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# Forecasting returns in reverse logistics: application to catalog and mail-order retailing<sup>\*</sup>

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## *Abstract*

An efficient management of returned items is the last way to keep an unsatisfied customer. For Catalog and Mail-Order Retailers, as more than ninety percent of the returned items go back to stock, returns can be concerned as the first supplier. Quality managers study the returns as they reflect the opinion of customers against the product's quality. Thus, a precise forecast of the returns and indicators of returns is compulsory in order to optimize the supply chain and improve the service quality.

The returns rate, ratio between returned and sent items, is a strategic indicator often used by several departments in catalog and mail-Order retailers. It's used to improve the Supply chain control by well forecasting the quantity of work and reducing the outstanding goods. It's also used to estimate the budget and define which items from the current season can be carried forward for the next season, and which items will need improvements.

This paper presents a study of a real returns phenomenon. A new way to estimate the returns rate is provided and a study of forecasting models is explained. A phased approach to forecast returns rate is provided for distance selling sector.

*Key words:* Reverse Distribution, Forecasting, Returns, Phasing, Returns indicators, Mail-order retailing.

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## **1 Introduction**

Distance selling sector has been generally stagnant or even declining for many years ago. Because of the increased supply, the market has become more volatile and the competition extends now beyond the selling distance.

The logistical chain, as the customer relationship, is a priority where mail-order companies are relying on in their strategies in order to be able to stay competitive in the market and to increase their market share as well. Recently viewed as one of the logistical chain issues, the subject of returns management becomes increasingly important and regarded as a strategic business element.

In order to satisfy their clients, Distance Selling actors afford the opportunity of returning the product at almost any time even if it is specified on each sale support a return date limit for each item category. This strategy generates a very important stream of returns of around 25% in average sale in terms of quantity [8] which explains the consideration of returns as the leading supplier. Consequently, returns prediction has become the paramount importance.

Through this article we present a phased approach in order to predict the return rate early in the current season. This work was developed mainly for quality managers to provide them with a better visibility of customers'

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reaction toward their products for the current season. Thus, they could take decisions that are more precise about the products to be renewed for next season, and those to be eliminated or modified. Nevertheless, it is expected that logistic managers in particular suppliers can find in this work an efficient way to enhance managing procurement, and the returns processing managers to better control the work pace in the treatment workshop that feeds the stock with the non-defective returned products.

The paper is organized as follows. In the second section, we explain the phenomenon of returns in distance selling sector and we analyze it later. In the third section, we first give an overview of the forecasting models used. Subsequently, we detail the three steps of our approach to forecast returns. The fourth section is a conclusion of our work.

## 2 The product returns in Catalog and mail-order retailing

The first reflections on the reverse logistics began in the early 80s. Since then, several definitions and names have emerged [8]. In this article the term reverse logistics means “the returns, the reverse movement of a product based on its reuse, recycling or disposal” which corresponds to the current definition of reverse distribution.

Logistic is strongly affected by the phenomenon of return. For all that key logistical issues that have been answered to the area of distribution become more complex to manage for reverse logistics [1]. In addition, the issue of returns is far from being exclusively for logistical mismanagement of returns has primarily a negative impact on the main strategy of the company namely customer loyalty in terms of product quality and service. In fact, bad returns management creates a backlog which triggers a delayed repayment of customers and an increase in work-in-process. This causes problems of deferred and launched overestimated restocking causing overstock problems. In this chapter, we will explain concepts that have been identified in the field of reverse logistics in catalog and mail-order retailing sector; which will help us later in our approach to forecast the returns.

### 2.1 The reverse distribution

In catalog and mail-order retailing, the reverse distribution can be summarized in four steps (figure 1):

- First, the customer returns the products to a terminal (branch store, RVC<sup>1</sup> or shop), by phone or by post.
- Second, the provider responsible for products delivery and collection includes the returns and file them to the sorting center. The postal operator deposits also the packages to the sorting center.
- Third, the returns are sorted by type of items, and each type is sent to its appropriate destination for treatment.
- Last, information about returns is stored in the database. Returns that are flawless feed the stock, and those containing defects are sent elsewhere (liquidated at low prices or destroyed).

