Paper 354-2008

Small Improvements Causing Substantial Savings - Forecasting Intermittent Demand Data Using SAS® Forecast Server

Michael Leonard, Bruce Elsheimer, Meredith John, Udo Sglavo
SAS Institute Inc.
Cary, NC, USA

ABSTRACT

Businesses require accurate forecasts of time series data that is not continuous. Often, time series data is intermittent (discontinuous or interrupted). Intermittent time series data points are mostly zero (the base value), with occasional departures from the base value. Intermittent time series are common in business and economic data. For example, at progressively lower levels of data disaggregation (larger frequency, smaller geography, or both), the time series data is often intermittent. The most commonly used forecasting techniques are continuous time series methods such as exponential smoothing methods (ESM). Continuous methods are meant to forecast the future values with respect to future time periods. Because the most likely future value is zero (the base value), these models are inadequate when compared to the naïve model of simply zero (the base value). In contrast, intermittent demand methods (IDM) forecast the future average demand per period, which is more appropriate, especially for many inventory control systems. Additionally, IDM is useful for forecasting time series data that is hierarchical (for example, when the upper levels of aggregation are continuous and the lower levels of disaggregation are intermittent). This paper exposes the inadequacy of continuous time series methods when compared to IDM for forecasting future average demand per period for intermittent time series. This paper demonstrates a technique and system of large-scale automatic forecasting of intermittent demand series. This paper explains how SAS Forecast Server is used as this system.

INTRODUCTION

Businesses often want to generate a large number of forecasts based on time-stamped data that is stored in their transactional or time series databases. Web sites, point-of-sale (POS) systems, call centers, and inventory control systems are examples of transactional databases. A skilled analyst can forecast a single time series by applying good judgment based on his or her knowledge and experience, by using various time series and demand domain analysis techniques, and by using quality software based on proven statistical theory. Generating large numbers of forecasts or frequently generating forecasts requires some degree of automation. Common problems that a business faces are:

- No skilled analyst is available.
- Many forecasts must be generated.
- Frequent forecast updates are required.
- The forecasting model is not known for each time series.
- The time series data is continuous or intermittent.

This paper helps solve these problems by proposing a technique for large-scale automatic forecasting of intermittent time series data. This paper provides a background on intermittent demand analysis, decomposition, forecasting, and evaluation, and demonstrates how SAS Forecast Server can be used for automatic forecasting.

BACKGROUND

This section provides a brief theoretical background on time series analysis and automatic forecasting. It is intended to provide the analyst with motivation, orientation, and references. An introductory discussion of these topics can be found in Makridakis, Wheelwright, and Hyndman (1997), Brockwell and Davis (1996), and Chatfield (2000). A more detailed discussion of time series analysis and forecasting can be found in Box, Jenkins, and Reinsel (1994), Hamilton (1994), Fuller (1995), and Harvey (1994). A more detailed discussion of intermittent time series analysis and forecasting can be found in Croston (1972) and Willemain, Smart, and Shocker (1994). A more detailed discussion of large-scale automatic forecasting can be found in Leonard (2002), and a more detailed discussion of large-scale automatic forecasting systems can be found in Leonard (2004a).

INTERMITTENT TIME SERIES DATA

A time series that consists of mostly zero values (or some other base value) is called an interrupted or intermittent time series. These time series are mostly constant valued. Intermittent time series must be forecast differently from continuous time series. Higher frequencies and lower levels of disaggregation tend to be more intermittent than lower frequencies and higher levels of disaggregation.

Most forecasting techniques are designed for continuous time series data and for forecasting future values. However, these techniques can be applied to intermittent time series data for forecasting the average demand per period by first decomposing the time series, and then forecasting the components.

INTERMITTENT MODELS

Intermittent or interrupted time series models are used to forecast intermittent time series data. Because intermittent series are mostly constant valued (usually zero), it is often easier to predict when the series departs and how much it departs from this constant value, or to predict the average departure per time period, as opposed to predicting the next time series value.

A decomposition intermittent demand model decomposes the time series into two components: the interval component and the size component. The interval component measures the number of time periods between departures. The size component measures the magnitude of the departures. After this decomposition, each component is modeled and forecast independently. The interval component forecast predicts when the next departure will occur. The size component forecast predicts the magnitude of the next departure. After the interval and size component predictions are computed, they are combined (predicted magnitude divided by predicted number of time periods before the next departure) to produce a forecast for the average departure from the constant value for the next time period. An example of a decomposition intermittent demand model is Croston's method.

Another intermittent demand model computes the average component by dividing the size component values by the interval component values. The average component is then modeled and forecast to produce a forecast for the average departure from the constant value for the next time period.

The interval, size, and average component are collectively referred to as the demand series or demand components.

EXAMPLE OF INTERMITTENT DEMAND SERIES DECOMPOSITION, ANALYSIS, MODELING, AND FORECASTING

For a simple example of an intermittent demand series, suppose that a time series data set contains just three nonzero demands:

$N = 3$: $\{y_4 = 28, y_{10} = 18, y_{18} = 20\}$

The time index is $t = 1,\dots,T$ and $T = 22$.

This intermittent time series can be decomposed into the demand components as follows:

- The demand index is the index of nonzero demands, $i = 1,\dots,N$ where $N = 3$ is the number of demands. The demand index maps to the time series index, $\{t_1 = 4, t_2 = 10, t_3 = 18\}$ where $t_0 = 0$ and $t_4 = T + 1 = 23$ are the periods before and after the end of the series, respectively.
- The demand intervals are the number of time periods between nonzero demands, $\{q_1 = (t_1 - t_0) = 4, q_2 = (t_2 - t_1) = 6, q_3 = (t_3 - t_2) = 8, q_4 = (t_4 - t_3) = 5\}$.
- The demand sizes are the nonzero demands, $\{d_1 = y_4 = 28, d_2 = y_{10} = 18, d_3 = y_{18} = 20\}$.
- The average demands are the ratios of the demand sizes and the demand intervals, $\{a_1 = d_1 / q_1 = 7, a_2 = d_2 / q_2 = 3, a_3 = d_3 / q_3 = 2.5\}$.

In general, any time series $\{y_t\}_{t=1}^{T}$ can be decomposed into the demand interval series $\{q_i\}_{i=1}^{N+1}$, the demand size series $\{d_i\}_{i=1}^{N}$, and the average demand series $\{a_i\}_{i=1}^{N}$. This decomposition offers an alternative to the time domain analysis, which relies on the time index $t = 1,\ldots,T$ by providing a demand domain analysis based on the demand index $i = 1,\ldots,N$.

Figure 1 illustrates this intermittent demand series. Figure 2 illustrates the intermittent demand series decomposition using time series plots.

