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Forecasting the returns in reusable containers' closed-loop supply chains. A case in the LPG industry.*

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Abstract

In this paper we review the returns forecasting models described in the academic literature. Next, we build a model not requiring item-level information in the context of a case study conducted in Repsol GLP, the liquefied petroleum gases (LPG) division of Repsol group. Results are unexpected and put under scrutiny the estimates of the return rate and the return delay distribution obtained through this type of models when using a direct replacement policy. We think that the main cause for these results resides in the exchange of full for empty containers imposed by this policy; deliveries and returns are linked in time, and thus the hypothesis of unidirectional causality might not be respected.

1. Introduction

Reverse Logistics is still in its infancy as an academic discipline. The academic community has been able to determine the kind of activities that are generally carried out when dealing with reverse flows (Thierry et al., 1995). Quantitative models already proven in the operations management field have been successfully applied to strategic, tactical and operational decision-making in reverse networks (Dekker et al., 2003). New quantitative models have been developed when the special characteristics of the reverse logistics activities recommended so. However, the complexity and the management importance of the activities carried out in reverse supply chains can vary from one business scenario to the other and, therefore, the understanding we achieve of the field is still incomplete. In this context, logistics systems dealing with reusable containers have not received yet a global and in-depth analysis from the scientific point of view. Our literature review shows that only few scholarly publications directly address this topic (Goh y Varaprasad, 1986; Kelle and Silver, 1989a&b; Kroon and Vrijens, 1995; Del Castillo and Cochran, 1996; Flapper, 1996; Duhaime et al., 2001; Van Dalen et al., 2005; Johansson and Hellstrom, 2007). The case study on which this paper is based on, and other industrial field studies previously carried out (Carrasco-Gallego, 2007), reveal the need of deepening in our understanding of reusable containers life-cycle.

Within the current social and economic context, where there is a growing concern about the depletion of natural resources and the sustainability of our productive models, the design and management of reusable containers systems might acquire a greater relevance. Industrial

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sectors utilizing today reusable containers to handle their products make it almost as an "obligation", because of the restrictions imposed by the product itself, that make physically impossible the use of a disposable packaging (e.g. cylinders), or because of the clear cost savings achieved when introducing reusable handling elements (e.g. pools of palets, plastic containers, etc.). Nevertheless, we can't rule out that, in the medium-term, industries currently choosing disposable packaging elements for distributing their products (recycle), can reorient their choice to returnable containers (reuse), as the new sustainability paradigm, grounded in resources' scarcity, gains momentum, and it becomes more and more evident the need of switching our use-and –dispose model (one-way economy) to a closed-loop economic model, where a packaging element can have multiple lives.

In our interaction with companies dealing with reusable packaging elements, managers have frequently reported difficulties in managing these logistics systems. The returnable items, even if they usually are a quite expensive asset, are not tightly controlled and many items are reported to be lost or irreparably damaged. The decision on when to buy new items and how many should be ordered is usually taken depending on marketing considerations or on financial resources availability rather than on the real grasp of the organization's operational needs. Little or nothing is known about the items rotation in the system and when some operational know-how on this topic exists, is usually based on rough estimations. The required installed-base of items (the pool size) is usually unknown and managers report a need of establishing methodologies for calculating this pool size.

All this reasons (scarce academic literature dealing with reusable containers, sustainability paradigm increasing the relevance of reuse, reports on difficulties to manage these systems in industrial settings) make us think that there are opportunities for researchers to make contributions in this field. That is why we have identified reusable containers management as an interesting research area and as the object of our study in this manuscript.

In this manuscript the objective is to review the state of the art reflected in academic literature on returns forecasting techniques used in industry and to apply this tools to a real industrial case in the LPG sector. To achieve these objectives, we used the following methodology: we carried out a bibliographic review of the returns forecasting techniques described in academic literature. Next, the techniques not requiring item-level information were applied to a set of real data provided by a company using high value reusable containers for distributing LPG to end customers. Previously, a case study was carried out in this company to characterize their logistical practices.