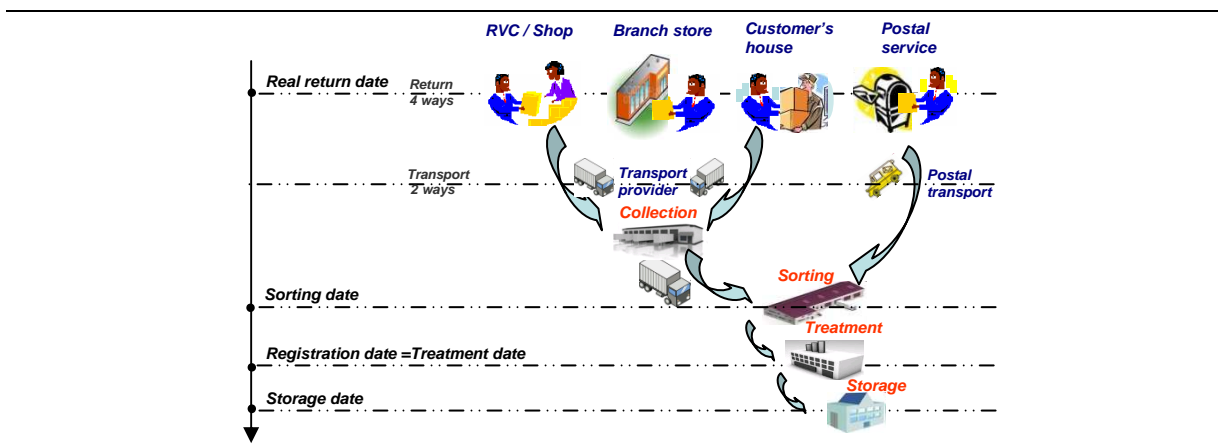


Fig. 1. Reverse distribution in catalog and mail-order retailing

In our industrial case, due to the existence of different means of feedbacks (RVC, shop, branch store, customer’s home and postal office) as well as the lack of a continuous and homogeneous traceability system, returns are

<sup>1</sup> RVC: French abbreviation of meeting catalogue office; the place where customers consult catalogues, choose items and place orders then come back to get the chosen items.

finally recorded at the treatment date. Therefore it's not possible to locate the bottleneck in the reverse supply chain in case of a problem of backlog of customer feedback.

If the return is done in RVC or in the store or by phone, the return motif of the customer is requested to provide. This is not the case for the half of the returns that are done in relay and by post. Information about returning reasons allows quality managers to better understand their products and also allows to the treatment center to locate defects if they exist.

In addition to the reason of the return, quality managers is willing to know the fitting time taken by the customer to perceive that the product does not satisfy him. This time is the period between the delivery date and the date of return. However, the date of return available in the database does not match the real date of return where the customer has effectively returned the product but rather an earlier date which is the treatment date as already explained. This effect puts the quality managers back from the idea of analyzing the behavior of their customers and puts us back in our study from the idea of forecasting returns with causal methods.

### 2.2 Returns Phasing

We define the phasing of returns as the speed of product returns after expedition. Returned products among those sold in a week of expedition are recorded in several following weeks. We define the coefficients of the returns phasing by the percentages of returns recorded in each of these weeks. See figure 2.

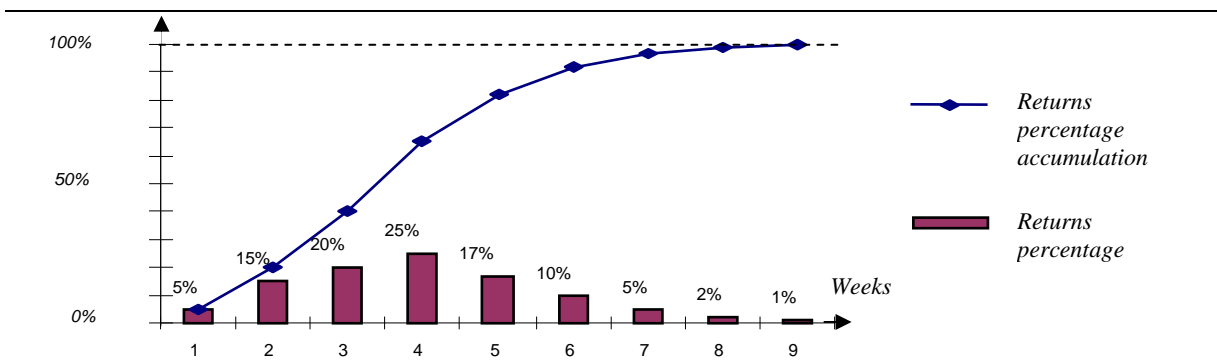


Fig. 2. Example of returns Phasing

In [11] the coefficients of returns are calculated with probabilities. This is quite possible while a rich history exists in the database. The analysis that we conducted on returns phasing (figure 3) showed that:

- The curve of phasing is not stationary. Phasing is more spread out in some specific periods such as vacation periods and periods of sales. Thus the coefficients of the phasing should be previewed, rather than estimated
- It takes several weeks to get all the product returns. Figure 3 shows that the accumulation of 8 coefficients reaches at average 99% of all the returns. This is true for all products in the department where we did our study. By analyzing data from other department working with completely different category of products, we found phasing wider spans over 12 coefficients.

