LUMPY DEMAND CHARACTERIZATION AND FORECASTING PERFORMANCE: AN EXPLORATORY CASE STUDY

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ABSTRACT

Not many studies have been undertaken on forecasting lumpy demand. This exploratory study proposes two measures for characterizing lumpy demand: a *lumpiness factor* and a *coefficient of skewness*. These measures are applied to actual lumpy demand data of an electronics distributor operating in Monterrey, Mexico. Guidelines for short-term forecast performance are suggested. Three forecasting methods, exponential smoothing, Croston's method, and neural networks, are applied to the data set. Forecast performance is evaluated, and preliminary observations are presented.

INTRODUCTION, METHODOLOGY AND INDUSTRIAL DATASET

The problem of controlling items with *lumpy* demand patterns—e.g., extremely irregular with major differences between each period's requirements and with a large number of periods with zero requirements—has received relatively little attention, even though these items constitute an appreciable portion of the inventories in parts and supply types of stockholdings. Lumpy demand arises in service parts and electronics components when there are variations in volumes associated with the product mix, and also with intervals between demands being fairly erratic and unpredictable. This study aims to identify relationships between forecast performance and lumpy demand patterns across three forecasting methods. These methods are applied to actual demand data of an electronics distributor in Monterrey, Mexico, involving 24 products and 967 weekly observations, exhibiting a wide range of demand values.

We propose two measures for characterizing lumpy demand: (i) a *lumpiness factor* and (ii) a *coefficient of skewness*, which consider spread and skewness as key factors for forecasting performance in lumpy data. *To the best of our knowledge, this is the first paper to suggest the use of either measure.* However, due to space limitations, we are able to discuss only the lumpiness factor here.

Lumpiness Factor

The lumpiness classification is based on the coefficients of variation of both the demand transactions (sizes of non-zero demands) and the numbers of periods of zero demand. In this discussion, we focus on six of the 24 products under study (products 4, 8, 14, 17, 21, and 22). Table 1 depicts the differences in terms of non-zero demand sizes and the numbers of periods of zero demand. While all six items shown in Table 1 exhibit lumpy demands, significant differences do appear to exist among their demand patterns. The lumpiness factor, $\gamma = {CV_S}/{CV_I}$, provides a measure of the relative variability between the stochastic distributions of non-zero demand sizes (S) and the number of intervals (I) between non-zero demands. For instance, products 4 and 22 have lumpiness factors of $\gamma = 4.667$ and 4.674, respectively.

These lumpiness factors are higher than those of products 17 and 14, which are, respectively, $\gamma = 1.366$ and 1.426. This implies that, in relative terms, products 4 and 22, when compared with products 17 and 14, have relatively larger variation in non-zero demand sizes vis-à-vis the variation in number of periods of zero demand. In other words, products 4 and 22 have relatively much lumpier demands than products 17 and 14. For purposes of this exploratory study, we introduce three categories of lumpiness factors: *low* ($\gamma < 1.5$), *medium* ($1.5 < \gamma < 3$), and *high* ($\gamma > 3$). Products 8 and 21 have lumpiness factors of $\gamma =$ 2.514 and 2.554, respectively, which suggest medium demand lumpiness as compared to the low lumpiness of demands for products 17 and 14 and the high lumpiness of demands for products 4 and 22.

Table 1. Statistical data for lumpy demand classification

	17	14	8	21	4	22
Intervals						
Mean	4.304	4.679	4.731	4.196	3.966	4.370
Std. Dev.	4.682	3.797	4.015	3.924	2.710	3.982
Skewness	3.191	1.868	1.849	2.222	0.790	1.826
Coeff. Of Variation	108.801	81.138	84.875	93.506	68.327	91.125
Sizes						
Mean	258.380	466.484	561.273	950.610	783.372	2058.263
Std. Dev.	383.877	539.803	1197.596	2270.318	2498.223	8765.903
Skewness	2.373	8.256	3.253	4.363	6.461	6.021
Coeff. Of Variation	148.571	115.717	213.372	238.827	318.906	425.888
Lumpiness Factor	1.366	1.426	2.514	2.554	4.667	4.674

FORECASTING TECHNIQUES

In the current study, we deal with products whose lumpiness factors fall under the low, medium, and high categories as defined above. We apply three forecasting techniques in our evaluation: simple exponential smoothing, Croston's method, and neural networks. Croston's method was developed primarily to forecast seasonal intermittent demand of P&O Steam Navigation Co. of London, England [3]. The model is based on forecasting two separate components, the time between consecutive transactions and the size of the individual transactions.