This manuscript is organized as follows. In section 2, we present the results of the literature review we conducted and provide a state of the art on returns forecasting in closed-loop supply chain contexts. In section 3, we present the company originating the raw data used in this analysis; we detail some characteristics of LPG cylinders closed-loop supply chain and explain how data were obtained and how our forecasting model was built. In section 4, we present the results obtained within the models and explain why the results resulted unexpected. Finally, in section 5, we conclude and introduce our future research directions.

2. Literature review. State of the art in returns forecasting

Forecasting techniques have been traditionally applied in the operations management area to obtain an estimate of future demands. Sales forecasts are used for decision-making at tactical and operational level, as they are an input from which we derive procurement plans, manufacturing plans, inventory management plans, distribution plans, human resources plans, and in general, different types of arrangements for the allocation of resources in the short and medium term. Plans are usually updated on a monthly basis along a rolling horizon of one to three years. Demand forecasting techniques analyze the dynamic structure of past sales data series, project the past structure to the future and then provide a forecast for future sales values, which is valid in the short and medium term (Fig.2a). As the forecast of future sales is based in the past values of the same variable, the mathematical approach used in industry is univariate time-series forecasting methods. The complexity of techniques varies from the classical “deterministic” approach of methods such as exponential smoothing or Winters models to the contemporary “stochastical” approach of ARIMA models.

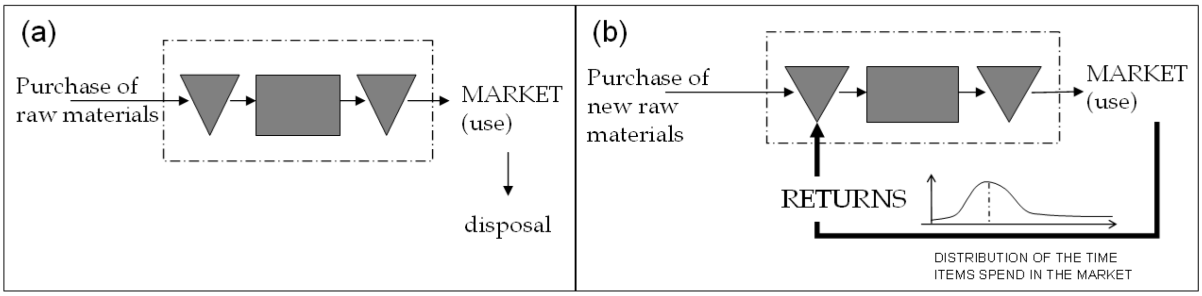

Figure 1. (a) One-way supply chain, (b) Closed –loop supply chain (remanufacturing, reuse)

Unlike the classical one-way supply chain (Fig. 1a), in order to have an effective planning and control process when dealing with a closed-loop supply chain (CLSC), forecasts on future sales and future returns are both needed (Fig. 1b). From these two inputs the above mentioned plans are derived. When we refer to returns forecasting, we refer to predicting the timing and quantity of returns in a given system as defined in Toktay et al. (2000). Uncertainty in the quality of the returns is a well-known characteristic of closed-loop systems but it has not been addressed for the moment in none of the returns forecasting models described in literature. It remains an interesting point of future research.

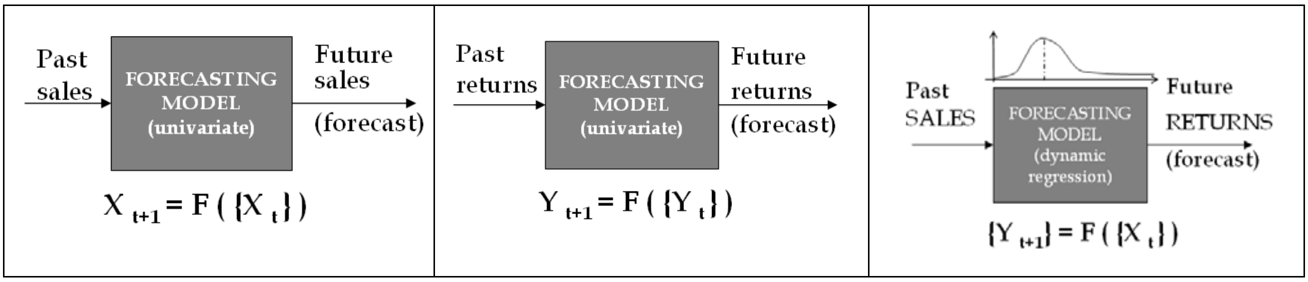

Figure 2. (a) Demand forecasting; **(b)** Returns forecasting, one-way approach; **(c)** Returns forecasting, CLSC approach

