revenue data for years 1994-2003

From figure 1 it is seen that the data follows trends whereby the sales in the fourth quarter of each year are consistently higher than the first, second and third quarters. This trend exhibits the presence of seasonality, which refers to the short-term fairly regular variations in the data. The trend component is the long-term upward or downward shift in the data which attempts to reflect a gradual change in the series (Firth 1977). If such a pattern does not exist, the MA and exponential smoothing methods are used to smooth out the random fluctuations in the data. However, if there is a trend in the data, other methods are more appropriate.

3. Measurement Error and Forecast Control Measure

In general, every forecast contains some errors, but it is important to understand the extent that the forecasts might deviate from actual data. In practice, this gives the user a better indication of how accurate or inaccurate a forecast might be. This paper utilized the error analysis as a basis for determining the best method to forecast IBM's quarterly sales data for 2003. There are two sources of errors that may occur while forecasting, these include bias and random errors. Bias errors are those that are consistently made, for instance, using the wrong variable, wrong relationship among variables, wrong trend line and not detecting a trend (Chase 2001). Nonetheless, random errors are those that cannot be explained by the forecast model being employed. However, the forecast performs adequately when there are only random errors. The measurements of errors that will be utilized throughout this paper are discussed in the next paragraph.

First of all, the errors are nothing but the difference between actual and forecasted observations. The mean absolute deviation (MAD) is the average of absolute errors present in the forecasts and it relates to standard deviation as σ is equal to 1.25MAD. Under usual context, if control limits were set to $\pm 3\sigma$ (or $\pm$ 3.75MAD), then 99.7% of the points would fall within these limits. These control limits provide a range of forecast error that may be useful in indicating how inaccurate the forecast is. In evaluating the forecast results, the method that has the lowest MAD would be considered superior to the other methods using the MAD value as a measure of effectiveness. Furthermore, the mean sum square (MSE) is the average of squared error and the standard deviation σ can be estimated as the square root of MSE. Again, whichever method yields the lowest MSE would be the optimal method using MSE as a measure of effectiveness. Finally, the mean absolute percentage error (MAPE) provides a percentage of ratios of errors to the actual data based on absolute values. Again the method that yields the lowest MAPE would be the optimal method using MAPE as a measure of effectiveness.

To monitor the forecast we utilized the tracking signal (TS) test that is the ratio of cumulative forecast error to the MAD. The TS reflects the bias error in forecasts. In a perfect forecasting model, the sum of the actual forecast error would be zero. However, TS values are compared to predetermined limits based on judgement and experience (Stevenson 2002). The values often range from ± 3 to ± 8; however a TS value within the range of ± 4 is acceptable, which is roughly comparable to 3σ limits. The same methodology was used for all forecasting techniques applied throughout this paper. Based on all these measurement errors and forecast control measure, a forecast evaluation was prepared and the selected optimal method would be utilized to forecast IBM's sales quarterly revenue in 2003. Using the curve estimation function on SPSS (Norusis 1997), the time-series data is plotted and compared to several models in an attempt to find an appropriate model.

4. Methods, Analysis and Findings

While a forecast must deal with the future, we can never observe the future; the raw material for forecasting must lie in the past (Wills 1987; Bowerman and O'Connell 1987). In this section, several forecasting models have been utilized to forecast the IBM's sales data, these include: seasonal composition using moving averages, weighted moving average, adaptive response-rate exponential smoothing, and double exponential smoothing. Details description of those models including their major findings are discussed next. Other models such as linear trend, log linear regression, single exponential smoothing and first order autoregressive models have also been tried and summary of their findings are given next.

4.1 Seasonal Composition Using Moving Average

Since simple moving average (MA) technique does not directly incorporate the seasonality that exists within the revenue data to the respective forecasted periods, we begin our analysis with the seasonal composition using moving averages. That means an analysis of a forecast that takes seasonality into account may be appropriate due to the seasonal nature of the sales data. Note that the seasonal factor is the amount of correction needed in a time series to adjust for the seasonal fluctuations that exist throughout the year (Chase 2001). Hence, this forecast is an extension of the simple MA technique, but incorporates seasonal factors to create a more accurate forecast. MA can be useful in removing random fluctuations that occur in the data to be forecasted. This technique averages a number of recent actual values, updated as new values become available (Stevenson 2002).