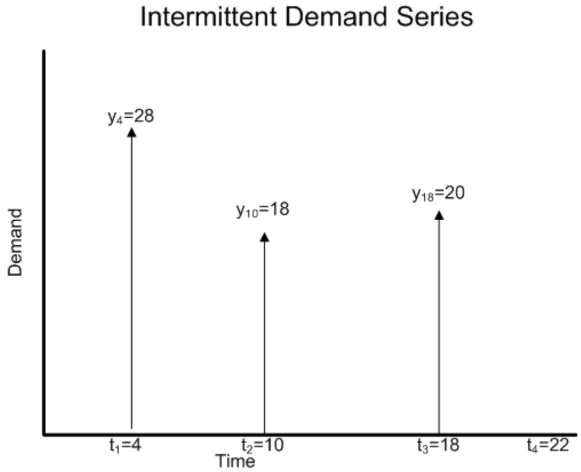


Figure 1: Intermittent Demand Series

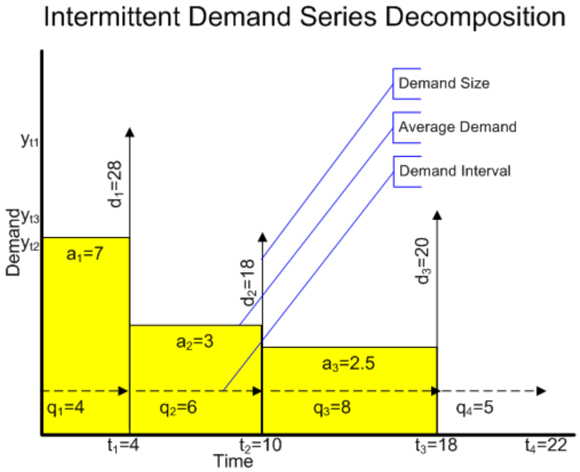


Figure 2: Intermittent Demand Series Decomposition

Because the first observed demand, $y_4 = 28$, occurs at time index $t_1 = 4$, the first demand interval $q_1 = 4$ is only partially observed. Likewise, the first average demand $a_1 = 7$ is only partially observed because the time when the previous demand occurred is unobserved. The previous demand index must be greater than or equal to 4. The first demand size $d_1 = 28$ is fully observed.

Because the last observed time period occurs at $t_4 = 22$, the last demand interval $q_4 = 5$ is only partially observed because the next demand is unobserved, and the next demand must be greater than or equal to 5. Because the next demand at demand index $N+1$ is unobserved, the fourth demand size and average demand are unobserved.

For the statistical analysis of the demand component series, only fully observed components are used. Because there are only two fully observed demand intervals, $\{q_2 = 6, q_3 = 8\}$, the average of the demand intervals is $\bar{q} = 7$. Because there are three fully observed demand sizes, $\{d_1 = 28, d_2 = 18, d_3 = 20\}$, the average of the demand sizes is $\bar{d} = 22$. Because there are only two fully observed average demands, $\{a_2 = 3, a_3 = 2.5\}$, the average of the average demands is $\bar{a} = 2.75$.

For estimating the demand component series model parameters, the fully observed components and the beginning partially observed components are used. The beginning partially observed demand intervals and average demands are used in determining the beginning smoothing states.

For demand component series forecasting, both the fully observed and partially observed components are used. The beginning partially observed demand intervals and average demands are used in determining the beginning smoothing states. The ending partially observed demand intervals act as a lower bound for the next demand interval prediction. Unobserved demand components are not used.

Figure 3 illustrates the intermittent demand size component series, average size, and prediction. Figure 4 illustrates the intermittent demand interval component series, average interval, and prediction.

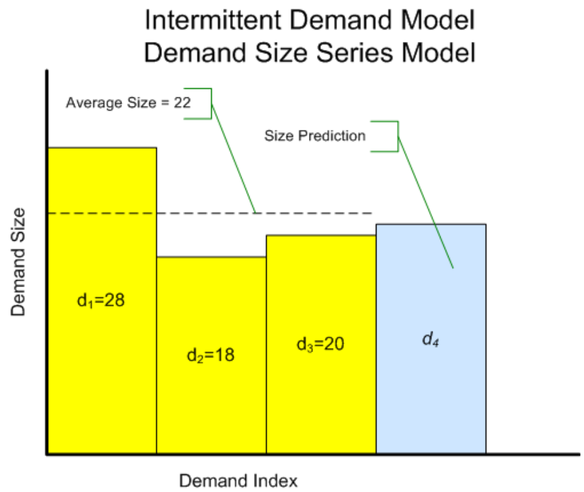


Figure 3: Demand Size Series Model

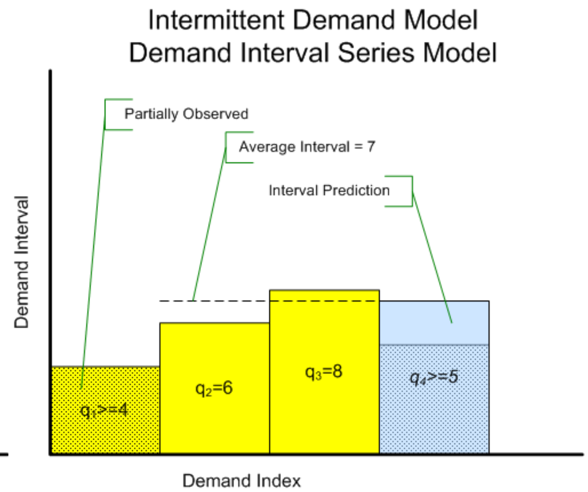


Figure 4: Demand Interval Series Model

In this example, the partially observed components have little influence on the demand interval series model prediction because the backcast of the fully observed demand intervals is greater than the partially observed demand intervals. When there are a large number of demands, N , the beginning partially observed demand intervals have less influence on the demand interval predictions. The ending partially observed demand intervals have the greatest influence on the demand interval predictions.

The goal in forecasting intermittent time series is to forecast the average demand per period. Croston's method uses the ratios of the demand interval and size predictions, which are independently computed. The average demand method uses the average demand predictions directly. Figures 5 and 6 illustrate these intermittent demand models in demand series plots.

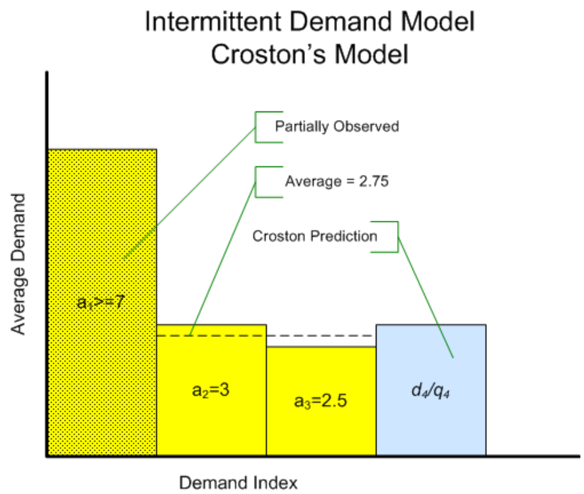


Figure 5: Croston's Model

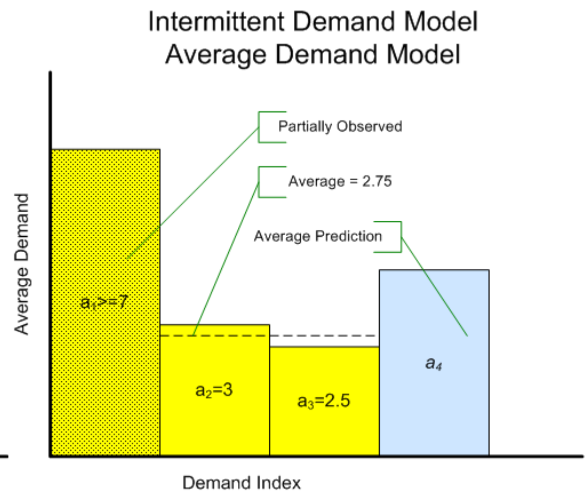


Figure 6: Average Demand Model

In this example, the partially observed components have greater influence on the average demand method than on the Croston's method because there are so few demands. The backcast of the fully observed average demand is less than the partially observed average demand. When there are more demands, N , the results should be more similar because the beginning smoothing states have less influence on the final prediction.