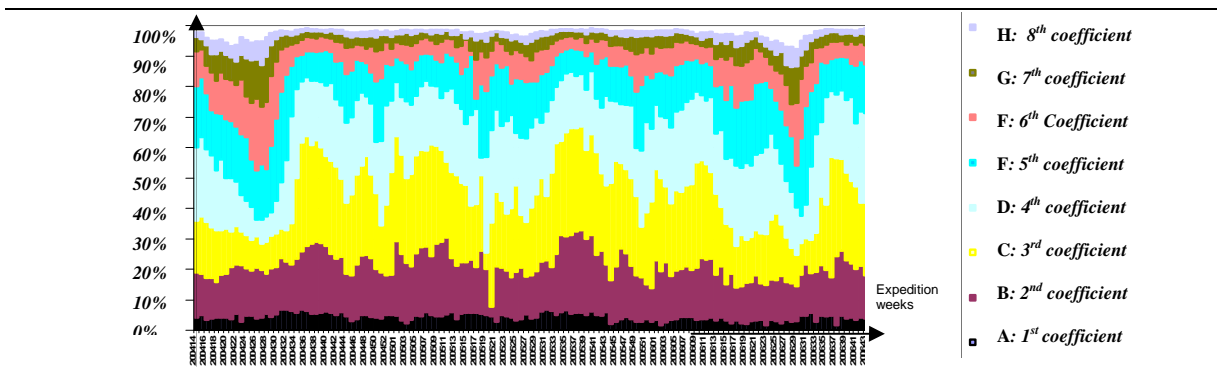


Fig. 3. Variation of returns coefficients per expedition week for a family of products

In figure 3, the  $i^{th}$  coefficient represents the percentage of returns recorded with  $i-1$  weeks of lag between sending and receiving.

2.3 The returns rate : a strategic indicator :

Managers at the strategic level use returns rate to estimate the budget. Returns rate is also an essential indicator for decision makers because it reflects the customer reaction to products. The returns rate indicator is defined as the ratio of returned products to the expedited products. It can be calculated in different ways. We retain in this paper two estimation formulas called weekly returns rate and indexed returns rate.

The weekly returns rate is formulated as following:

$$\tau_{weekly}(s) = \frac{r(s)}{E(s)} \tag{1}$$

With:

- r(s): returns recorded among expeditions of the week s
- E(s): Expeditions of the week s.

It is obvious that the weekly returns rate of a week s couldn't be calculated unless the returns from expeditions of the week s are all recorded. So, with this formula we must wait the week s+8 to calculate the returns rate of the week s: which is an unacceptable condition in our study case where the estimation is needed early in the current season.

Presumably, the curve of returns rate is barely fluctuating around a fixed value, but in reality large disturbances occur during the season and cause complications to the analysis of changes in returns rate. Several factors are behind these disturbances mainly: the balance periods, holiday periods, the beginnings of Price-Lists, the hearts of seasons and times of beginnings and ends of seasons where cannibalism between the products of two current seasons comes in a remarkable way. Figure 4 shows the pace of the weekly returns rate presenting large fluctuations particularly in the middle of the season which corresponds to the price-list period.

Managers, in strategic level, require a stable index of the returns rate which considers for each current week s the cumulative returns and cumulative expeditions from the beginning of the season until the finished last week. See figure 4. The formula is:

$$\tau_{index}(s) = \frac{\sum_{i=1}^{s-1} R(s-i)}{\sum_{i=1}^{s-1} E(s-i)} \tag{2}$$

With:

- s: current week
- R(s): The feedback received in the week ( $R(s) \neq r(s)$ ).
- E(s): Expeditions of week s.