The seasonal method is the most basic method of computing the seasonal factors for a given series of data. A widely used scheme to estimate the initial values of the seasonal factors involves the simple division of the observation in each period by the average for the season (Montgomery et al. 1990). Prior to the actual forecasts, preliminary calculations were performed to estimate the appropriate seasonal factors. The obtained seasonal factors were 0.905, 0.976, 0.957, and 1.162 for the first, second, third and forth quarters, respectively. Once the seasonal factors were obtained, forecasts were then determined by multiplying the average of the prior four, six and eight periods of data by the seasonal factor that corresponds to the quarter being forecasted. The classical multiplicative time-series model suggests that any observation may be theoretically expressed as the product of trend, seasonal, and irregular factors (Anderson et al. 2005). Figure 2 illustrates the forecasts versus actual sales.

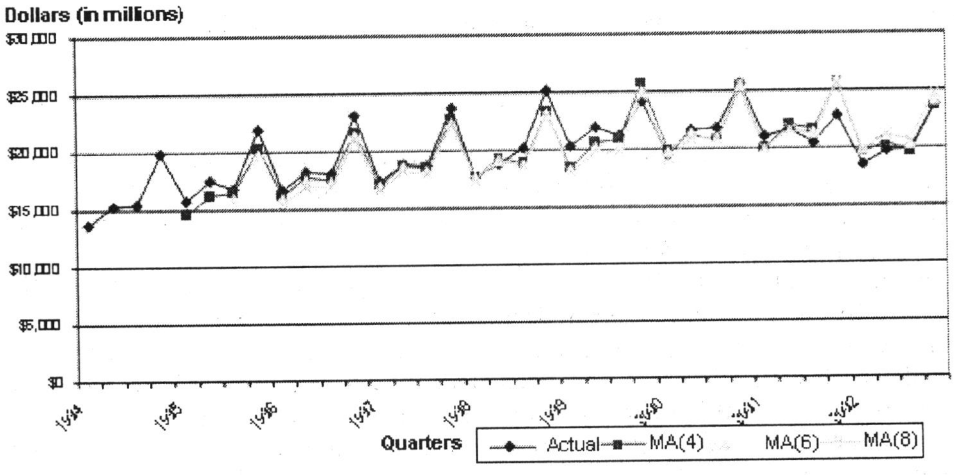

Figure 2. Seasonal composition using MA

The 'four period' moving average forecast most closely models the actual sales data. However, due to the fact that each of the three forecasts incorporates the seasonality that exists, they all tend to forecast relatively well. The error chart is shown in Figure 3.

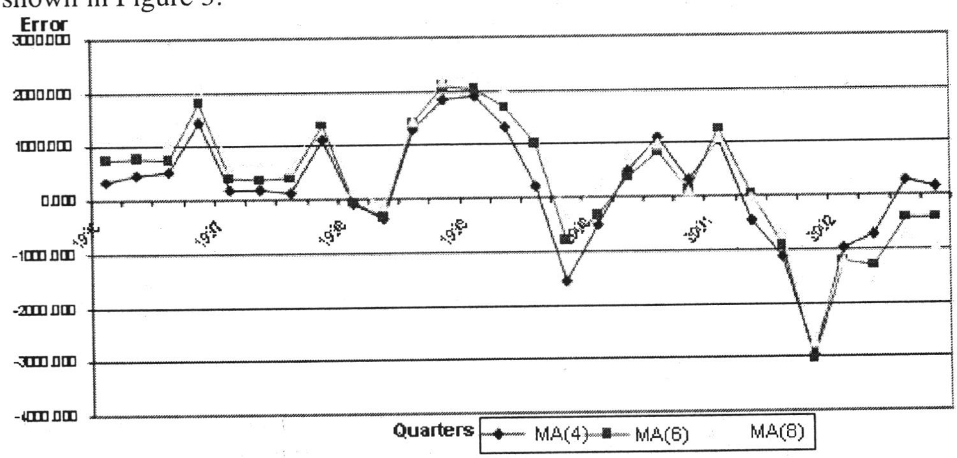

Figure 3. Seasonal composition using MA errors

An examination of the MAD values reveals that the control limits as defined by 3 standard deviations are 3240 for MA-4, 3677 for MA-6 and 4012 for MA-8. Since the values of these limits are relatively small, the forecasts are relatively accurate in modeling the series however; the MA-4 was more accurate. When observing the TS values, none of the values are within ± 4 for any of the forecasts. This indicates that this technique is not suitable for forecasting, as the forecasts are too erratic.