A possible approach for obtaining returns forecasts would be to apply univariate time series models to a set of data on historical past returns (Fig.2b). When the only information available is historical returns series, this seems to be a reasonable approach. Organizations managing linear reverse logistics systems, such as, for instance, sectorial recycling networks, would use historical series of collected volumes in order to forecast future collection volumes and thus elaborate plans on recycling activities (production plans) or on the number of vehicles required to assure proper collection at disposal points. However, as long as the wider-focused “closed-loop supply chain” approach is involved (i.e. coordinated management of the direct and reverse flows), using a univariate technique would mean ignoring the very relevant information on future returns that is contained in past sales. That’s why the returns forecasting methods described in academic literature are based on the idea that, with a given probability, past sales will generate a future return after a given delay, which represents the time the product is in the market. The natural forecasting approach is then the use dynamic regression models (Pankratz, 1991), that model the relationship between sales and returns (Fig.2c). These models are also known in literature as transfer function models or distributed lags models. Once the parameters of the model have been estimated, we can use current sales values (input variable, x_t) to predict future returns (output variable, y_{t+1}). These models rely on the hypothesis, that there is just unidirectional causality from $\{x_t\}$ to $\{y_t\}$, ruling out feedback from the output to the input. When properly built, Peña (2005) reports that dynamic regression models provide more accurate forecasts than those obtained from the univariate model.

The interest of obtaining a forecast for reusable containers returns resides not only in the estimation of future returned quantities and its timing, but also in the characteristics of containers' life-cycle that can be deduced from the forecasting model, as will be further explained in 2.1. More precisely, we are interested in approximating the probability distribution of the return delay (L), which we define as the time elapsed from issue to return for a given container. L is random variable representing the time a reusable container is in the market. This distribution asymptotically tends to a value 1-r, which represents the probability that an issued container will never come back. Thus, let r denote the container return rate. L and 1-r are intuitively depicted in Figures 1b and 2c.

2.1. Dynamic regression models for returns forecasting

Let hypothesize that aggregate data on issues and returns are available for a given time period, such as the month. We are dealing then with two time series:

- Let the series $\{y_t\}$ represent the number of items returned in month t (output series).
- Let the series $\{x_t\}$ represent the number of items issued (sales) in month t (input series).

Let a set of parameters v_0, v_1, v_2, …, v_∞ represent the probability that a given item issuing the system on period t, returns to the system either on the same period t, on the next period t+1, on period t+2, and in general, i periods afterwards, i=0,1,2,…, provided that the item will ever be returned. v_∞ represents the probability that an item will never be returned (v_∞=1-r). Thus, the number of articles being returned on period t as a function of the issues in previous periods can be expressed as follows,

$$y_t = v_0 x_t + v_1 x_{t-1} + v_2 x_{t-2} + \ldots + N_t \tag{1}$$

where N_t can either be gaussian white noise or not ($Nt \sim N(0;\sigma)$).

If item-level tracking information is available, the set of parameters v_i, i=0, 1,…∞ can be empirically determined through the analysis of the distribution of the return delay (L) and the return rate (r) of a statistically significant sample of returnable items. When item-level information is not available, it is possible to estimate the dynamic regression model in (1) using historical data (time-series) of container issues and returns. For estimating the model, either transfer function or distributed lag approaches can be used. The estimation of the forecasting model in (1) enable us to identify the value of parameters v_0, v_1, v_2, …and v_∞ (1-r), and consequently, to obtain estimates of containers' return delay distribution L and the return rate r. Through the estimation of a dynamic regression model we circumvent the need of tracking individual items for obtaining important parameters of the life-cycle of returnable items.