TESTING FOR INTERMITTENCY

Intermittent demand models are appropriate only for intermittent demand series. Therefore, before using an intermittent demand model, you must first determine whether the time series is intermittent. To determine whether a time series is intermittent, you must first determine the intermittency base value if it is not provided, and then provide an intermittency threshold.

Given a time series $\{y_t\}_{t=1}^{T}$, let the base value be the most common time series value, unless a base value is explicitly provided (for example, zero). If the most common value is a missing value, assume zero. Decompose the time series, $\{y_t - base\}_{t=1}^{T}$, using the demand domain analysis previously described to obtain the demand interval series, $\{q_i\}_{i=1}^{N+1}$. If the median value of $\{q_i\}_{i=1}^{N+1}$ is below some specified threshold, the series is continuous; otherwise, the series is intermittent.

The median should be used instead of the average because continuous time series that are seasonal can have many contiguous seasons that have the same value (typically, zero). These zero values might represent seasons when a product or service is unavailable. For example, summer goods and winter services might have many contiguous periods that are zero valued, followed by many periods that are nonzero that repeat with the seasonal cycle. These contiguous periods can significantly decrease the demand interval average, but have a lesser effect on the median. Using an intermittent demand model for a seasonal and continuous time series is inappropriate.

When testing for intermittency, the most important decision you make is the threshold value.

FORECASTING INTERMITTENT DATA

For a typical example of an intermittent demand series, suppose that a daily time series data set contains 10 nonzero demands, $N = 10$: $\{y_t\}_{t=1}^{T}$, where $T = 153$. The time range under investigation ranges from 30MAR2000 to 29AUG2000. Table 1 illustrates this intermittent demand series data.

date	units
09APR2000	125
19APR2000	89
26APR2000	107
09MAY2000	118
27MAY2000	123
05JUN2000	159
17JUN2000	167
03JUL2000	150
16JUL2000	161
05AUG2000	189

Table 1 – Intermittent Demand Series Data

The data in table 1 is transactional (no fixed time intervals) and intermittent (most of the time periods are assumed to be zero valued) when considered a daily time series. The graphical representation of the series is:

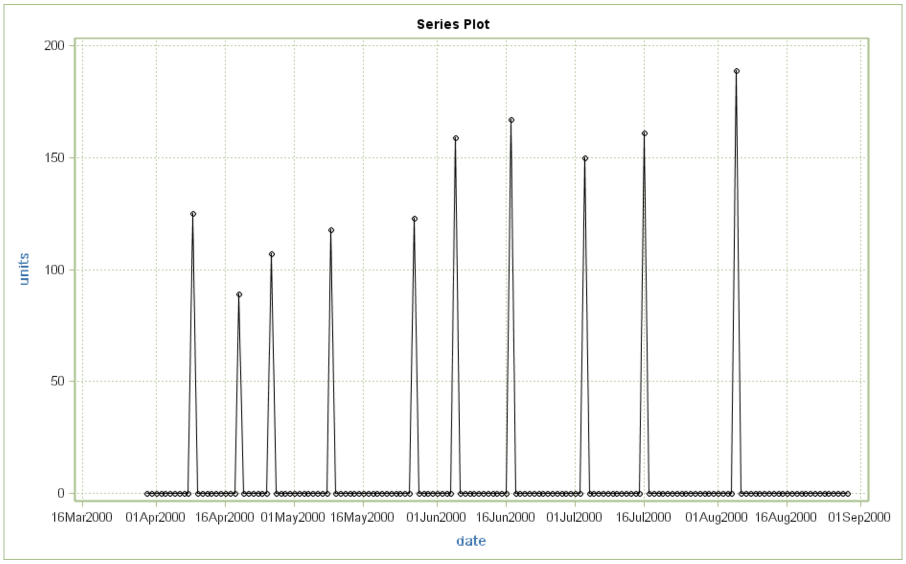


Figure 7: Intermittent Data

Although the scale of the demands might be small or large for this intermittent demand series, compared to the scale you might experience, the analysis that follows is invariant to the scale of the demands. In other words, if you divided or multiplied the previous demand values by a constant, the conclusions will be similar. What matters is relative departure from the base value (typically, zero). In fact, the analysis that follows is valid when the time series is binary (the base value is zero, and departures from the base value are 1), although other techniques might provide better results.

AUTOMATIC DEMAND COMPONENT FORECASTING

Using the data from table 1, the intermittent demand series can be decomposed into demand series components. Each demand series component can be automatically modeled and forecast.

The demand series components and forecasts are plotted in figures 8, 9, and 10. The demand interval and demand size series are trending upward, and the average demand series is relatively flat. In other words, the intervals between demands are increasing, but so are the sizes of the demands. However, the average demand per period is fairly constant with possibly a time-varying trend.

