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Demand forecasting and inventory control: A simulation study on automotive spare parts

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ABSTRACT

This paper presents results of a large-scale simulation study on spare parts demand forecasting and inventory control to select best policies within each SKU category. Simulations were conducted over 10,032 SKUs of an automaker that operates in Brazil, considering six years of demand data. Literature review drove the selection of different models simulated. The study included three alternatives to record demand data (individual orders data, weekly and monthly time buckets), three demand forecasting models (SMA – Simple Moving Average, SBA – Syntetos–Boylan Approximation and Bootstrapping) and six models for demand distribution during lead-time (Normal, Gamma, NBD-Negative Binomial Distribution, compound Poisson-Normal, compound Poisson-Gamma and Bootstrapping) resulting in 17 "combined" policies. These policies were applied under (s, nQ) inventory control (reorder point, multiples of fixed order quantity), considering two alternative frequencies for model parameters revision (monthly and semi-annually) and four Target-Fill-Rates (TFR=80%, 90%, 95% and 99%), totalizing 136 simulation runs over each SKU. Parameter values (s, Q) were calculated towards TFR using methods from literature. Performance of each combined policy was measured by total costs and RFR – Realized-Fill-Rate. Major contributions of the research are the policy recommendations within each SKU category, a new Bootstrapping procedure and the highlight of Single Demand Approach (SDA) as a promising area for future theoretical and empirical studies. Results shall be used as guideline for practitioners under similar operations.

1. Introduction

In many segments, including automotive, products have little differentiation among brands and other factors gained increased attention to maintain customer satisfaction and loyalty. After sales activities have received strong attention, as quick response and high quality services help companies to accomplish their objectives. Spare parts have significant impact over these services, so good management practices on inventory control are desired.

From practical and academic points of view, spare parts inventory control is a complex and defying activity, involving thousands of SKUs and demands spreading from thousand units per month to quite few units a year.

The literature shows several studies focusing on different aspects of spare parts demand forecasting and inventory control, including items classification (Eaves and Kingsman, 2004; Syntetos et al., 2005), time bucket selection (Krever et al., 2005; Bartezzaghi and Kalchsmidt, 2011), demand forecasting models (Croston, 1972; Syntetos and Boylan, 2005; Teunter and Duncan, 2009), Lead-Time Demand distribution (Porras and Dekker, 2008; Nenes et al., 2010; Bacchetti et al., 2013) and parameter revision frequencies (Babai et al., 2009; Syntetos et al., 2010).

Studies on spare parts inventory control considered different time buckets for demand recording, including individual orders and different time buckets (weekly, monthly, bi-monthly and quarterly). Examples of such approach are found on Eaves and Kingsman (2004), Krever et al. (2005), Porras and Dekker (2008), Boylan et al. (2008), Nenes et al. (2010), Syntetos et al. (2010) and Bacchetti et al. (2013). The study of Krever et al. (2005) proposed an interesting and different approach by using individual order data (called SDA – Single Demand Approach) and developed specific formulations to such cases. Krever et al. (2005) showed that SDA performed better than monthly data for highly sporadic items. On the other hand, Bartezzaghi and Kalchsmidt (2011) showed that larger time buckets (10 or 30 days) implied on lower inventory levels necessary to achieve a 94% TFR for most items. In the current study, simulations included procedures to deal with individual orders as developed by Krever et al. (2005) as well as weekly and monthly time buckets records.

Croston's (1972) seminal paper introduced the idea of separating demand sizes and time intervals to obtain forecasts better than

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traditional SES – Simple Exponential Smoothing. Later developments such as SBA – Syntetos–Boylan-Approximation, improved Croston's proposal, as confirmed on further comparison studies (Syntetos and Boylan, 2005, 2011). Many authors such as Johnston and Boylan (1996), Ghobbar and Friend (2003) and Teunter and Duncan (2009) report comparisons between different spare parts demand forecasting models. In this paper, SBA forecasts were included together with a base model (SMA – Simple Moving Average) and a Bootstrapping model (adaptation of Zhou and Viswanathan (2011)).

Efron (1979) developed the Bootstrapping technique, which was later used for demand distribution and inventory control as proposed by Bookbinder and Lordahl (1989). A milestone on such applications is the paper of Willemain et al. (2004), which showed the superior performance of their Bootstrapping forecasts when empirically compared with SES and Croston models. Porras and Dekker (2008) empirical study also compared Bootstrapping models with parametric (Normal and Poisson) alternatives and showed that Normal distribution provided slightly better results than Bootstrapping models.

Apart from the non-parametric alternative (Bootstrapping), several other parametric distributions are suggested on literature to model LTD. In current study, Normal, Gamma and Negative Binomial Distribution (NBD) were adopted together with SBA and SMA forecasting models. Under SDA, three compound distributions (demand intervals and demand sizes) were used: Poisson-Normal, Poisson-Gamma and Poisson-Logarithm (same as NBD).