In the case of **transfer function models**, the relationship (1) between input and output time-series can be expressed as:

$$y_t = v(B)\, x_t + N_t \tag{2}$$

where $v(B) = v_0 + v_1 B + v_2 B^2 + \dots$ is the Box-Jenkins filter transfer function and Nt is the noise in the system (in transfer function models it doesn't need to be white noise). Coefficient set v_i, known as impulse response function, represent how the effect of an impulse in x_t in period t causes a reaction in the output time-series y_t with a given time lag that is distributed across several time periods. The linear operator B is the backward shift operator. The number of parameters in the model as expressed in (2) is potentially infinite, and thus the model cannot be easily estimated. Therefore, the transfer function is usually expressed as quotient of two finite polynomials:

$$y_t = \frac{w_0 - w_1 B - w_2 B^2 - \dots - w_s B^s}{1 - \delta_1 B - \delta_2 B^2 - \dots - \delta_r B^r} x_{t-b} + N_t, \qquad v(B) = \frac{w(B) B^b}{\delta(B)} \tag{3}$$

A sample of the values of the issues $\{x_t\}$ and returns $\{y_t\}$ time-series enable us to carry out the Box-Jenkins procedures of transfer function identification, model estimation and diagnostic checking. Goh and Varaprasad (1986) used a 60 months sample to estimate a transfer function model that provided the return rate and the coefficients v_i for three different product lines utilizing reusable bottles in a soft drink plant. In their results, they observed that the amount of returns from a single issue was statistically significant only in the first three months, with close to two-thirds of the containers being returned in the same month of issue. The proportion of lost containers was below the 5%.

Another possible approach would be to use Bayesian inference in a **distributed lag model**, where we assume a specific form, based on theoretical considerations, of distribution for the lag in order to reduce the number of parameters to be estimated. A distributed lag model has the same form expressed in (1), but in this case, Nt necessarily has to be gaussian white noise Nt~N(0, σ). Theoretical distributions usually assumed for the lags are geometrically distributed lags (v_i coefficients that decline exponentially, Koyck model, Pankratz (1991)) or Pascal (negative binomial) distributed lags. The disadvantage of this approach is that a given distribution is imposed on the data, while the advantage resides in the relatively parsimonious form of the model, where less parameters are to be estimated and, thus, requires smaller sample sizes for estimation.

Toktay et al. (2000) use this approach to estimate a model for forecasting the returns of the reusable parts (circuit boards, plastic body and lens aperture) of the single-use Kodak camera. With a series of 22 months of sales and returns provided by Kodak, they obtain an estimate of 0.5 for the return rate (r) and test the hypothesis of geometric, Pascal lag one and Pascal lag two distributions for the lags. The hypothesis test reveal that geometric distribution with an estimated parameter ^q=0.58 is the most plausible distribution, which is consistent with cameras being purchased, used and returned quickly after sale.

Either through distributed lags models or through transfer function models, the academic state of the art in closed-loop supply chain management reveals that is possible to obtain an estimation of the L distribution (coefficients v_i) and the return rate (r) just using information of the aggregate sales (issues) and returns in each period of analysis.

2.2. The value of individual containers track information in returns forecasts

Based on the seminal work by Goh and Varaprasad (1986), Kelle and Silver (1989 a&b) provided tools for forecasting the net demand of containers during a given lead time, which is the forecasted demand of full containers minus the forecasted flow of returned empty containers. As the time from issue to return of an individual container is not known with certainty and there is a finite probability for the container of never being returned, purchases of new containers have to be initiated when the inventory level of containers reaches a given reorder point. Kelle and Silver then calculate containers return forecasts and the corresponding reorder points under four different levels of information availability. They evaluate the performance of the four different forecasting methods and they conclude that, although having additional information obviously increase the forecasting method performance, most of the benefits obtained by using individual tracking of the containers (the most informed method) can be achieved by recording only the aggregate issues and aggregate returns period by period. This work was later on extended in Toktay et al. (2003) and in de Brito and van der Laan (2009), where the robustness of the four previous forecasting methods was analyzed in the case of imperfect information. The conclusion is that in the case of imperfect information the most informed method (item-level tracking) does not necessarily lead to the best performance.