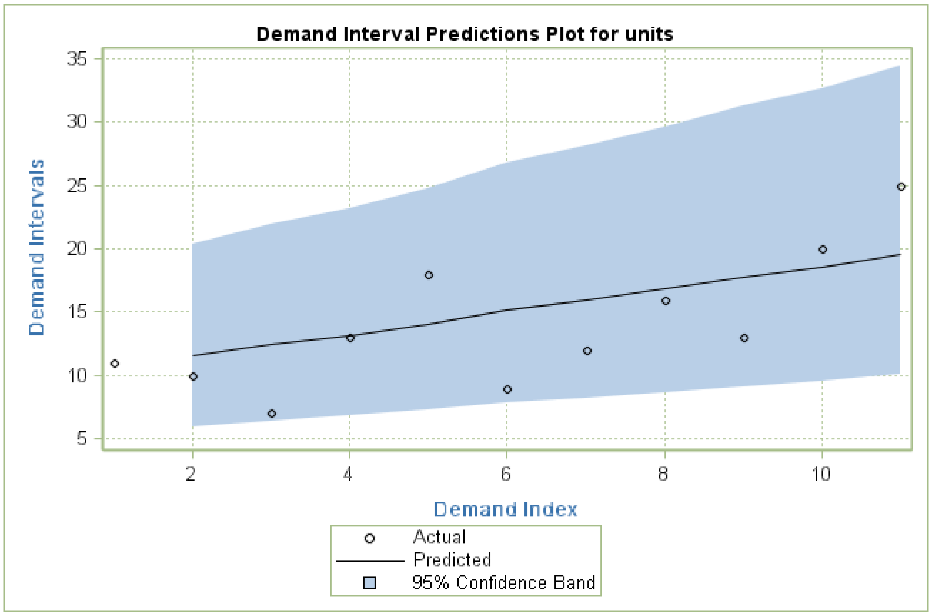


Figure 8: Demand Interval Series Model

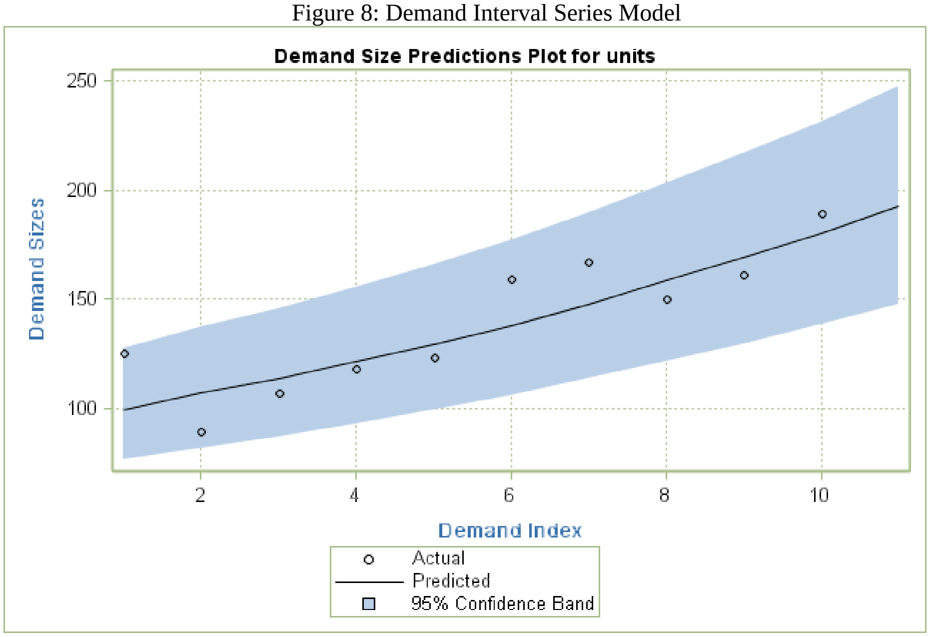


Figure 9: Demand Size Series Model

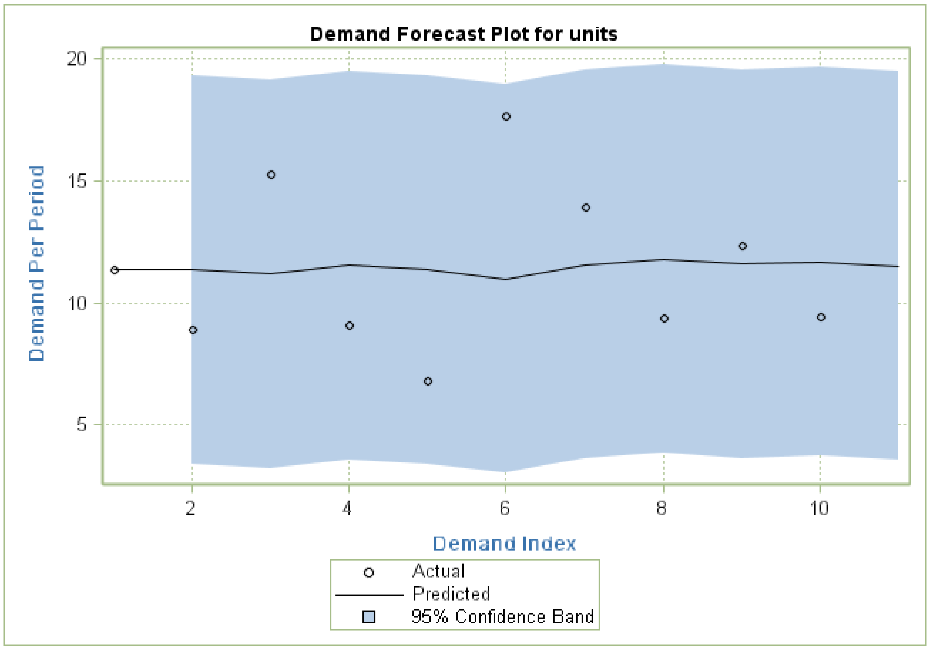


Figure 10: Average Demand Series Model

AVERAGE DEMAND PER PERIOD FORECASTING

The goal of forecasting an intermittent demand series is to predict the average demand per period, not the future values per period, which are most likely to be zero (the base value).

Given predictions and variances for each component of the demand series, $\{\hat{q}_i\}_{i=1}^{N+1}$, $\{\hat{d}_i\}_{i=2}^{N+1}$, and $\{\hat{a}_i\}_{i=2}^{N+1}$, forecasts (predictions and variances) for the average demand per period can be computed. Both predictions and variances are needed for inventory control systems. The variances in predictions depend on the forecasting model that is used to make the prediction.

The estimated average demand per period, y_i^*, can be computed two ways. Croston's method uses the ratio of the demand size and interval series predictions. The average demand method uses the average demand series predictions directly. The following equations describe these two methods:

Croston's Method: $y_i^* = \hat{d}_i / \hat{q}_i + base$ where the base value is typically zero

$$Var(y_i^*) = (\hat{d}_i^2 / \hat{q}_i^2)(Var(d_i)/\hat{d}_i^2 + Var(q_i)/\hat{q}_i^2)$$

Average Demand Method: $y_i^* = \hat{a}_i + base$ where the base value is typically zero

$$Var(y_i^*) = Var(a_i)$$

The average demand per period is converted from the demand domain (demand index) to the time domain (time index):

$\hat{y}_t^* = y_i^*$ when $t_i \le t < t_{i+1}$

$Var(\hat{y}_t^*) = Var(y_i^*)$ when $t_i \le t < t_{i+1}$

The * indicates that these predictions are based in the demand domain, not in the time domain. The naïve prediction for the future time series value is $\hat{y}_t = base$.

Using the data from table 1, the intermittent demand series can be decomposed into demand series components. Each demand series component can be automatically modeled and forecast. The demand series component predictions can be used to forecast the average demand per period using Croston's method or the average demand method.

The average demand per period series and forecasts for both methods are plotted in the time domain in figures 11 and 12. The Croston's method prediction drops promptly after the last observed demand. This drop is because the partially observed interval between the last observed demand and the last observation of the time series, 25, is greater than its predicted value, 19.5. Therefore, the partially observed interval is used instead of the predicted value when computing the prediction for average demand per period.

