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Spare parts management: Linking distributional assumptions to demand classification

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ABSTRACT

Spare parts are known to be associated with intermittent demand patterns and such patterns cause considerable problems with regards to forecasting and stock control due to their compound nature that renders the normality assumption invalid. Compound distributions have been used to model intermittent demand patterns; there is however a lack of theoretical analysis and little relevant empirical evidence in support of these distributions. In this paper, we conduct a detailed empirical investigation on the goodness of fit of various compound Poisson distributions and we develop a distribution-based demand classification scheme the validity of which is also assessed in empirical terms. Our empirical investigation provides evidence in support of certain demand distributions and the work described in this paper should facilitate the task of selecting such distributions in a real world spare parts inventory context. An extensive discussion on parameter estimation related difficulties in this area is also provided.

1. Introduction

Many industries rely on the effective management of spare parts, including aerospace and defence, transportation, telecommunications and information technology, utilities and durable goods suppliers. Spare parts are held by firms for internal use in the maintenance of tools and equipment. They are also held by suppliers at the retail or wholesale supply chain level for sale to customers. The costs associated with the inventory management of spare parts can be substantial. According to US Bancorp, spare parts relate to a $700 billion annual expenditure that constitutes about 8% of the US gross domestic product (Jasper, 2006). Given the very high level of inventory investments, it is clear that there is significant opportunity for cost-savings through better management.

The demand of spare part items is typically intermittent with demand orders arriving sporadically; the demand can also be highly variable as well as intermittent, in which case it is referred to as lumpy (Boylan & Syntetos, 2008). Kalchschmidt, Verganti, and Zotteri (2006) have also defined lumpy demand as:

- variable, and therefore demand is characterised by fluctuations;
- sporadic, because the demand series are characterised by many periods of very low or no demand; and
- 'nervous', reflecting the low auto-correlation of the demand.

The area of inventory management has received a lot of attention in the Operations Research (OR) literature. Conventional inventory control approaches rely on a number of assumptions that are usually valid when demand is fast-moving. Demand over lead time is assumed to be normally distributed and standard forecasting methods are used to estimate the parameters of the normal distribution (see, for example, Strijbosch & Moors, 2005; Porras & Dekker, 2008). However, it has long been shown that such an assumption is invalid in a spare parts context where demand is usually intermittent (Botter & Fortuin, 2000; Mak & Hung, 1993). Moreover, the intermittent nature of the demand makes it very difficult to forecast future requirements with much accuracy (Fortuin & Martin, 1999). This problem is exacerbated when the replenishment lead times are long. Blumenfeld, Daganzo, Frick, and Gonsalvez (1999) have demonstrated, amongst others, that the longer the lead times are, the higher the levels of inventory required in order to accommodate the demand uncertainty. Forecasting is an integral part of inventory management systems. However, the challenges in forecasting intermittent demand have implications beyond inventory control; demand forecasts are also used in product development, production and supply chain planning.

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Another important issue involved in inventory management is the categorisation of inventory items for the purpose of facilitating forecasting and stock control. When there is a large number of Stock Keeping Units (SKUs), it is not practical to evaluate them on an individual basis. In such cases, the SKUs will typically have to be categorised in order to facilitate decision-making and allow managers to focus their attention on the most important SKUs (however this is judged) (Teunter, Babai, & Syntetos, 2010). There have been a number of studies in the area of demand classification for inventory items with intermittent demand. A review of the studies in this area can be found in a number of papers including Bacchetti and Saccani (2012), Heinecke, Syntetos, and Wang (2013) and Van Kampen, Akkerman, and van Donk (2012).

The main objective of this study is to advance the current state of knowledge in spare parts management by bringing together the issues of distributional assumptions and SKU classification. These issues will be linked together by using compound distributions to model demand during lead time. A number of authors (including Friend, 1960; Kemp, 1967) have suggested that compound distributions (compound Poisson distributions in particular) may provide a good fit for the demand distributions of such SKUs. Compound distributions are appealing because their underlying structure is similar to the demand-generating process associated with intermittent demand.