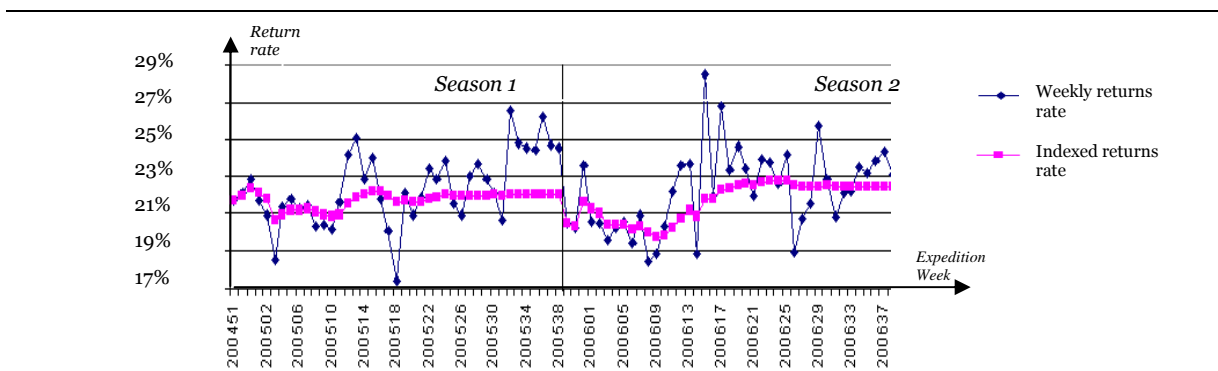


Fig. 4. The weekly returns rate and the indexed returns rate for a family of products

The index formula is an underestimation of the returns rate when applied to the last 8 weeks. Indeed, the numerator does not contain all the last 8 weeks returns and yet the denominator contains the total expeditions. Thus, the formulas 1 and 2 are completely inadequate for the early season where returns are not yet registered in their entirety. We will offer better estimates formulas in 3.3 by exploiting our knowledge of the returns phasing.

### 3 Phased approach to forecast returns rate

Recent works deal with the problem of forecasting returns [4], [6] and [7]. Nevertheless they offer formulas for research field which are not yet adapted to the industry. Indeed, in order to apply them, it would probably need to hire an expert in stochastic models [4] and [6] or in artificial intelligence [7]. Manufacturers, seek to have simple models that provide acceptable results which can be easily integrated into the tool for handling data which they have to be able to quickly generate dashboards with creating simple queries. See figure 5.

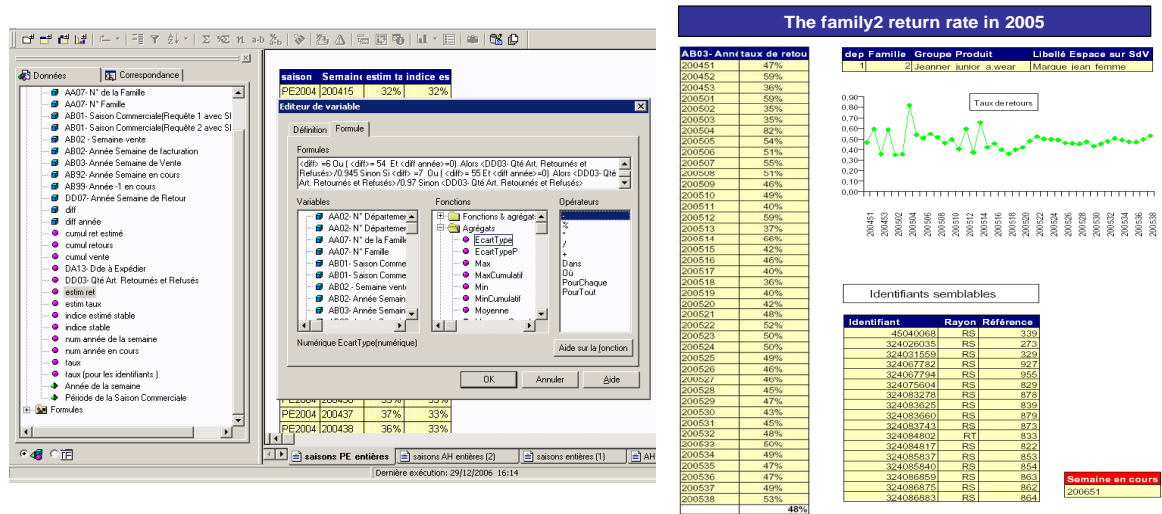


Fig. 5. Designing queries and integrating formulas in the business Object tool for obtaining a dashboard with indicators on returns.

We suggest a forecasting approach which combines returns observation with the application of forecasting techniques that are adapted from those designed for time series extrapolation. In this section, we present forecasting models in general and those used in our work in particular. Subsequently, we present step by step our approach to forecasting returns rates.