4.2 Weighted Moving Average

This method is similar to the moving average technique, except a weighted moving average allows any weights to be placed on the values in the time series

(Chase 2001). Note that these weights must sum to one and the forecast for the period t is expressed as:

$$F_t = w_1 A_{t-1} + w_2 A_{t-2} + \ldots + w_n A_{t-n}, \tag{1}$$

where, w_1 is the weight to be given to the actual data (A_{t-1}) for the period t-1, w_2 is the weight to be given to the actual data (A_{t-2}) for the period t-2, w_n is the weight to be given to the actual data (A_{t-n}) for the period t-n, and n is the total number of periods in the forecast.

Weights are chosen based on experience and through trial and error. Generally, the most recent value is a better indicator of the future and should be allocated a higher weight. Therefore, two different weighted moving average forecasts were calculated. The first forecast was calculated using a weight of 0.5 for the most recent prior period, 0.3 for the next most recent period and weights of 0.1 were both attributed to the third and fourth most recent periods. For the second forecast, weights of 0.4, 0.3, 0.2, and 0.1 were used in the same manor as described for the first forecast. The results of these forecasts are shown in Figure 4.

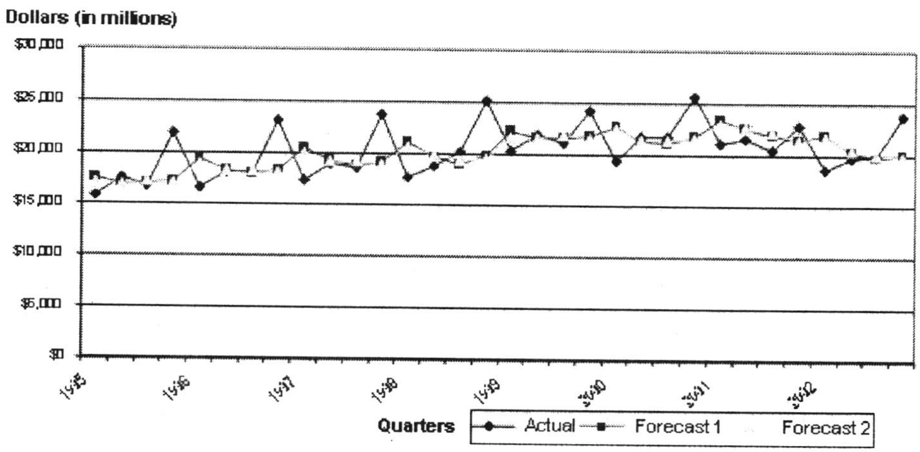

Figure 4. Weighted moving average

Based on the average errors calculated, it appears that forecast 1 was slightly better in providing an accurate forecast. Figure 5 illustrates this as follows: An observation of the MAD values reveals that the control limits of 3 standard deviations are ±7229 for forecast 1 and ±7106 for forecast 2. These values are relatively high when compared to the other methods employed and seems that this method is not very accurate. With the exception of the third quarter in 2000 through the first quarter in 2001, all the TS values appear to be reasonable, that is they are within the range of ± 4. This indicates that this model was relatively successful in forecasting the sales revenue accurately. However, it is not the optimal model. The advantage of this method is its ability to vary the effects of the past data and it is more reflective of the most recent occurrences. On the other hand, the disadvantages of the method are: it is more inconvenient, costly than other methods (Chase 2001); choice of weights is somewhat arbitrary, and uses trial and error to find a weighting scheme (Stevenson 2002).

