FACTORS INDICATIVE OF RELATIVE PERFORMANCE OF METHODS FOR LUMPY DEMAND FORECASTING

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ABSTRACT

A recent study compared the performance of neural network modeling to those of three traditional time series methods (simple exponential smoothing, Croston's method, and a modification of Croston's method) as applied to actual lumpy demand time series. The current study, which is an extension of the previous study, seeks to identify factors that may indicate relative performance of the alternative forecasting methods. Preliminary results suggest that cluster analysis may provide useful insights.

INTRODUCTION

Lumpy demand is characterized by intervals in which there is no demand and, for periods with actual demand occurrences, a large variation in demand levels. A recent study [2] applied neural network (NN) modeling in forecasting lumpy demand. That study compared the performance of NN forecasts to those of three traditional time series methods: (i) single exponential smoothing, (ii) the Croston method [1], and (iii) a modification of the Croston method [4].

The four forecasting methods were applied to 24 lumpy demand time series in a set of industrial data from an electronics distributor operating in Monterrey, Mexico. Each of the 24 series consists of 967 demand observations showing a wide range of demand values and intervals between demand occurrences. In the study, the four low smoothing constant α values of 0.05, 0.10, 0.15, and 0.20, as used in [5], were applied in the three traditional forecasting methods.

While [2] reported on the relative performance of NN modeling and the three traditional time series forecasting techniques, no attempt had been made as yet to identify conditions under which either NN or traditional forecasting models would be expected to perform better. The current study constitutes an attempt to identify factors that may be predictive of relative performance of forecasting techniques.

Previous Study: Neural Network Models and Findings

NN models could be an ideal choice in dealing with disturbances in a diffusion process due to external factors. The most widely used method used for flexible nonlinear modeling, a *multi-layered perceptron* (MLP) trained by a back-propagation (BP) algorithm [3], was adopted in [2]. Three layers of MLP were used: one input layer for input variables, one hidden unit layer (with three nodes), and one output layer (with a single node). All input nodes were fully connected to all hidden unit nodes. The hidden nodes were in turn connected to the output node. The input nodes represent two variables: (i) the demand in the immediately preceding period and (ii) the number of periods separating the last two nonzero demand transactions as of the end of the immediately preceding period. The output node represents the predicted value of the demand transaction for the current period. A learning rate value of 0.1 and a momentum factor value of 0.9 were used, in line with past research [3].

Each of the 24 time series in the set of industrial data consists of 967 observations. The first 624 observations of each series were used to "train" and validate the models (the *training* sample). The four forecasting methods under consideration were then tested, at each of the four values of α, on the final 343 observations (the *test* sample). Based on the test results, the four methods were ranked using the overall mean absolute percentage error (MAPE) as forecasting performance criterion. The statistical results reported in [2] and in the current study were obtained using SAS software version 9.1.

NN models were found to generally outperform the three traditional time series methods [2]. However, NN modeling was outperformed by all three traditional methods in the case of series 24 at all four α values used, particularly for smaller α. Furthermore, for series 22 and 23, the NN model MAPE is inferior to that of the modified Croston method when $\alpha = 0.05$. Plots in [2] of overall MAPEs graphically indicate the general superiority of NN models, except for the time series 22, 23, and 24.

Factors Under Consideration in the Current Study

We identify two variables that are of interest: (i) the sizes *S* of nonzero demand transactions and (ii) the lengths *I* of intervals of consecutive zero demands (between nonzero demands). We calculate, for each time series, "average proximity" statistics in terms of averages of the absolute values of the differences (or absolute deviations) of individual observations of *S* or *I* from their respective mean values, $\bar{S}$ and $\bar{I}$. The average absolute deviations from the means, denoted by $AADS_{mean}$ and $AADI_{mean}$, are as follows:

$$AADS_{mean} = \frac{\sum_{j=1}^{M} \left| S_j - \bar{S} \right|}{M} \tag{1}$$

$$AADI_{mean} = \frac{\sum_{j=1}^{N} \left| I_j - \bar{I} \right|}{N} \tag{2}$$

where *M* is the number of nonzero demand observations in the series and *N* is the number of intervals with consecutive zero demands.