#### 3.1 Overview of forecasting models

In the forecasting world, there are three classes of techniques:

- The qualitative technique that is used when data are scarce or when the information is qualitative. It uses intuitive judgment to transform qualitative data into quantitative estimates.
- The chronological series extrapolation technique which is a projection of the history, the latter must be available and reliable over a series of years past.
- The causal or explanatory technique that is used when possible to determine correlations between the series and to provide explanatory factors.

Qualitative techniques are simpler since they are based on intuitions, but they are inaccurate. Contrariwise causal models are more complicated and generally more reliable. Unfortunately, the use of these causal methods is impossible in our study case. We justified this by the inaccuracy of the recorded returns dates. Finally, we turned to the extrapolation methods of chronological series despite of the low history that exists in the database.

The models used in our approach of forecasting returns rate are the following:

- Single and double exponential smoothing [3].
- Additive and multiplicative smoothing of Holt [5] and Winters [12]
- The stationary process ARMA and non-stationary process SARIMA of Box and Jenkins [2] including the MA [9] and the AR process [13].

Other more complex models are used in sales forecasting [10]. The complexity of our study focuses on developing a process to follow the prediction of returns which is a new concept compared to the sales forecast. Thus, we limit ourselves to apply the models listed below and compare them to keep the best one that fit our data sets. Applying other methods would be possible in the frame of our approach.

3.2 Forecasts of returns phasing: First step

Impressive results have led us to believe in the predictability of the coefficients of Phasing:

- The returns phasing curve is seasonal and cyclical (figure 3). Therefore, forecasting models will be applied on each phasing coefficient.
- The pace of the phasing is the same for families of products from the same category. Therefore, we can apply the prediction of phasing coefficients once on only one family of products.

It always begins by tracing the graphs of our chronological series in order to visualize the evolution of chronic, detects potential accidents (peaks or troughs), and derives a general trend. To help better visualize the chronological series, it is possible to apply a filter or transformation. The best known filter is the moving average.

In the case of phasing coefficients, we notice an apparent seasonality. Thus, the reliable models that can be applied are exponential smoothing models, Holt-Winter models, and Box-Jenkins models. We present in this paper the forecasting process established for the first coefficient (A). The same approach is applied to the other coefficients.

In our database, we have a short series of 82 periods which are equivalent to two seasons. Unlike the naive forecasting methods such as moving average, chronological series extrapolation methods previously mentioned are recommended to produce a forecast for a maximum period equivalent to 1/3 of the history we have. Thus, in our case, the forecast projection will be reliable only for 28 periods. Among the chronological series extrapolation methods, the additive model Holt-Winter is the one we selected for the prediction of coefficients of phasing as it best fits the series. The smoothing coefficients of the Holt-Winter technique can be optimized. However, in order to make it simple they are set to 0.2 (figure 6).

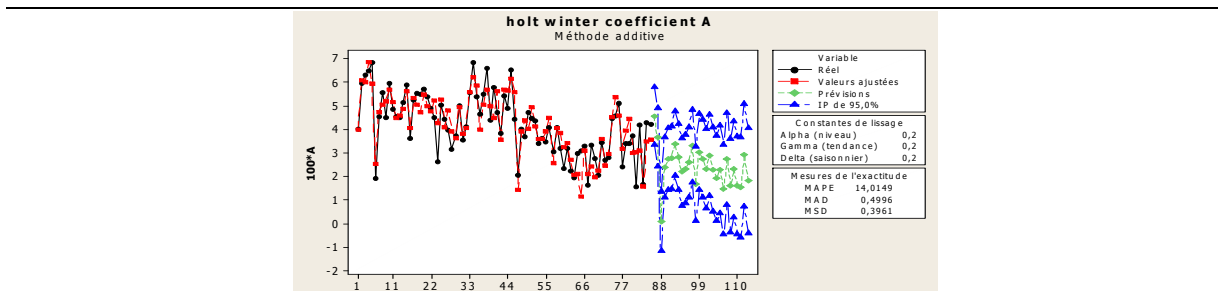


Fig. 6. Prediction of the coefficient A with the additive Holt-Winter method

Box and Jenkins methods start by observing the stationarity of the series. In fact, before applying SARMA model which is suitable for series presenting apparent seasonality as is the case for the coefficients of phasing, the series must be stationary i.e. null variance and trend.