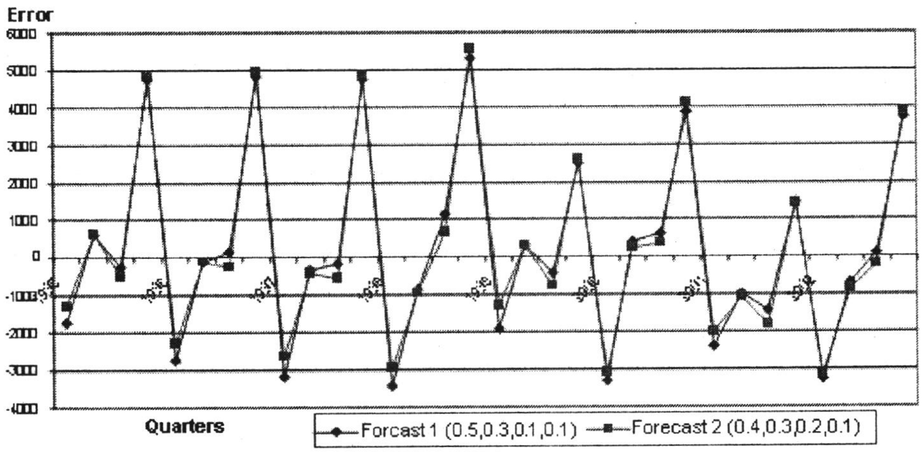

Figure 5. Weighted MA errors

4.3 Adaptive Response Rate Exponential Smoothing (ARRES)

Under the simple exponential smoothing method each new forecast is updated based on the previous forecast plus a percentage (α) of the previous error and the required model is:

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1}), \tag{2}$$

where F_t is the forecast for period t, F_{t-1} is the forecast for the previous period, α is the smoothing constant, and A_{t-1} is the actual data for the previous period (Stevenson 2002). The value for the constant is determined both by the nature of the product and by the managers sense of what constitutes a good response rate...the more rapid the growth, the higher the reaction rate should be. It is common practice to approximate α as $2/(n+1)$, where n is the number of time periods (Chase 2001). The closer the α value is to 0, the slower the forecast will be to react to the forecast errors, therefore the greater the smoothing effect. The closer the α value is to 1.0, the more it will react to the forecast errors and therefore a lesser smoothing effect. However, the TS findings indicate that this method is unsuitable for accurately forecasting the IBM's sales data.

On the other hand, adaptive response-rate exponential smoothing (ARRES) method is an extension of the exponential smoothing method; the difference is that this method chooses a value of α based on the errors in previous periods. Therefore, the advantage is that the smoothing constant (α), adapts to the data. This method essentially increases the α when errors are high and decreases the α when errors are low. The way this is accomplished is through the use of the TS in the following equations:

$$TST_t = |SAD_t/MAD_t| \tag{3}$$

$$SAD_t = \beta(A_t - F_t) + (1-\beta)\, SAD_{t-1} \tag{4}$$

$$MAD_t = \beta|A_t - F_t| + (1-\beta)\, MAD_{t-1}. \tag{5}$$

After calculating the above equations the exponential smoothing equation that was used in the previous method is employed. The difference in this equation, however, is that the α value is replaced by the value in the TST_t equation above and the equation for forecasting is:

$$F_t = F_{t-1} + TST_{t-1}\,(A_{t-1} - F_{t-1}), \qquad (6)$$

where TST_t is the TS in period t used for α in forecasting period $t+1$, β is the smoothing constant for *SAD* and *MAD*, typically chosen to be 0.2, SAD_t is an exponentially weighted average deviation (mean forecast error) in period t, and MAD_t is an exponentially weighted mean absolute deviation (mean absolute forecast error) in period t (DeLurgio 1998).The use of this method required initial values of *SAD*, *MAD* and *TST*. An arbitrary value of TST_1 was used to initiate the process for several periods until representative values of *SAD*, *MAD* and *TST* were obtained.

