European Journal of Operational Research 000 (2016) 1–12

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Production, Manufacturing and Logistics

Exploiting elapsed time for managing intermittent demand for spare parts

Clint L. P. Pennings*, Jan van Dalen, Erwin A. van der Laan

Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, 3062 PA Rotterdam, The Netherlands

ARTICLE INFO

Article history:
Received 21 October 2015
Accepted 7 September 2016
Available online xxx

Keywords:
Spare parts
Intermittent demand
Croston
Stock control
Bootstrap

ABSTRACT

We present an intermittent demand forecasting method that conditions on the elapsed time since the last demand occurrence to anticipate incoming demand and show, using empirical data, that this can substantially reduce both stock investment and lost revenue for spare parts management. We extensively benchmark our method against existing forecasting and bootstrapping methods on forecast accuracy and inventory performance and demonstrate that its performance is robust under general conditions. Our method is the first to incorporate that activities at the demand side, such as aggregation of demand, preventive and corrective maintenance, can lead to a positive relation between demand size and inter-arrival time of demand occurrences. By anticipating incoming demand, our method offers substantial financial gains.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

Spare parts management is of great business value and is important for competitive success (Cohen & Lee, 1990). It is often applied to large numbers of stock keeping units (SKUs), ranging into the thousands. Service levels have to be met, while stock investments, which can represent a large capital, are curtailed. Forecasts drive inventory decisions, directly affecting stock investments and customer satisfaction, but are challenging to generate in the case of spare parts. Johnston, Boylan, and Shale (2003) describe a company with 50,000 different SKUs of which the products with intermittent demand represent 87% of the total stock value and 60% of the value of sales. Glueck, Koudal, and Vaessen (2011, p. 28) survey the service and spare parts management activities of manufacturing companies and report that forecast accuracies are poor, and that almost “70% of the manufacturers surveyed are unable to report on the forecast accuracy for their service and parts activities”.

Spare parts are especially challenging to forecast because demand is typically intermittent with substantial and variable periods of time between demand occurrences. As a consequence, variability can occur not only in the demand size, but also in the inter-arrival time of demand occurrences. In spare parts management, inter-arrival times of more than a year are no exception (e.g. see data descriptive statistics in Section 4.2). Also, when demand arrives, it can be for large quantities of items, even ranging into the thousands. This particular setting requires special forecasting methods, as demonstrated by Croston (1972), whose forecasting method is still widely used today.

Croston proposed an intermittent demand forecasting method that distinguishes between the demand size and the inter-arrival time of subsequent demand occurrences. The method assumes independence between the demand size and the inter-arrival time of demand. However, empirical data can exhibit substantial cross-correlations between these two (Willemain, Smart, Shockor, & DeSautels, 1994). Simulations show that ignoring these cross-correlations adversely affects the service level (Altay, Litteral, & Rudisill, 2012). Since Boylan and Syntetos (2007, p. 513)’s claim that “no methods have yet been published to address the general case of non-independence”, newer methods have been developed to relax the initial assumption, starting with Teunter, Syntetos, and Babai (2011). These recent methods specifically address inventory obsolescence, which the other methods ignore. Yet no method addresses more general forms of cross-correlations observed in empirical data. More importantly, behavior on the demand side, which characterizes the demand process, is ignored. Inderfurth and Kleber (2013) provide an example of such behavior, where a final large quantity of parts is ordered at the end of the life cycle. Wang and Syntetos (2011) are the first to characterize the maintenance driven models, such as preventive maintenance and corrective maintenance, as a source of generating intermittent demand. Later work, such as by Romeijnders, Teunter, and van Jaarsveld (2012), assumes

* Corresponding author.
E-mail addresses: cpennings@rsm.nl (C.L.P. Pennings), jdalen@rsm.nl (J. van Dalen), elaan@rsm.nl (E.A. van der Laan).

http://dx.doi.org/10.1016/j.ejor.2016.09.017
0377-2217/© 2016 Elsevier B.V. All rights reserved.

that maintenance schemes drive demand and are the source of variability in the inter-arrival times and the demand size. If demand is indeed generated by this behavior, the independence of the size and the inter-arrival time is clearly violated, but not in a way captured by methods that incorporate obsolescence: any period without a demand occurrence should then lead to a higher, rather than lower, expectation of demand.

If available, extra information can be used to improve inventory management of spare parts (Li & Ryan, 2011). However, when customers are external parties, context-specific information, such as ordering policies and maintenance schemes of buyers, is often unavailable. In most cases, the only available information is a short history of previous demand from which little can be inferred due the intermittent nature of the demand.

Our main contribution is that we develop a method that incorporates the overlooked case of positive cross-correlation between inter-arrival times and demand sizes to anticipate incoming demand. Using empirical data, we show that our method substantially reduces both stock investment and lost revenue for spare parts management. We extensively benchmark our method against existing forecasting and bootstrapping methods on forecast accuracy and inventory performance, and show that its performance is robust under general conditions. Our insights contribute to the spare parts and inventory management literature in general, and specifically to the literature concerned with improving forecast accuracy and inventory performance for spare parts with an intermittent demand pattern (e.g. Altay et al., 2012; Boylan, Syntetos, & Karakostas, 2008; Boylan & Syntetos, 2007; Croston, 1972; Snyder, Ord, & Beaumont, 2012; Syntetos & Boylan, 2001; 2005; 2006; Syntetos, Babai, & Altay, 2012; Teunter et al., 2011; Willemain, Smart, & Schwarz, 2004).