ANALYSIS AND OBSERVATIONS

The key idea is to determine if there are clusters of the time series that have similar demand patterns (in terms of demand size and arrival) based on $AADS_{mean}$ and $AADI_{mean}$. With the identification of these clusters, we seek to specify which forecasting techniques appear to perform better for each cluster. More significantly, we may calibrate different forecasting methods within the clusters for better demand prediction estimates from the models. The plots of $AADS_{mean}$ vs. $AADI_{mean}$ are shown in Figure 1.

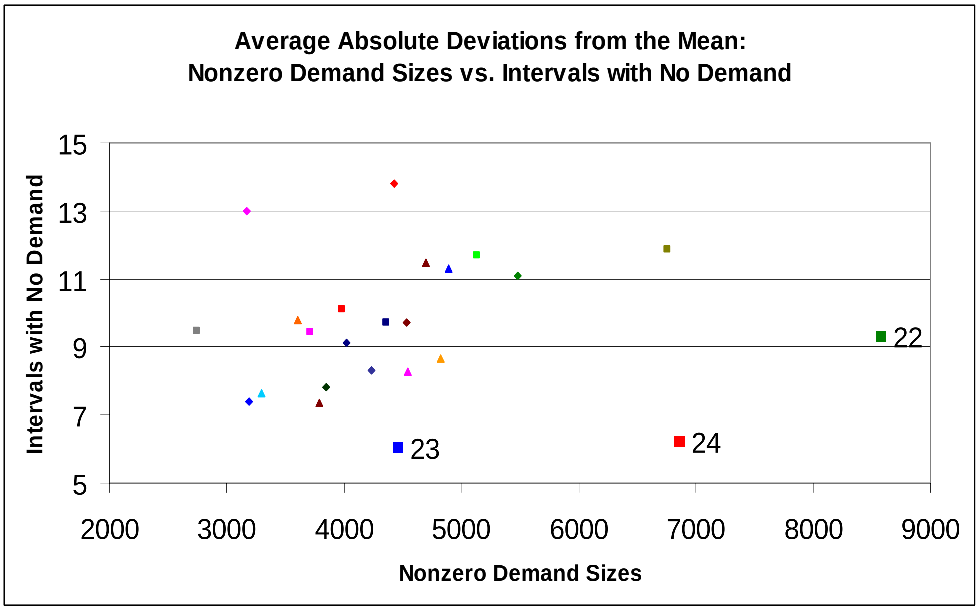

Figure 1. Average Absolute Deviations from the Mean of *S* and *I*

It is interesting to observe that, in Figure 1, series 22, 23, and 24 stand out in relation to the 21 other time series with respect to $AADS_{mean}$ vs. $AADI_{mean}$, and may well constitute one cluster. We had earlier noted that in the case of series 24 all three traditional time series methods outperformed NN modeling at all four values of α used. We find in Figure 2 that series 24 exhibits an 'extreme' combination of low $AADI_{mean}$ and high $AADS_{mean}$. In this case, relative to the other series, there is a wide dispersion in nonzero demand sizes *S* with respect to the mean nonzero demand size $AADS_{mean}$, as well as a small dispersion in the lengths *I* of intervals with no demand with respect to the mean length $AADI_{mean}$ of such intervals. On the other hand, series 22 clearly stands out among all time series with the highest $AADS_{mean}$, while series 23 has the lowest $AADI_{mean}$ among all the series. As noted earlier, for both series 22 and 23, the modified Croston method yielded MAPEs superior to those of NN models when $\alpha = 0.05$. These preliminary observations require a more thorough investigation, particularly by way of proper cluster analysis. Nonetheless, the observations derived thus far do appear promising.

REFERENCES

[1] Croston, J.D. Forecasting and stock control for intermittent demands, *Operational Research Quarterly*, 1972, 23(3), 289-304.

[2] Gutierrez, R.S., Solis, A.O., & Mukhopadhyay, S. Lumpy demand forecasting using neural networks, 2005, under review with the *International Journal of Production Economics*.

[3] Rumelhart, D.E., Hinton, G.E., & Williams, R.J. Learning internal representations by error propagation, in: *Parallel Distributed Processing Explorations in the Microstructure of Cognition*, Cambridge, MA: MIT Press, 1988, 328-330.

[4] Syntetos, A.A., & Boylan, J.E. On the bias of intermittent demand estimates, *International Journal of Production Economics*, 2001, 71(1-3), 457-466.

[5] Syntetos, A.A., & Boylan, J.E. The accuracy of intermittent demand estimates, *International Journal of Forecasting*, 2005, 21(2), 303-314.