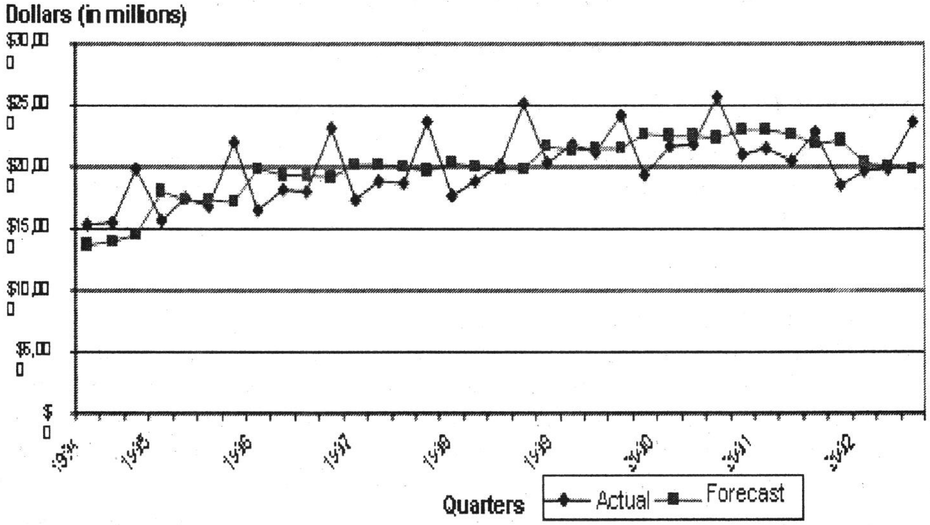

Figure 6. ARRES forecast and actual data

Here, TST_1 was set to 0.2 for the first two forecasting periods (periods 2 and 3). Thereafter, the calculated TST_t was used. SAD_1 and MAD_1 were also estimated. SAD_1 was estimated to be 0, because the mean error is expected to be zero. MAD_1 was estimated to be the error of the initial periods. The results of this forecast are depicted below in Figure 6. With the α set to the TS, it is seen in Figure 6 that the forecast closely tracks the actual. The average error of this method is relatively low at 107.201. Figure 7 graphically depicts the error. An observation of the MAD values reveals that the control limits of 3 standard deviations is $\pm$ 7796 as outlined in section 2.0 of this report. Most of the TS values are within the boundaries of $\pm$ 4. This indicates that this model forecasted the sales revenue with relative accuracy. The main advantage of this method is that it does not have as much of a smoothing effect on the data as single exponential smoothing.

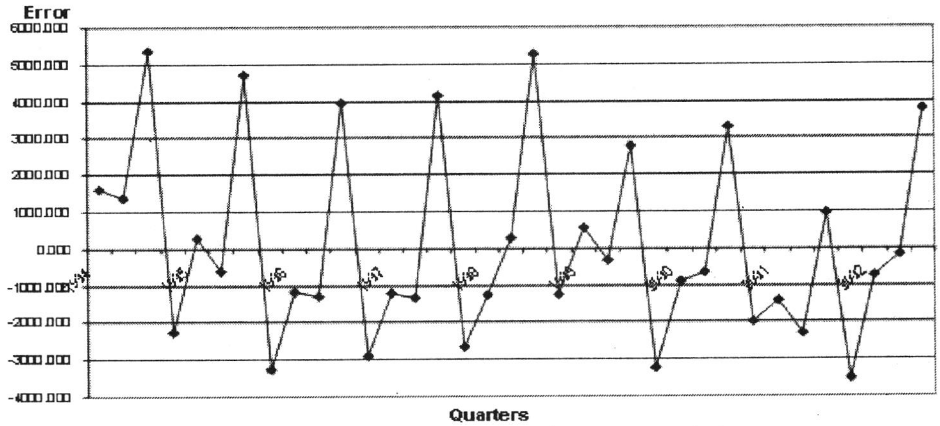

Figure 7. ARRES errors

4.4 Double Exponential Smoothing

This method uses a second smoothing constant, β, to separately smooth the trend. The values used for α and β is 0.4 and 0.3 respectively. The trend estimate was calculated by adding the actual data from quarter 1 and 4 and dividing by 3. The starting forecast was then calculated as the actual fourth quarter data plus the trend estimate. Figure 8 illustrates the forecasted versus actual values using double exponential smoothing.

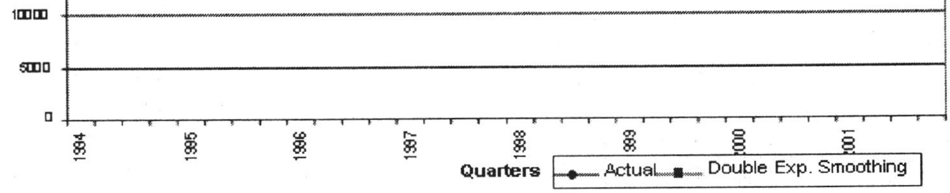

Figure 8. Double exponential smoothing forecast

This method seemed to have a much-lessened smoothing effect on the data forecasted. It was much better at forecasting the trend compared to the single exponential smoothing method. However, from the error graph in Figure 17 below it is apparent that the forecast was not very accurate.