Box-Cox transformation of A coefficient series is proposing a value of  $\lambda = 1$ . Thus we have the stationarity in term of variance. The curve of coefficient A shows a decreasing trend. To stabilize the series in terms of trend we proceed to differentiation. We choose the best differentiation that offers us a modified set with a horizontal trend and minimal deviations. Differentiation of order 1 is sufficient in the case of factor A. See Figure 7.

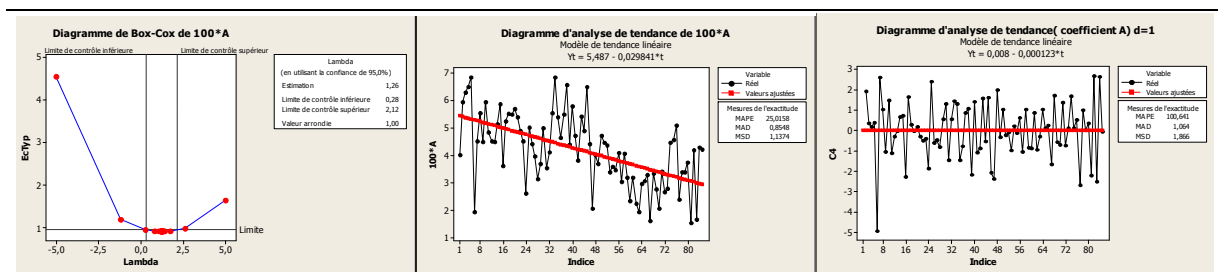


Fig. 7. Analysis of variance (Box Cox Transformation) and analysis of trend before differentiation and after differentiation with the ordre1 of the coefficient A

Once the series becomes stationary with the differentiation of order 1, we analyze the ACF (Autocorrelation functions) and PACF (Partial Autocorrelation functions) correlograms. See figure 8.

We check the last buttoners coming out the confidence intervals in the ACF and PACF in order to define the coefficients of the SARIMA model (Figure 8). In our case, this reasoning isn't efficient. In fact, we know that the frequency is 41 weeks (number of periods per sale season), and we only have 84 periods in the history. Technically speaking, the lag value of these correlograms doesn't exceed the one quarter of observations which is 21. Thus, through the history that we dispose, we could not affirm the existence of a seasonality which value is greater than 21 through the correlograms. Similarly, the spectral analysis provides us with insignificant values of frequency equal to 16.

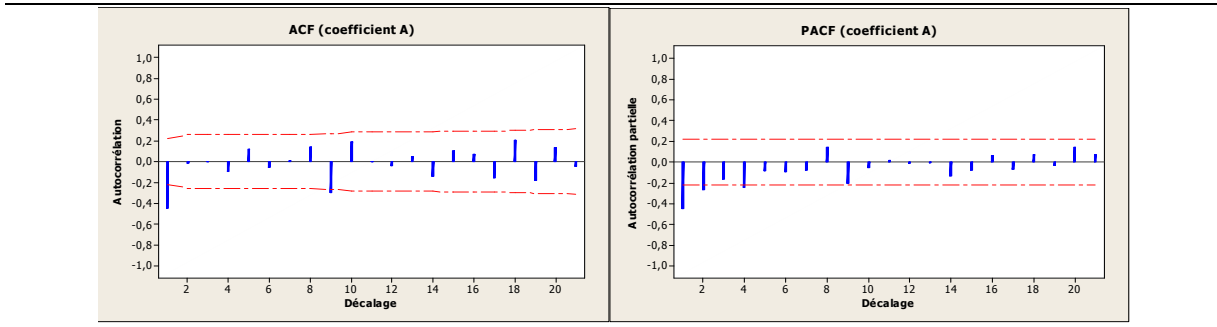


Fig. 8. ACF and PACF on coefficient A series

Finally, with the available data, the model of Holt-Winter forecasting seems to solve the problem. The SARIMA model would be useful if we would have recorded data from at least 4 seasons.

### 3.3 Returns estimation: Second step

In order to avoid the lack of adaptability of the formulas 1 and 2, we exploit our estimates of the returns phasing coefficients to define new formulas for the returns rate that will be called partial returns rate (adjusted weekly returns rate) and global returns rate (adjusted indexed returns rate).

$$\tau_{partiel}(s-i) = \frac{r(s-i) / \sum_{j=0}^i Coeff(j, s-i)}{E(s-i)} \quad (3)$$

$$\tau_{global}(s) = \begin{cases} \sum_{i=0}^{s-1} \left[ r(s-i) / \sum_{j=0}^i Coeff(j, s-i) \right] / \sum_{i=0}^{s-1} E(s-i) & \text{if } s \leq s_8 \\ \left[ \sum_{i=0}^7 \left[ r(s-i) / \sum_{j=0}^i Coeff(j, s-i) \right] + \sum_{i=8}^{s-1} [r(s-i)] \right] / \sum_{i=0}^{s-1} E(s-i) & \text{if } s > s_8 \end{cases} \quad (4)$$