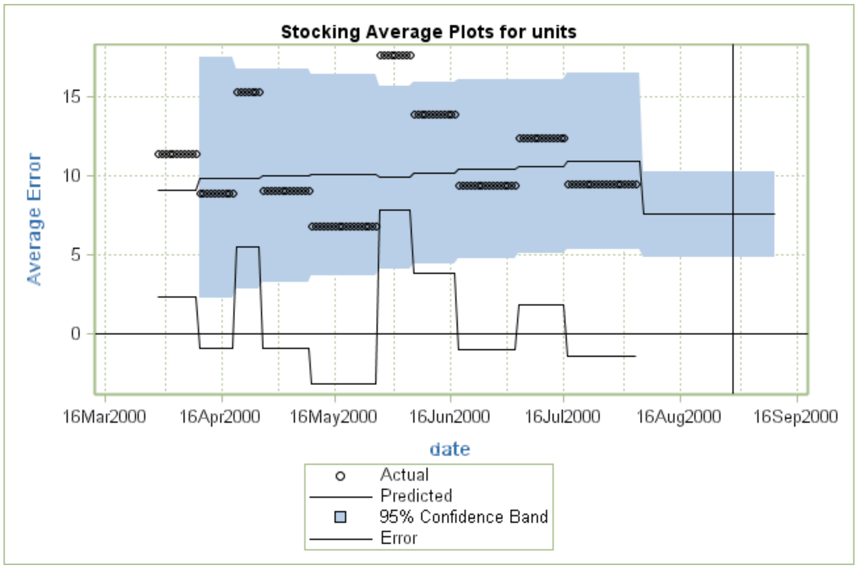


Figure 11: Croston's Method

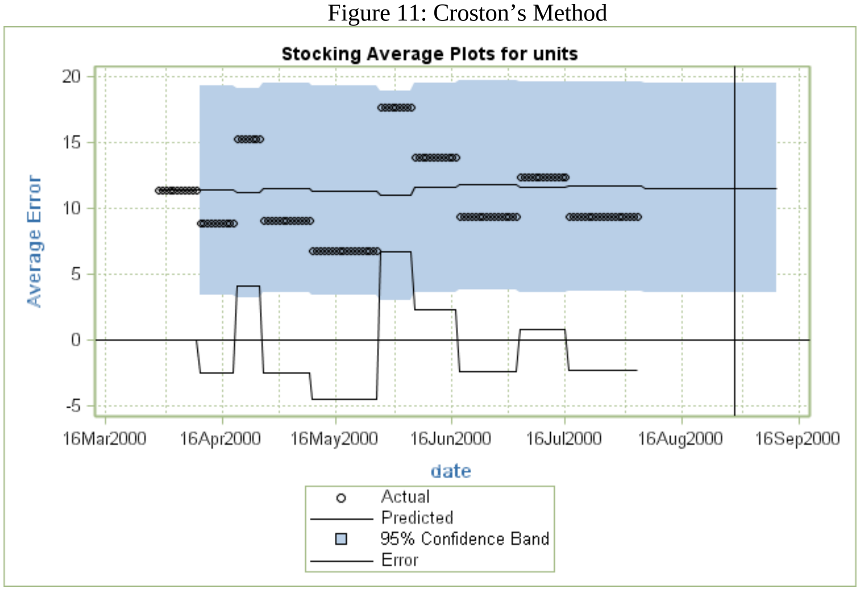
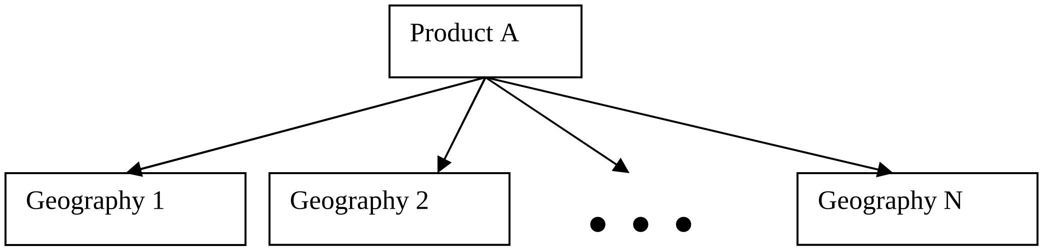


Figure 12: Average Demand Method

HIERARCHICAL TIME SERIES AND INTERMITTENT DEMAND SERIES

Often, time series data is hierarchical. A set of similar time series can be aggregated to form aggregate time series. Another set of similar time series can be aggregated to form another aggregate time series. One aggregate time series can be combined with another aggregate time series to form yet another aggregate time series, and so on.

For example, the hierarchy below illustrates data for the sales of a single product, Product A, across different geographic locations, Geography 1,…,*N*. The highest level of aggregation is at the product level, and the lowest level of disaggregation is at the product-geography level.



Other hierarchies are possible. More than two levels of aggregation or disaggregation are possible. For example, similar products can be aggregated to a product category—Product A, Product B, and so on.

At progressively lower levels of disaggregation, hierarchical time series data eventually becomes intermittent. For example, in geographic time series data, if frequency is made sufficiently large (for example, monthly to daily), or the locale is made sufficiently small (for example, country to postal code), or both, the time series might become intermittent. The time series at higher levels of aggregation are more likely to be continuous. The time series at lower levels of disaggregation are more likely to be intermittent.

Higher levels of aggregation might exhibit properties of trend, seasonality, price effects, calendar effects, and other explanatory inputs of concern. These properties might be harder to identify at lower levels of disaggregation. The ability to identify these properties is difficult when the lower levels of disaggregation are intermittent.

HIERARCHICAL FORECASTING WITH INTERMITTENT DEMAND SERIES

When forecasting hierarchically, forecasts are often generated for every time series in the hierarchy, and then the forecasts are reconciled using top-down, middle-out, or bottom-up methods. In general, the reconciliation method that provides the best forecasts at the level of aggregation of concern should be used.

Typically, when the time series are intermittent at a certain level, and continuous at higher levels, reconciling downward from the levels where the series are continuous often provides the best forecasts.

One approach is to use hierarchical forecasting when lower levels of disaggregation are intermittent demand series.

1. Analyze, select, model, and forecast the upper levels of aggregation with continuous time series models, which are more suitable for identifying and modeling properties (trend, seasonality, and so on).

2. Analyze, select, model, and forecast the lower levels of disaggregation with continuous time series models and intermittent demand models as the data suggests.

3. Reconcile the forecasts between the levels of aggregation and disaggregation using downward (top-down or middle-out) reconciliation methods.

In general, reconciling downward determines the share or percentage of the aggregate series forecast associated with a given disaggregate series forecast. Typically, for intermittent demand series, forecasts of the average demand per period (intermittent demand models) provide better estimates of the share than next time period forecasts (continuous time series models). But, the out-of-sample results should be compared.

EXAMPLE OF HIERARCHICAL FORECASTING WITH INTERMITTENT DEMAND SERIES

Figure 13 is a weekly time series plot of an aggregate time series. Figure 14 is the distribution of its values. Clearly, this time series is continuous. Using continuous time series automatic forecasting, linear (Holt) exponential smoothing was selected to forecast the continuous series. Figure 15 illustrates the model and forecasts. Figure 16 illustrates the distribution of the prediction errors. Figure 17 is a plot of the prediction error autocorrelation. Figure 18 illustrates the white noise probabilities at each time lag.