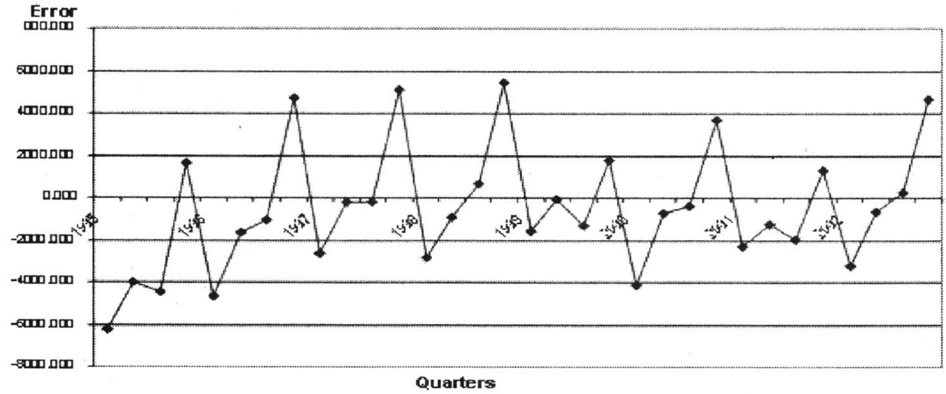

Figure 9. Double exponential smoothing errors

The MAD values reveal that the range of three standard deviations is ± 8864, which is a large range of forecast, and therefore not very reliable. The TS values were outside of the ± 4 range, which indicates that this method is not in control. Therefore, this method does not forecast these values well.

4.5 Other Model Findings

First, a linear trend model was carried out in the time series data of the year 1994 to 2002 labeling periods 1 to 36. An observation of the errors chart reveals that there is a wide range amongst them. This is likely due to the fact that the linear regression model does not incorporate seasonality into the forecasts. The MAD values for this method reveal that three standard deviations are within the range of ±6640. The TS values computed using this method indicate that there were only a few exceptions throughout the period between the third quarter of 2000 and the first quarter of 2001 where the TS values were not between ± 4. Then, we considered the log linear model and observed both forecast and forecast errors plot. However, there were some periods in which the TS was outside ±4 range indicating that this technique was not an accurate predictor of the IBM's sales data. Next, we have tried the double moving average (DMA) technique which goes one step further than the simple moving average method. The moving averages for four, six and eight periods were calculated. The results of this forecast do not seem to be too accurate. The MAD values reveal that the three standard deviations for this method are ±6359 for DMA (4), ±6597 for DMA (6) and ±7174 for DMA(8). These figures are higher than the simple moving average technique; therefore, this method is not considered as an appropriate method. These numbers are also significantly higher than the seasonal composition method. This means that this is not an optimal method.

Furthermore, we applied the simple exponential smoothing method. However, the TS findings indicate that this method is unsuitable for accurately forecasting the IBM's sales data. Finally, the first order autoregressive time series model were considered, however, this model provides extremely large errors indicating that this is not optimal. The MAD values are quite large and none of the TS calculated values are within the range of ±4, which indicates that this model is not adequate for forecasting the revenue data.

5. Conclusion and Discussion

The results of each forecast have been discussed throughout this paper with the findings of each method using the forecast accuracy measures MAD, MSE and MAPE. It is determined that the adaptive response rate exponential smoothing (ARRES) method would be the optimal technique to forecast the 2003 IBM sales data. This decision is based on the fact that the ARRES method produces the best TS values of all of the methods analyze. However, forecast accuracy measures for linear regression and weighted moving average methods are lower than ARRES method but their TS shows out of control that is biased forecast. Therefore, the ARRES method would produce the most reliable and controlled forecast for the time series data under study. Using this method, the forecasted data for the first three quarters of the year 2003 were estimated. It was found that the three quarters of 2003 forecasts are: for the first, second and third quarter sales forecast is 20125, 20122 and 20475 dollars (in millions), respectively.

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