With:

- $s$ : Current week,
- $s_8$ : The 8<sup>th</sup> week in the new season,
- $r(s)$ : Received feedback received among the expeditions of the week  $s$ ,
- $E(s)$ : Expeditions of week  $s$ ,
- $coeff(j, s)$ : The  $j^{th}$  coefficient of phasing returns the week of expedition  $s$  ( $Coeff(0, s) = A(s)$ ,  $coeff(1, s) = B(s)$ , ...,  $Coeff(7, s) = H(s)$ ).

These two estimates 3 and 4 have a negligible gap with the real returns rate calculated at the end of the season. Furthermore, the mass effect in the expression 4 completely covers the gap. The advantage of the two expressions 3 and 4 is that they provide good estimates of returns rates at any time of sale.

We call partial return and overall return rate the respective numerators of partial returns and global returns rate. Subsequently, we focus on predicting the returns rate, which seems more interesting to study than the returns themselves. Multiplication by the expedited quantities put us back easily to the prediction of returns.



3.4 Forecasting the returns rate: Third step

To predict the global returns rate of a specific study area we take into consideration both the history we have in our database, and estimates made for the final weeks of sale. Consideration of the estimates for the current year is essential. In fact, this is the main key that allows knowing the starting trend in the series which reflects the customers' reaction to the current season's products. The evaluation of forecasting methods that we are going to elaborate is based on the difference between values and estimated values. A final validation will be done by the end of season when all returns are recorded and thus the true values of the rate of return can be calculated.

We consider the same predicting approach as that one applied for the returns phasing. To compare the model predictions, we consider, in addition to the pace of the previewed series, the sum of differences (SE) and the sum of squared deviations (SCE) between previewed values and estimated values.

Among the extrapolation of chronological series methods, the Holt-Winter multiplicative model is the one we select for the prediction of the global returns rate with  $SE=4.26\%$  and  $SCE=0.00387\%$  (figure 9). With the double exponential smoothing model  $SE=4.58\%$  and  $SCE=0.0458\%$ , and with Holt-Winter additive model  $SE=5.36\%$  and  $SCE=0.0506\%$ .

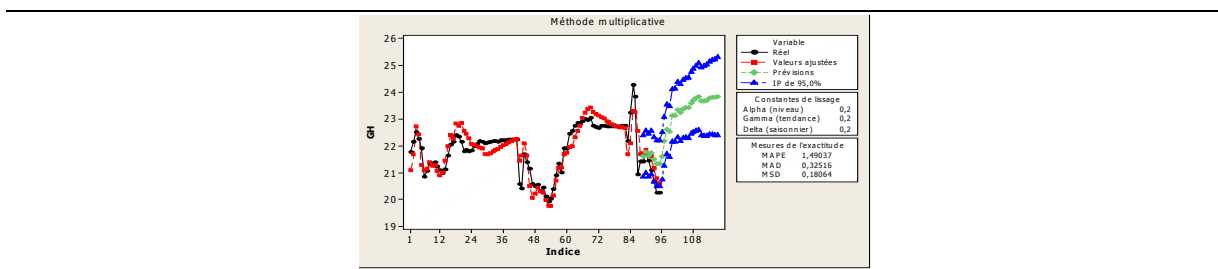


Fig. 9. Returns rate forecast using the multiplicative Holt-Winter model

Starting from the crude series of the returns rate, with a transformation of CoxBox  $\lambda = 3$  (the transformation function:  $F(x) = (100 * x)^3$ ) and differentiation of order 1, we get a modified series which is stationary. See figure 10.