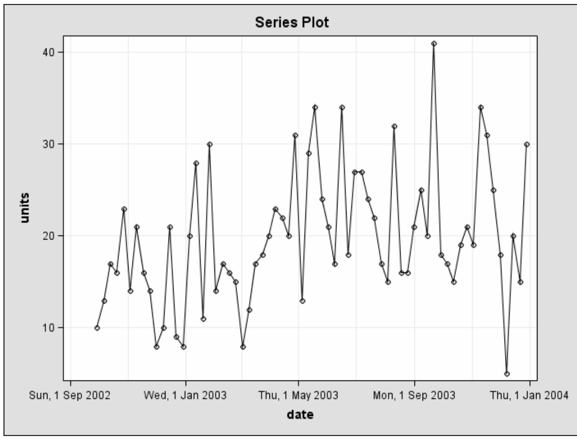


Figure 13: Aggregate Time Series Plot

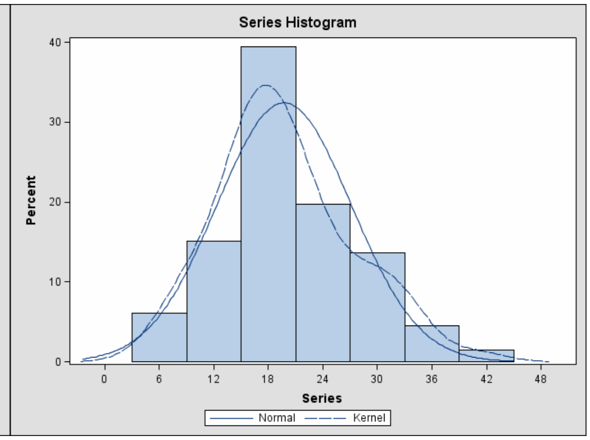


Figure 14: Aggregate Series Distribution

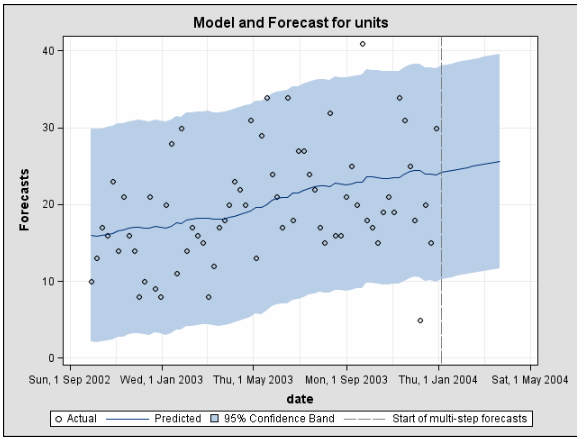


Figure 15: Aggregate Time Series Model

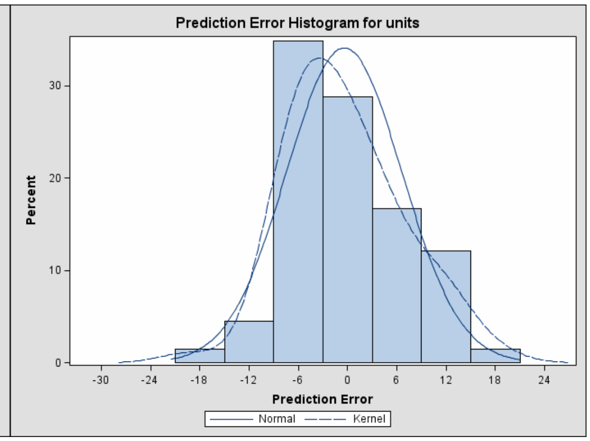


Figure 16: Prediction Error Distribution

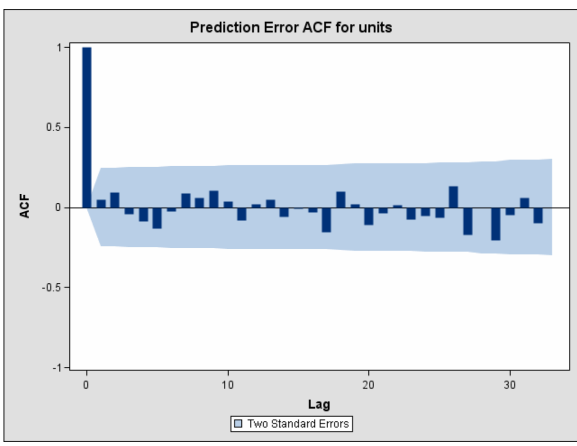


Figure 17: Error Autocorrelation Plot

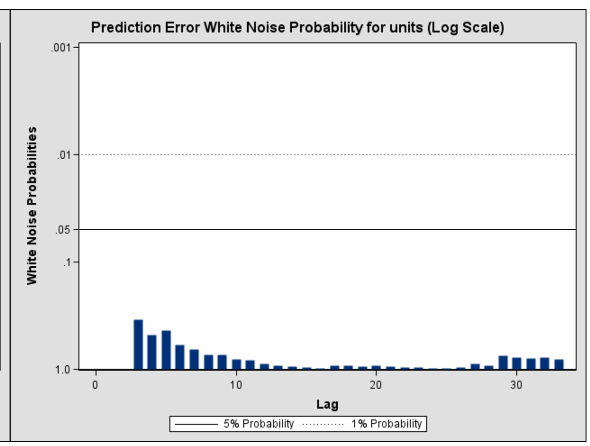


Figure 18: Error White Noise Probabilities

The aggregate time series plot indicates an upward trend. The aggregate series distribution indicates that the series is continuous. The aggregate time series model indicates future increases are expected. The prediction error distribution and the error autocorrelation plot indicate no significant autocorrelation. The error white noise probabilities indicate no significant patterns in the prediction errors. Given this information, continuous time series automatic selection provides a good model for forecasting. A better model might be provided by a skilled analyst, but, when none is available, this model is good.

Figure 19 is a weekly time series plot of one of the many disaggregate time series. Figure 20 is the distribution of its values. Clearly, this time series is intermittent. Using intermittent time series automatic forecasting, linear (Holt) exponential smoothing was selected to forecast the demand intervals. Simple exponential smoothing was selected to forecast the demand sizes. Figure 21 illustrates the demand interval model and forecasts. Figure 22 illustrates the demand interval distribution. Figure 23 illustrates the demand size model and forecasts. Figure 24 illustrates the demand interval distribution.