3. Applying returns forecasting techniques. The Repsol LPG case

Once the state of the art in returns forecasting in closed-loop supply chains had been established, we went on to apply these techniques to a real industrial case. More specifically, to a data set provided by the LPG division of Repsol group. Repsol is integrated oil and gas company included in the group of the ten largest private oil companies worldwide and is the fifth largest European oil company in terms of stock exchange quotation, just behind BP, Total, Royal Dutch Shell and Eni. The LPG division has operations in Spain (where it holds a market share of roughly 80%) and the neighbouring countries (France, Portugal) and several iberoamerican countries (Ecuador, Peru, Argentina, Chile and Brazil). While LPG consumption grows in the developing countries, in the advanced economies LPG is a very mature or even declining market, where domestic use of LPG is being strongly substituted by safer or cleaner alternatives such as natural gas or renewable energies.

An in-depth case study was previously conducted in order to study the characteristics of Repsol's LPG cylinders' closed-loop supply chain. When consumption volumes are low or moderate, which is usually the case of domestic customers, LPG products are ordinarily distributed by the means of cylinders. Repsol and their distributors deal simultaneously with the cylinder direct and reverse flow: cylinders are filled up in Repsol plants and sent out to distributors' facilities, from where full LPG cylinders are delivered to domestic end users houses. When delivering the full cylinders, distributors are also responsible for collecting any empty cylinders coming from end users, which are finally redirected to Repsol plants in order to be refilled. Some cylinders need to receive specialized maintenance operations before they can be refilled again. The control policy installed in this system is direct replacement, using the terms defined in Flapper (1996), or "full for empty", if we use the terms employed by Repsol management. This policy implies that distributors would only deliver n full cylinders if the customer can provide n empty cylinders in exchange. The first time a customer wants to buy LPG, a fee is to be paid in order to have the right of being delivered without providing the same amount of empty cylinders. When an LPG delivery contract expires (the customer quits the system) some money would be refunded if the empty cylinders are returned to a distributor. However, it is not exactly a deposit as the amount refunded is significantly lower than the fees paid for entering the system.

Repsol registers in their information system the delivery notes of the exchanges they have with their distributors (number of full cylinders delivered and number of empty cylinders recovered by a given distributor). This information is the basis for further invoicing processes, so its accuracy should be guaranteed. The information coming from the delivery notes was aggregated in a monthly basis in order to obtain eight time series instances of 60 observations each, corresponding to the number of cylinders monthly issued and returned from two different Repsol plants located in mainland Spain - Gijón and Pinto- and for two different LPG products, butane and propane, during the 2003-2007 period.

From these data sets four transfer function models were built in order to establish a relationship between the issues and returns for each product in each plant. Repsol managers were much more interested in obtaining the information on the cylinder life-cycle parameters that can be derived from the transfer function model, such as the statistical distribution of the return delay (L) or the return rate (r), than in the return forecast itself. Repsol cylinders, for the moment, are not equipped with any track-and-trace technology that can univocally identify each single cylinder. Therefore, the knowledge managers have on cylinders life-cycle is limited and based in rough estimations and on their own "hands-on" experience.

Next, we present how the four transfer function models were built. First, we graphically represented the eight time-series. All them are characterized by a marked seasonality, which is coherent with LPG market's features: energy consumption for domestic heating during winter months is noticeable higher when compared with the rest of the year. In addition, the eight time-series present an also expected decreasing trend, given the decline of the LPG market in Spain. The time-series were seasonally adjusted using the free software applications TRAMO and SEATS, which can be obtained from the web page of the "Banco de España" (Spanish national central bank). Figure 3 depicts the two time series corresponding to Gijon plant and propane product before and after the seasonal adjustment process.