The remainder of this paper is organized as follows. In Section 2 we provide an overview of the relevant literature about intermittent demand forecasting methods and their underlying assumptions, specifically with respect to time dependence. In Section 3, we propose a general model and formulate a specific application to address the time dependence. In Section 4 we describe our empirical data and the basis on which we compare the various methods in terms of forecast accuracy and inventory performance. Section 5 lists the results and their implications, while Section 6 concludes and gives suggestions for future research.

2. Theoretical background

This section reviews the available methods for forecasting the intermittent demand of spare parts. Forecasting methods are often classified as either parametric or non-parametric. The group of parametric approaches mostly consists of adjustments to Croston's method. In the non-parametric group, various forms of the bootstrap are most prominent. Emphasis is given to the time dependence in the forecasting methods and the current state of research.

2.1. Forecasting methods

The demand for most spare parts exhibits large variation in the inter-arrival times between the demand occurrences. Also, demand volumes are often seen to vary considerably. The popular forecasting method single exponential smoothing (SES) only captures the variation in the demand size as:

$$\hat{d}_{t+1|t} = \hat{d}_{t|t-1} + \alpha(d_t - \hat{d}_{t|t-1})$$

where $\hat{d}_{t+1|t}$ denotes the forecast of demand for period $t+1$ made at time t, d_t denotes the observed demand at time t, and α is a smoothing parameter constrained as $0 \leq \alpha \leq 1$. Croston (1972) shows that if SES is used to forecast intermittent demand, the forecast is lowest just before a demand occurrence, and highest just after it. As an alternative approach, Croston proposes to smooth the demand size s_t and the inter-arrival time i_t separately, where i_t denotes the number of periods since the last demand occurrence. This method is widely used today and is becoming more popular (Boylan & Syntetos, 2007). At the end of time period t, if no demand has occurred ($s_t = 0$) the forecast made at the end of time $t-1$ remains unchanged ($\hat{d}_{t+1|t} = \hat{d}_{t|t-1}$), but if demand does occur ($s_t > 0$) then the forecasts for $t+1$ are updated:

$$\hat{s}_{t+1|t} = \begin{cases} \hat{s}_{t|t-1} & \text{if } s_t = 0 \\ \hat{s}_{t|t-1} + \alpha_0(s_t - \hat{s}_{t|t-1}) & \text{if } s_t > 0 \end{cases}$$

$$\hat{i}_{t+1|t} = \begin{cases} \hat{i}_{t|t-1} & \text{if } s_t = 0 \\ \hat{i}_{t|t-1} + \alpha_1(i_t - \hat{i}_{t|t-1}) & \text{if } s_t > 0 \end{cases}$$

for given smoothing parameters α_0 and α_1. The use of separate smoothing parameters is a later suggestion by Schultz (1987). The demand forecast results from the combination of the two separate forecasts:

$$\hat{d}_{t+1|t} = \frac{\hat{s}_{t+1|t}}{\hat{i}_{t+1|t}}$$

If there is a demand occurrence in every period, Croston's method conveniently collapses to single exponential smoothing. The method is therefore applicable to multiple patterns of demand. As the demand size is assumed to be independent of the elapsed time, the demand forecast remains the same in periods between demand occurrences.

Croston's method is biased, as $E(d_t) = E(s_t/i_t) \neq E(s_t)/E(i_t)$ (Syntetos & Boylan, 2001). Several modifications of Croston's method have been proposed to address this (Levén & Segerstedt, 2004; Shale, Boylan, & Johnston, 2006; Snyder, 2002; Syntetos & Boylan, 2001; 2005; 2006). Though some of the variants perform better than the original (Syntetos & Boylan, 2006), others overcompensate and have an even stronger bias by forecasting too low (Teunter & Sani, 2009). The adjustment proposed by Syntetos and Boylan (2005), hereafter referred to as SBA, has the most empirical support and incorporates a correction factor to reduce the forecast:

$$\hat{d}_{t+1|t} = \left(1 - \frac{\alpha_1}{2}\right)\frac{\hat{s}_{t+1|t}}{\hat{i}_{t+1|t}}$$

An extension to Croston's method has been proposed based on the risk of inventory obsolescence, as the forecast of Croston's method does not change if there are no more demand occurrences. Teunter et al. (2011) (TSB) propose to update the probability that demand occurs $\hat{p}$ instead of the inter-arrival time in every period:

$$\hat{s}_{t+1|t} = \begin{cases} \hat{s}_{t|t-1} & \text{if } s_t = 0 \\ \hat{s}_{t|t-1} + \alpha_0(s_t - \hat{s}_{t|t-1}) & \text{if } s_t > 0 \end{cases}$$

$$\hat{p}_{t+1|t} = \begin{cases} (1-\alpha_1)\hat{p}_{t|t-1} & \text{if } s_t = 0 \\ (1-\alpha_1)\hat{p}_{t|t-1} + \alpha_1 & \text{if } s_t > 0 \end{cases}$$

$$\hat{d}_{t+1|t} = \hat{p}_{t+1|t}\hat{s}_{t+1|t}$$

Smoothing constant α_1 reduces the demand probability, and so also the demand forecast, in every period in which there is no demand, unless it is strictly equal to 0. The demand forecast $\hat{d}_{t+1|t}$ is then dependent on the elapsed time since the last demand occurrence at every period t. The smoothing using constant α_1 makes the method more similar to SES, because the forecast is again lowest just before and highest just after a demand occurrence.

Snyder et al. (2012) use a selection of count distributions (Poisson, negative binomial, and a hurdle shifted Poisson) to forecast intermittent demand, and add two dynamic specifications so that

Download English Version:

https://daneshyari.com/en/article/4959781

Download Persian Version:

https://daneshyari.com/article/4959781

Daneshyari.com