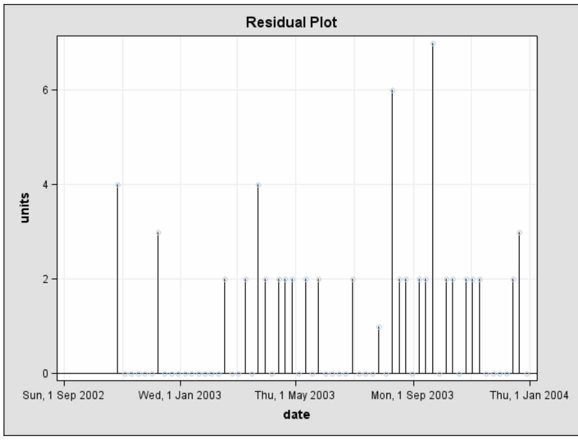


Figure 19: Disaggregate Time Series Plot

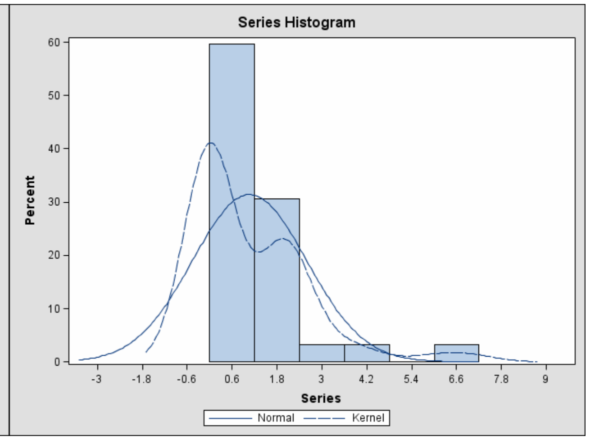


Figure 20: Disaggregate Series Distribution

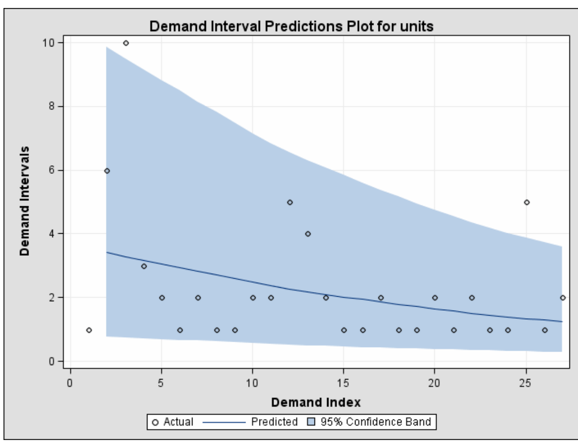


Figure 21: Demand Interval Model Plot

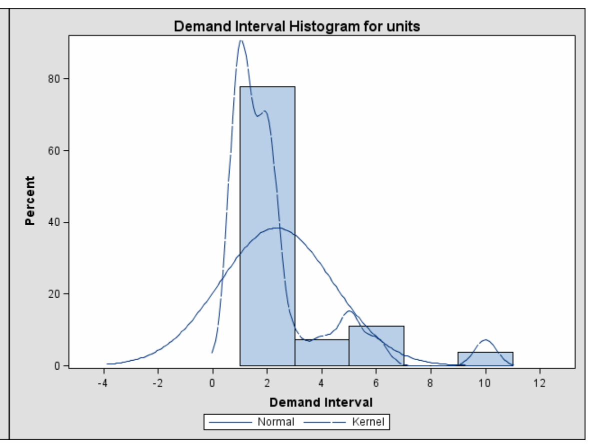


Figure 22: Demand Interval Histogram

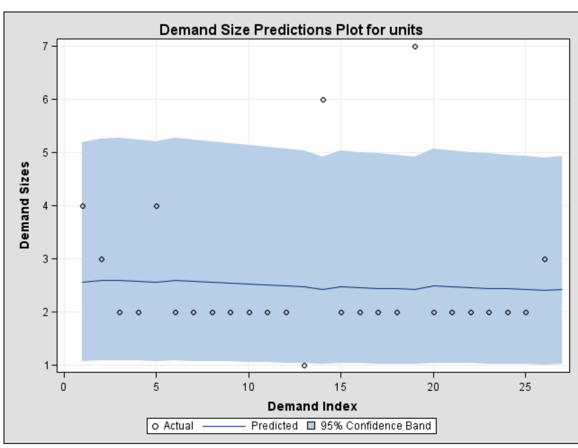


Figure 23: Demand Size Model Plot

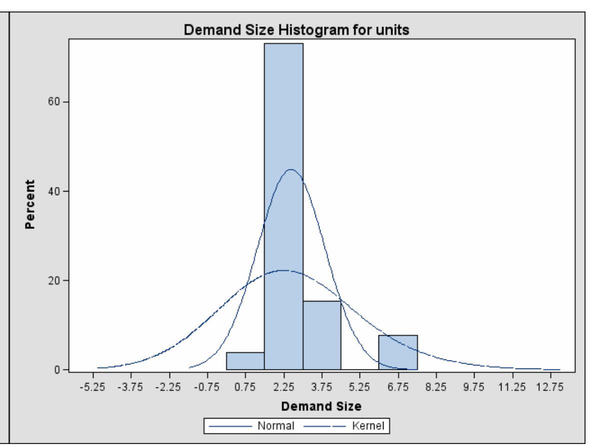


Figure 24: Demand Size Histogram

The demand intervals are trending downward, and the demand sizes are trending slightly downward. The overall average demand is trending upward, just as the aggregate time series forecasts in figure 15.

The forecasts of the demand components were used to forecast the average demand per period of the previous disaggregate series. Figures 25 and 26 illustrate the disaggregate model forecast in a time series plot and the prediction error distribution, respectively.

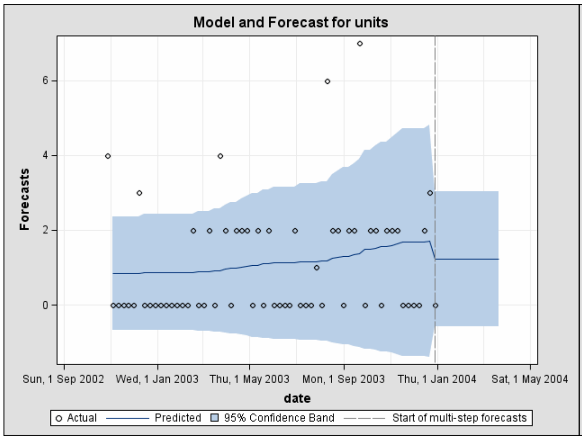


Figure 25: Disaggregate Model Plot

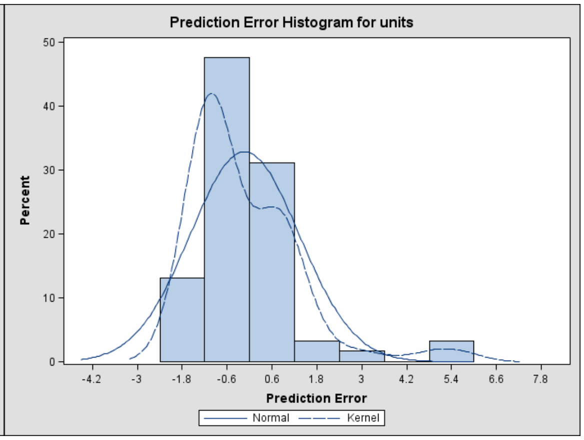


Figure 26: Prediction Error Histogram

The forecasts of the average demand per period are constant for the future periods. In general, the time series forecasts that are generated by intermittent demand models are constant for the future periods because the models forecast the average demand per period.

The forecasts of the previous disaggregate time series, along with the forecasts of many other disaggregate time series (there are not shown), were reconciled using downward reconciliation (in this case, middle-out using a three-level hierarchy). Figures 27 and 28 illustrate the disaggregate reconciled plot and the prediction error distribution, respectively.