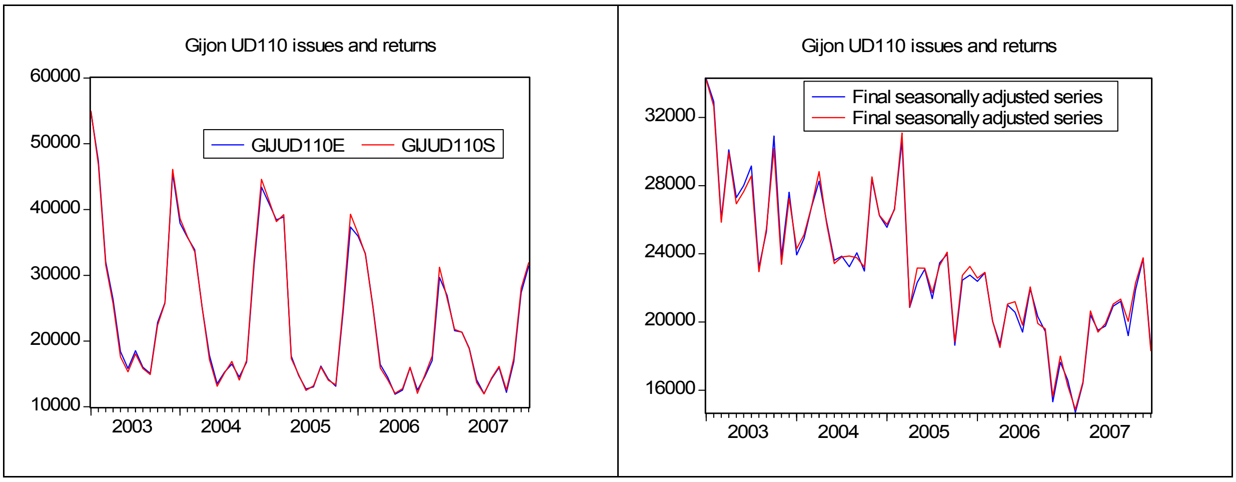

Figure 3. Joint graphical representation of input (issues, red line) and output (returns, blue line) time-series before and after the seasonal adjustment.

As can be observed in the figures, monthly cylinders issues and returns time-series are extremely close, being almost the same time-series, except for slight differences that seem to be achieved in the peak sales months, where sales (issues) slightly surpass returns. Not an appreciable lag can be observed in this graphic representation.

Table 1. Returns forecasting models for Repsol LPG cylinders

	PINTO	**GIJÓN**
PROPANE	y_t=0.959 x_t +0.036 x_{t-1} + N_t	y_t=0.954 x_t +0.018 x_{t-1} +0.0229x_{t-2} + N_t
BUTANE	y_t=0.997 x_t +0.0105 x_{t-2} + N_t	y_t=0.989 x_t +0.0085 x_{t-3} + N_t

The four transfer function models were built using e-views, a well-known time-series analysis commercial package. The resulting models are depicted in Table 1. The coefficients given here are the statistical estimates of the v_i coefficients that resulted statistically significant. For the four models residuals are white noise.

4. Results

The joint graphical representation of cylinder issues and returns time-series showed that the monthly values of issues and returns are very close, being almost the same time-series. This is not strange, given the direct replacement policy used in this system. Repsol delivery notes show that distributors usually respect the equal exchanges policy (provide as many empty cylinders as full are going to be retrieved) and if any discrepancies exist between the two figures they tend to be minimal (1 or 2 cylinders of difference in a usual delivery of 140 cylinders (4 baskets)). This is also a consequence of how transportation is organized, as the empty leg is used for transporting the empty containers, and vehicles tend to be charged to their full capacity. This makes us wonder if there is really a need in industry for obtaining a forecast on monthly returns: when using a direct replacement policy, it would be sufficient to forecast our monthly sales in order to have a quite good estimation of our monthly returns. This information can be then used as an input for elaborating sourcing, manufacturing, distribution, etc. plans. How to deal with daily manufacturing scheduling remains unsolved.