Another important decision practitioners must take is how frequently to update the inventory control parameters (the reorder point and order size, for example). Although some previous case studies (Syntetos et al., 2009, 2010; Nenes et al., 2010) considered parameters revision on inventory control simulation, only Babai et al. (2009) actually compared dynamic updating (every period) against static parameters and showed superior performance for dynamic alternative, in spite of the additional computational effort required.

Among other alternatives (see Silver et al. (1998)), Target-Fill-Rates (TFR) are commonly used to set the parameters of the inventory control. Fill-Rate refers to the fraction of demand directly filled by the inventory, without backordering or stockout. An alternative performance measure can be the Cycle-Service-Level (CSL), the desired probability of not running out of stock in any one ordering cycle. In a (s, nQ) inventory control model, both parameters are linked to the TFR, while CSL is dependable only on the reorder point (s). In this paper, parameters are obtained considering four levels of TFR: 80%, 90%, 95% and 99% (analog to Nenes et al. (2010)). It is important to remark that SDA models developed by Krever et al. (2005) considered CSL objectives so a "conversion" to equivalent TFR was necessary for comparison purposes, as explained later.

This paper includes simultaneous evaluation of all above aspects by simulation over empirical data obtained from 10,032 SKUs from an automaker that operates in Brazil. Suitable choices of the above parameters and two revision frequencies alternatives lead to 34 combined policies. These 34 alternatives were simulated under the four different TFR, totalizing 136 simulation runs for each SKU. Empirical data included demand records from 6 years (2007–2013) of 10,032 SKUs. Performance under each policy was measured by its total costs, using TFR as a minimum requirement to RFR.

SKUs were classified within four categories according to the criteria defined by Syntetos et al. (2005) which considers demand size variability (measured by the CV^2 – square of coefficient of variation) and average demand inter-arrival interval (measured by the $\bar{I}$).

The remaining of this paper is organized as follows: Section 2 reviews the literature on spare parts inventory management, Section 3 presents the methodology and simulation model, Section 4 shows the results and Section 5 reports the conclusions.

2. Background

This section presents main references on each model simulated in current study. The sections refer to time bucket choice, demand forecasting, usage of Bootstrapping, reorder point and lot size calculation, Lead-Time-Demand (LTD) distribution, converting CSL objectives into TFR, parameter revision frequency and items classification.

2.1. Time bucket choice

Krever et al. (2005) developed SDA in a similar way as used by Croston (1972). While Croston (1972) developed a forecasting model splitting total demand into two variables (demand sizes and demand interval), Krever et al. (2005) applied same idea to develop order point (s) formulation linked to a CSL objective. They argue that usage of data grouped into time buckets can mislead demand sizes and tendencies, bringing poor performance on inventory control systems. Krever et al. (2005) developed analytical formulations for some special distributions (compound Poisson-Normal and compound Poisson-Gamma, as detailed on Section 2.5) and provided basic formulations to be adapted under other distributions. Their results showed superior performance of the proposed models when compared to traditional time bucket approach (which they called PDA – Period-Demand-Approach).

Traditionally, considering Lead-Time variability and its independence from demand distribution, LTD average and variance are expressed (Silver et al., 1998) as

$$\overline{D_L} = \bar{L} \cdot \bar{D} \tag{2.1}$$

$$\sigma^2_{D_L} = \bar{L} \cdot \sigma^2_D + (\bar{D})^2 \cdot \sigma^2_L \tag{2.2}$$

where $\bar{L}$ = lead-time average, $\bar{D}$ = demand average (per unit time), $\overline{D_L}$ = LTD average (units), σ^2_D = demand variance (per unit time), σ^2_L = lead-time variance, $\sigma^2_{D_L}$ = LTD variance.

By Krever et al.'s (2005) approach, the following formulations are obtained:

$$\overline{D_L} = \lambda_p \cdot \bar{L} \cdot \bar{q} \tag{2.3}$$

$$\sigma^2_{D_L} = \lambda_p \cdot \bar{L} \cdot \left[\sigma^2_q + (\bar{q})^2\right] + \lambda^2_p \cdot (\bar{q})^2 \cdot \sigma^2_L \tag{2.4}$$

where λ_p = average order arrivals per unit time (assumed Poisson), $\bar{q}$ = average order size (units), σ^2_q = order size variance, and other items as per traditional formulation.

In addition to SDA, the simulation herein includes time buckets approach with weekly and monthly records. The choice of such time buckets is supported by previous studies such as Eaves and Kingsman (2004), Porras and Dekker (2008), Boylan et al. (2008), Nenes et al. (2010), Syntetos et al. (2010) and Bacchetti et al. (2013). In a study comparing different time buckets (1, 2, 3, 10 and 30 days), Bartezzaghi and Kalchsmidt (2011) showed that larger time windows (10 or 30 days) implied on lower inventory levels to achieve a 94% TFR for most items. Exceptions occurred on items with high demand inter-arrival interval where increasing from 10 to 30 days implied on significantly higher inventory levels and over lumpy items where no significant conclusions were obtained.

2.2. Demand forecasting

Croston (1972) proposed to separate traditional Simple-Exponential-Smoothing (SES) forecasts into two basic components (demand sizes and demand interval), both modeled by exponential