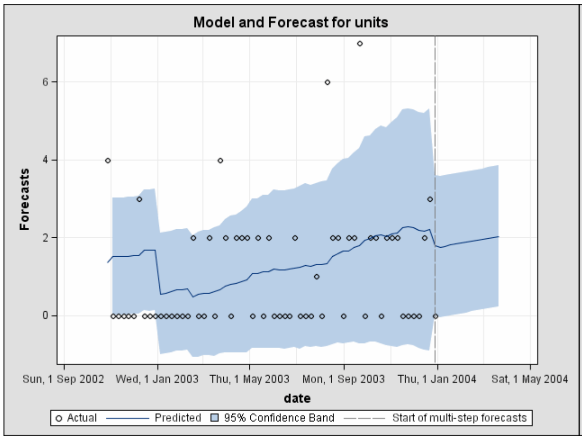


Figure 27: Disaggregate Reconciled Plot

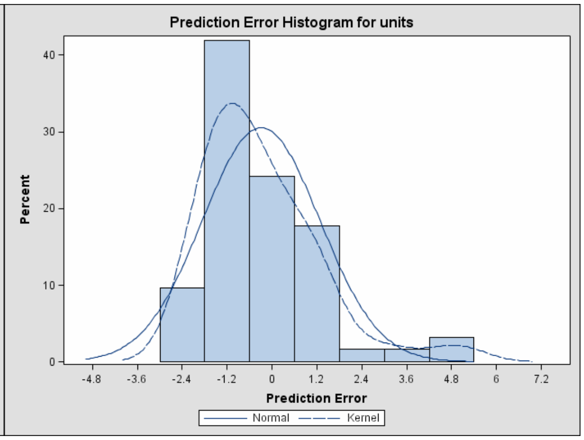


Figure 28: Prediction Error Histogram

The reconciled forecasts of the disaggregate time series exhibit a trend that more closely reflects the forecasts of the aggregate time series than the model forecasts (without reconciliation), which is illustrated in figure 25. The reconciled prediction error distribution is slightly more normally distributed than the model prediction error distribution, which is illustrated in figure 26.

Reconciliation allows information more easily identified at higher levels of aggregation to be used at lower levels of disaggregation (where information is harder to identify). Figure 29 illustrates both the model and reconciled forecasts of the disaggregate time series in the same plot. Figure 30 illustrates the weighting of the reconciliation between the two types.

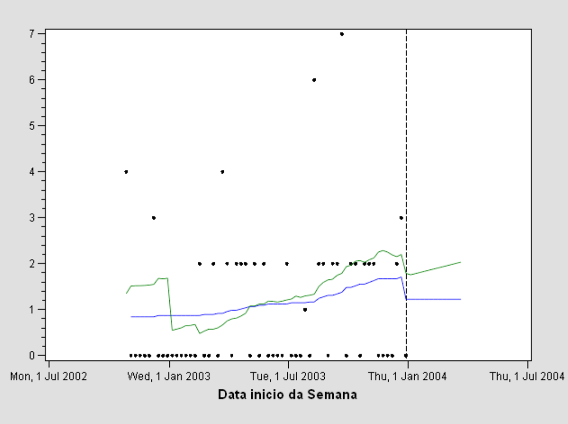


Figure 29: Model and Reconciled Plot

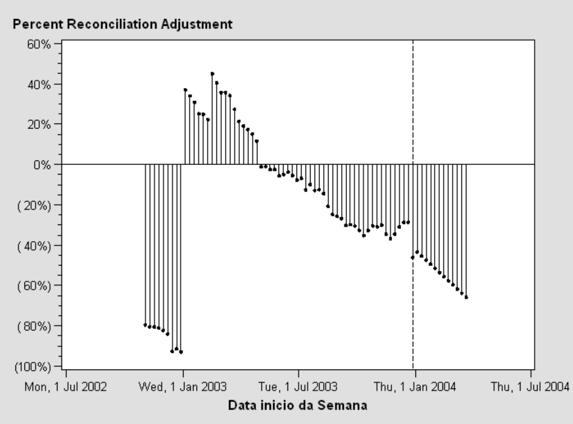


Figure 30: Reconciliation Weights Plot

The reconciled forecasts exhibit a trend and more closely fit the time series than the model forecasts. Large reconciliation weights coincide with the model forecasts that have greater deviation from the disaggregate time series. The future reconciliation weights explain the adjustment for the trend, which could not be identified at the lower level of disaggregation.

This example shows how lower levels of disaggregation can use information at higher levels of aggregation through the reconciliation process.

CONCLUSION

This paper describes a technique for large-scale automatic forecasting of intermittent demand series. This technique is both efficient and effective in forecasting millions of time series. Past empirical evidence suggests that the statistical forecasting models used with this technique are robust and effective in forecasting a variety of intermittent time series encountered by businesses. By using demand analysis to decompose the time series into components, and by using holdout sample analysis with a model selection criterion, an appropriate forecasting model can be chosen for each component without a skilled time series analyst. The component predictions can be combined to produce forecasts for the future average demand per period. This technique does not produce the very best forecast for each time series, but it can produce good forecasts for the large majority, making large-scale forecasting processes manageable. This technique can be used on both time series data and time-stamped transactional data after accumulation.

REFERENCES

Box, G. E. P., G. M. Jenkins, and G. C. Reinsel. 1994. *Time Series Analysis: Forecasting and Control*. Englewood Cliffs, NJ: Prentice Hall, Inc.

Brockwell, P. J., and R. A. Davis. 1996. *Introduction to Time Series and Forecasting*. New York, NY: Springer Science+Business Media, Inc.

Chatfield, C. 2000. *Time Series Models*. Boca Raton, FL: Chapman & Hall/CRC.

Croston, J. D. 1972. “Forecasting and Stock Control for Intermittent Demands.” *Operational Research Quarterly,* vol. 23, no. 3.

Fuller, W. A. 1996. *Introduction to Statistical Time Series*. New York: John Wiley & Sons, Inc.

Hamilton, J. D. 1994. *Time Series Analysis*. Princeton, NJ: Princeton University Press.

Harvey, A. C. 1993. *Time Series Models*. Cambridge, MA: The MIT Press.

Leonard, M. J. 2002. “Large-Scale Automatic Forecasting: Millions of Forecasts” (paper presented at the International Symposium of Forecasting).

Leonard, M. J. 2003. “Mining Transactional and Time Series Data” (paper presented at the International Symposium of Forecasting).

Leonard, M. J. 2004. “Large-Scale Automatic Forecasting Using Inputs and Calendar Events” (paper presented at the International Symposium of Forecasting).

Leonard, M. J. 2004. “Predictive Modeling Markup Language for Time Series Models” (paper presented at the International Symposium of Forecasting).

Makridakis, S. G., S. C. Wheelwright, and R. J. Hyndman. 1998. *Forecasting: Methods and Applications*. New York: John Wiley & Sons, Inc.

Willemain, T. R, C. N. Smart, and J. H. Shocker. 1994. “Forecasting Intermittent Demand In Manufacturing: Comparative Evaluation of Croston's Method,” *International Journal of Forecasting* 10: 529-538.

CONTACT INFORMATION

Your comments and questions are valued and encouraged. Contact the authors at:

Michael Leonard
SAS Institute Inc.
SAS Campus Drive
Cary, NC 27513
(919) 677-8000
Michael.Leonard@sas.com

Bruce Elsheimer
SAS Institute Inc.
SAS Campus Drive
Cary, NC 27513
(919) 677-8000
Bruce Elsheimer@sas.com

Meredith John
SAS Institute Inc.
SAS Campus Drive
Cary, NC 27513
(919) 677-8000
Meredith.John@sas.com

Udo Sglavo
SAS Institute Inc.
In der Neckarhelle 162
Heidelberg, Germany
+49 6221 415 0
Udo.Sglavo@sas.com