Besides the monthly returns forecast, the second output we expected to obtain from the four transfer function models was an estimation of the return delay distribution (L) and an estimate for the return rate (r), through obtaining the set of coefficients v_i , i=0,1,…∞. We observe in the four models that v_0 coefficient is always very dominant, that would mean that probability that a cylinder returns within the same month it was issued is above 95%. This contradicts the operational know-how of Repsol management, who estimates that cylinders trippage is around 3 or 4 refills per year, which entails a return delay of roughly 4 or 3 months, respectively. However, the dominance of v_0 coefficient in the model is coherent with the graphical representation of issues and returns series: the value of $\{x_t\}$ is roughly the value of $\{y_t\}$. This result seems to be a related with the direct replacement (full against empty) collection policy, which somehow forces the number of cylinders returned in a delivery note to be exactly same of cylinders issued. Cylinders don't "freely" return to filling plant when they are used up, but when a new delivery is arranged. The return forecast provided by the transfer function model is correct, but, on the other hand, the v_0 coefficient dominance in the model conceals the real values of cylinders return delay distribution. This result makes us question ourselves the applicability of dynamic-regression-based models for obtaining relevant parameters on cylinders life-cycle, when a full against empty policy is governing the system.

Another interesting result can be found when comparing the four transfer function models with each other. The choice of plants and products was not random. Regarding products, we expected a faster rotation (and a more pronounced seasonality) in the case of propane, as it is mainly used for domestic heating purposes. Regarding plants, Pinto is an urban plant, located in the south of Madrid region and delivering to distributors serving the city of Madrid. These distributors are able to provide service to all their end users in the 5 working days of a week. In contrast, Gijón is a rural plant, located in the Asturias region in the north of Spain, where a few distributors serve multiple scattered hamlet and small villages, which are served only once a week or a fortnight. Then, cylinder rotation was expected to be higher in Pinto than in Gijón plant. This seems to be reflected somehow in the model. If we compare butane and propane models for Pinto plant, we observe that while month 2 coefficient is statistically significant for butane, propane model in Pinto plant stops at month 1. When comparing, for instance, Pinto and Gijón butane rotation we observe that in Gijón month 3 is statistically significant while Pinto model stops in month 2.

5. Conclusions and further research directions

The results obtained in this research put under scrutiny the applicability of dynamic-regression based models for obtaining relevant parameters of the life-cycle of reusable containers, when a direct replacement control policy is used, which, on the other hand, is a quite frequent policy when dealing with high value reusable containers. Dynamic regression models are based on the assumption that a given impulse in the explanatory variable is freely transmitted to the future values of the endogenous variable with a given probability. A basic assumption in these models is that causality is unidirectional. However, when a direct replacement policy is used, cylinders do not freely return to the plant when they are used up, but only when the next purchase will occur. Due to the constraints imposed by transportation operations, issues and returns are linked in time in the real industrial situation.

The results of this work show that when a direct replacement policy is in place, the monthly forecast of returns is not very different from the monthly forecast of sales, so a forecasting model for returns adds no much additional value to the planning and control process. However, other outputs that were expected to be obtained from the model, such as the return rate (r) or the return delay distribution (L), are of the utmost interest for companies owning reusable containers in their assets, and at the light of this work, need of individual container tracking for being determined. L distribution and r rate are needed in order to establish the minimum container pool size required to carry out operations smoothly or in order to establish the adequate purchasing policies for replacing lost or permanently damaged containers. Thus, the value of the information obtained through item-level tracking might be revised. The state of the art presented in subsection 2.2. is based on the assumption that an estimate of the return probabilities v_0, v_1, v_2, ..., v_∞ can be obtained from aggregate issues and returns recorded period by period. If the return distribution cannot be obtained through this method, then it has to be estimated either by expert judgement or by direct observation of the distribution, which requires item-level tracking. However, for L and r estimation purposes, organizations dealing with this type of closed-loop supply chain do not need to install tracking devices in the complete pool of reusable containers, but just in a statistically significant sample that allow to conduct empirical observations of the return delay distribution and return rate. The insights we acquired during this work enable us to predict that the lag distribution would depend on product, plant and season (meaning that the lag is seasonal, for example, LPG cylinders are expected to rotate faster in winter than in summer, as consumption increases in the cold months).

As future developments of this research we propose to compare the return delay distribution in a given closed-loop system of reusable containers obtained through a dynamic-regression model and through the direct observation of the distribution by means of track-and-trace devices. This requires obtaining data form an organization registering aggregate issues and returns of containers and also tracking them in an individual basis.

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