FORECASTING LUMPY DEMAND

Jack C. Hayya, Department of Supply Chain and Information Systems, Pennsylvania State University, 441 College of Business, University Park, PA 16802, 814-685-4175, jch@psu.edu
John G. Tyworth, Department of Supply Chain and Information Systems, Pennsylvania State University, 454B Smeal College of Business, University Park, PA 16802, 814-865-1866, jet@psu.edu
Dean C. Chatfield Department of Management Science and Information Technology, Virginia Tech, 1007 Pamplin Hall, Blacksburg, VA 24061, 540-231-4593, Deanc@vt.edu

ABSTRACT

Lumpy demand is a phenomenon encountered in manufacturing or retailing when the items are slow-moving. So far, the seminal procedure of Croston's [4] has been the preferred method for forecasting it. Nevertheless, Croston [5] and others have suggested the use of all-zero forecasts under some circumstances. We put to the test this idea in the context of a simple inventory system. We create a full factorial study comparing five forecasting methods, including the all-zero method, under several levels of demand lumpiness, positive demand variation, ordering cost, holding cost, and shortage cost. We find that all-zero forecasts generate the lowest cost when lumpiness is high; is it also best for mid-lumpiness if the shortage cost is much higher than the holding cost.

INTRODUCTION

Slow moving items, expensive items such as jet engines, items at the trailing end of their life cycle and items dependent on weather conditions, such as utilities (Ward [6]), are examples. And it has been seen through extensive supply chain simulation that the demands at the upper echelons of a simple serial supply chain (customer, retailer, wholesaler, distributor, factory) become lumpy if returns (negative orders) are not allowed, even though the initial customer demand is smooth (Chatfield *et al.* [1] [2]). Croston [4] suggests analyzing the interval between successive non-zero demands and the volume of the non-zero demands separately. Thus, a forecast is made for when the next non-zero demand will occur, as well as how large it will be. An option that has been overlooked is the idea of all-zero forecasting. Such forecasts may have advantages under some conditions. We examine two questions. First, is the all-zero forecasting method a legitimate alternative to other forecasting methods for lumpy demand, under some circumstances? Second, do conventional measures of forecasting error provide the best means for choosing the proper forecasting method when demand is lumpy?

EXPERIMENTAL DESIGN

We design a set of simulation scenarios to evaluate the performance of the forecasting methods with respect to their forecasting accuracy and impact on inventory system cost. We investigate six different factors: the forecasting method (six levels), plus five others (three levels, each). We create a full factorial study with 243 different scenarios (3^5) for each forecasting method. Utilizing the six forecasting methods yields a total of 1458 scenarios. In all scenarios we set the size of non-zero demands to be normally distributed with mean 100. The following six factors are utilized in the experimental design of our simulation study of lumpy demand forecasting for inventory control:

Forecasting methods

- ***AllZero:*** we simply estimate the demand for period *t+1* to be 0.0, for all periods.
- ***MA***: a moving average with period length *p*.
- ***SES:*** simple exponential smoothing, with a smoothing constant α that is equivalent to *p*.
- **Croston*MA***: A simplified version of Croston's method, where the interval and demand volume are predicted separately using a moving average for each.
- **Croston*SES***: A version of Croston's method using simple exponential smoothing.
- ***Stutterin Poisson (sP)***: An implementation of Ward's [6] stuttering Poisson method.

Demand Lumpiness (P(D > 0)): values of P(D > 0) of 0.9 (low), 0.5 (mid), 0.1 (high).
Demand Variation (c.v.): coefficients of variation of positive demand of 0.1, 0.3, 0.5.
Ordering Cost (A): $100, $300, and $500 per order.
Shortage Cost (b): $1, $3, and $5 per unit per period**.**
Holding Cost (h): $1, $3 and $5 per unit per period.

Performance Measures

- *MAPE* (Mean Absolute Percentage Error, modified, because we cannot divide by a demand of zero)
- *MSE* (Mean Squared Error)
- Theil's *U*-statistic
- Total cost (holding + shortage + setup costs) per period
- Total cost per unit demanded

RESULTS

We take the results from all trials and fit a general linear model to determine the factors that significantly impact performance. For *MAPE* and *MSE* metrics, we find that

- *P(D > 0)*,
- forecasting method, and
- the *c.v.* of positive demands

to be significant at *p-value < 0.001*, with level of impact in that order. For Theil's U-statistic, the order of impact is

- forecasting method,
- *P(D > 0),* and
- the *c.v.* of positive demands.

SUMMARY & CONCLUSIONS

The Croston procedure, where the data are split into two subsets and each forecasted separately (we forecast the interval of zeroes separately from the positive demands) does well with lumpy data. However, an investigation of the properties of the lumpy data, for example, the probability of positive demands, would add more information, and hence could lead to a better forecasting method. Here, we undertake a factorial experiment to discern the effect of this probability. In the experiment we considered scenarios with *MA*(15), *SES* (with an equivalent α= 0.125), *AllZero*, the Croston*MA*, and the

Croston*SES* and find that *AllZero* does very well, that *SES* outperforms *MA*, contrary to the assertion of others, such as Chen *et al.* [3] and Zhang [7]. But the Croston*MA* and the Croston*SES* perform differently under different conditions.

AllZero provides the best forecasts in terms of forecasting error for high and mid lumpiness situations when using *MAPE* as the guidepost. However, all other situations resulted in *MA* and *SES*, usually MA, showing the best forecasts in terms of *MAPE*, *MSE*, and Theil's U-statistic. As for the criterion of cost, our analysis of variance shows that all factors affect cost (all *p-values* < 0.001). *AllZero* generates the lowest cost when lumpiness is high, and also for mid-lumpiness if the unit shortage cost (b) > the unit holding cost forecasting (h). As expected, the Croston*MA* and the Croston*SES* outperform *AllZero* when lumpiness is low, and also for mid-lumpiness in the unlikely event that $b < h$.

In answer to our two questions:

1) *AllZero* forecasts may be a practical forecasting method, particularly when $P(D > 0)$ is small.

2) We find that the best forecasts in terms of *MAPE*, *MSE*, or Theil's *U*, do not necessarily translate into the lowest cost inventory system, and that other metrics should be utilized for determining forecasting methods to use when demand is lumpy.

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