A top down approach will be used in order to identify compound distributions that may accommodate the distributional properties observed among SKUs with intermittent demand. Firstly, we will consider the shapes that frequency distributions of order sizes will usually take in an intermittent demand context. We will then propose a number of probability distributions that could be used to model such order sizes. Finally, we will introduce the assumption that demand orders arrive according to a Poisson process and, by bringing together the proposed order size distributions and the Poisson arrival process, we will obtain compound distributions that may be used to model intermittent demand. As part of this process, we also develop a demand classification scheme. The categorisation[1] in this scheme will be motivated by a conceptual understanding of the distributional properties of the order sizes rather than a theoretically consistent match of every possible SKU in a particular category. This approach is different from the bottom up approaches that have previously been introduced in the area of intermittent demand management (for example by Syntetos, Babai, & Altay, 2012). In the latter approaches, goodness-of-fit tests were first carried out for individual SKUs and the results of these tests were used towards the development of a possible classification scheme.

Our study also makes a number of further important contributions in the area including: (i) an empirical analysis in order to assess whether compound distributions provide a good fit for spare part SKUs; (ii) highlighting a number of challenges related to parameter estimation and goodness-of-fit testing in the area of intermittent demand management; (iii) the development of criteria that should be used when selecting distributions for modelling demand; and (iv) deriving insights for practitioners and setting an agenda for further research.

The remainder of this paper is structured as follows. In the next section, we shall provide a brief overview of the literature on inventory management related issues for SKUs with intermittent demand. Compound distributions that may model the distributional properties associated with intermittent demand are considered in Section 3. In that section, we will also propose a demand classification scheme that categorises SKUs based on the distributional properties of the order sizes. The empirical goodness of fit of the compound Poisson distributions discussed in this paper is then assessed on an extensive dataset of spare parts in Section 4. We will also compare the relative levels of fit achieved by the compound Poisson distributions in the different categories of the proposed scheme; this exercise allows us to assess the empirical validity of the proposed scheme with respect to the selection of demand distributions. The practical and theoretical implications of our study are discussed in Section 5. Finally, in Section 6, we will provide the conclusions of this study and also identify a number of areas of future research.

[1] The words 'classification' and 'categorisation' are used interchangeably in this paper.

2. Research background

In the context of intermittent demand, the demand arrival can be reasonably modelled as a Bernoulli process if time is treated as a discrete variable. The Bernoulli process models whether or not an order arrives during any given unit time period. Demand orders arriving during each unit period are 'bucketed' and the aggregate demand over that period is known as the demand size. If demand arrives according to a Bernoulli process, then the inter-demand intervals will follow a geometric distribution. Croston (1972), Janssen, Heuts, and De Kok (1998), Syntetos, Boylan, and Croston (2005), and Teunter, Syntetos, and Babai (2010), among others, have modelled the demand arrival process as a Bernoulli one.

If time is treated as a continuous variable, then demand arrival can be modelled as a Poisson process. The Poisson process models the arrival of individual demand orders; the orders are therefore not 'bucketed'. As a result, the Poisson process captures more information about the demand occurrence than the Bernoulli one. Shale, Boylan, and Johnston (2008) have found that order arrival can be well represented by a Poisson process. Other studies that have modelled order arrival as a Poisson process include Axsater (2006), Shale, Boylan, and Johnston (2005) and Larsen, Seiding, Teller, and Thorstenson (2008).

If orders arrive according to a Poisson process, then the intervals between order arrivals will have an exponential distribution. In this paper, we will assume that orders arrive according to a Poisson process; furthermore, we will assume that the order sizes (also known as 'transaction sizes') are distributed according to some arbitrary distribution. The distribution of demand during a fixed period of time will then have a compound Poisson distribution. Let us assume that demand has a compound Poisson distribution and let us denote sizes of the orders as X. In addition, let:

λ = the order arrival rate
$\mu = E(X)$ = the mean of the order sizes
$\sigma^2 = Var(X)$ = the variance of the order sizes
Y = the demand during a unit period of time.

Then the mean and variance of demand during a unit period of time are given respectively by:

$$E(Y) = \lambda\mu \tag{1}$$

$$Var(Y) = \lambda(\mu^2 + \sigma^2) \tag{2}$$

(Satterthwaite, 1942) One of the appealing properties of compound Poisson distributions is that they are Lévy processes and, as such, they are infinitely divisible (Sato, 1999). Furthermore, a linear combination of a finite number of independent Lévy processes is again a Lévy process. The practical implication of this property is that, if the demand over a unit period of time (denoted as Y) is assumed to have a compound Poisson distribution, then the demand over a fixed period of length L (where L is a positive rational number) will also have a compound Poisson distribution.