The most popularly used method for training 'perceptrons' in artificial neural networks is the back propagation (BP) algorithm [4]. We apply 3-layer and 5-layer BP networks in the current study. In addition, we use general regression neural networks (GRNN), which work by measuring how far a given sample pattern is from patterns in the training set in N-dimensional space, where N is the number of inputs in the problem [5]. GRNN interpolates the relationship between inputs, as well as between inputs and outputs, by applying smoothing parameters to moderate the degree of non-linearity in the relationships and serve as a sensitivity measure of the non-linear response of the outcome to changes in the inputs [1]. Table 2 presents the parameters for the three neural network models applied in the current study.

PRELIMINARY RESULTS AND FURTHER WORK

Table 3 presents the MSEs resulting from the forecasting methods under evaluation. In the case of product 17 (low lumpiness factor), there did not appear to be a clearly superior method, although the 5-layer BP neural model yielded the lowest MSE, followed closely by GRNN. For product 21 (medium lumpiness factor), the GRNN model shows an MSE far smaller than that of any of the other methods. However, for product 22 (high lumpiness factor), Croston's method yields the smallest MSE although GRNN is not far behind with respect to the MSE criterion. The results appear to be consistent with earlier findings by Caudill [2] who recommends GRNN for multiple output prediction, particularly for use with sparse data and data widely varying in scale.

Table 2. Neural Networks and Model Parameters

	Product 17			Product 21			Product 22		
	3 Layer Back Propogation	5 Layer Back Propogation	General Regression Network	3 Layer Back Propogation	5 Layer Back Propogation	General Regression Network	3 Layer Back Propogation	5 Layer Back Propogation	General Regression Network
Input Neurons	7	7	7	7	7	7	7	7	7
Output Neurons	1	1	1	1	1	1	1	1	1
Hidden Neurons	19	N/A	312	19	N/A	312	19	N/A	312
Neurons in 1st Hidden Layer	N/A	15	N/A	N/A	15	N/A	N/A	15	N/A
Neurons in 2nd Hidden Layer	N/A	15	N/A	N/A	15	N/A	N/A	15	N/A
Neurons in 3rd Hidden Layer	N/A	15	N/A	N/A	15	N/A	N/A	15	N/A
Activation Function	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic	Logistic
Learning Rate	0.1	0.1	N/A	0.1	0.1	N/A	0.1	0.1	N/A
Momentum	0.1	0.1	N/A	0.1	0.1	N/A	0.1	0.1	N/A
Initial Weights	0.3	0.3	N/A	0.3	0.3	N/A	0.3	0.3	N/A
Smoothing Factor	N/A	N/A	0.3	N/A	N/A	0.3	N/A	N/A	0.3

Table 3. MSEs for Various Forecasting Methods

	Product 17	Product 21	Product 22
Forecasting Method			
Neural Networks			
3 Layer Back Propagation	4,436	1,682,779	21,608,555
5 Layer Back Propagation	2,019	1,657,714	22,286,391
General Regression Network	2,984	50,050	8,566,566
Exponential Smoothing	5,009	3,048,608	40,812,885
Croston's Method	5,496	3,514,186	8,193,469

Thus far, the GRNN neural model appears to perform fairly well across low, medium, and high lumpiness factors. It is not generally easy to obtain lumpy demand data, and the relatively significant amount of data made available for this exploratory study may provide a wealth of information waiting to be mined. We intend to continue evaluating the alternative models for the remaining 21 items in the 24-product data set at hand, and we will report on our progress down the road.

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