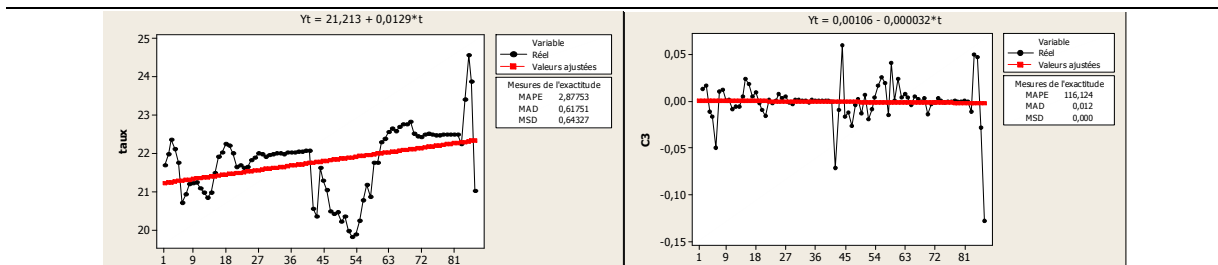


Fig. 10. Analyse of the returns rate series trend before and after differentiation

ACF and PACF analyses of the modified series enable us to choose the coefficients of the autoregressive  $AR(q)$  and moving average  $MA(p)$ . In our case, the last barred out of the certitude range in the correlogram ACF is present in period 2. Therefore, we choose  $q = 2$ . Similarly, as the last barred out of the confidence interval in the correlogram PACF is present in period 2, we choose  $p = 2$  (figure 11). Consequently, we apply  $ARMA(p, q) = ARMA(2,2)$  to the changed series of the returns rate and we observe the new ACF and PACF correlograms. See figure 12.

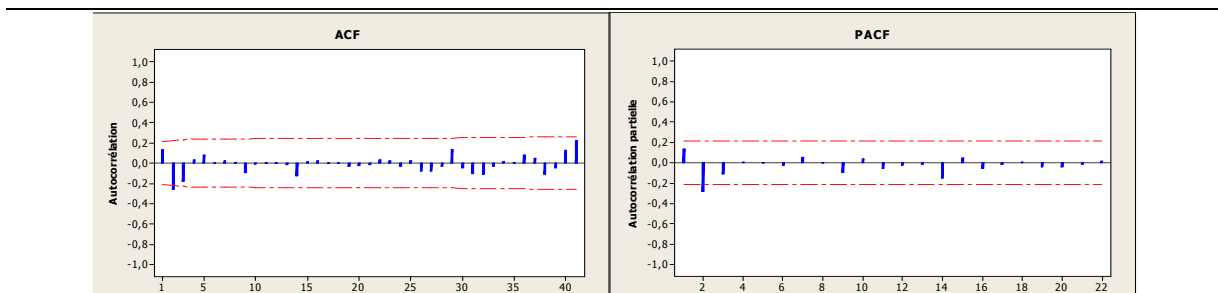


Fig. 11. ACF and PACF on the modified series of the returns rate

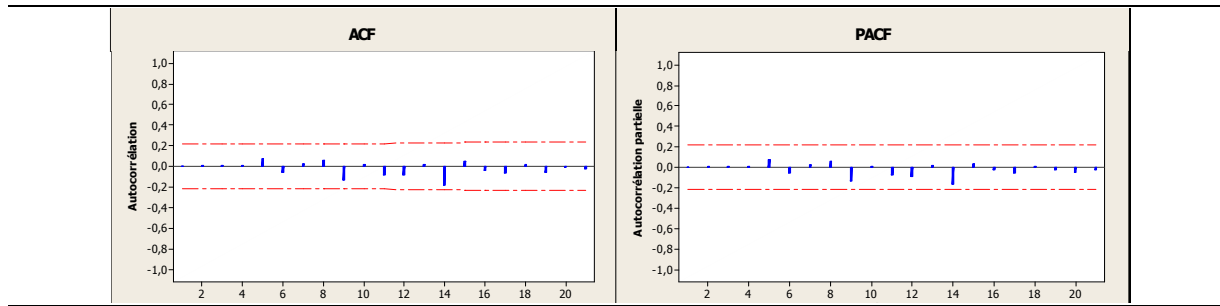


Fig. 12. ACF and PACF after applying the ARMA(2,2) model on the modified series of the returns rate

We found no barred exceeding the confidence interval in the new ACF and PACF. Thus, the ARMA (2,2) can be selected for the series which changed the returns rate. Having applied the differentiation of order 1 to get the modified series, we can conclude that the ARIMA (2,1,2) is the best Box and Jenkins model for predicting the returns rate with SCE = 0,14% and SE = 9,86%.

Finally, for the prediction of the global returns rate Holt-Winter model is the most suitable since it provides better results than Box-Jenkins models and other models of extrapolation of chronological series. Box-Jenkins models will certainly be more efficient if we would have a broader history but this will not change our overall approach to forecasting.

#### 4 Conclusion

The importance of the returns phenomena encouraged mail-order managers to develop a warning system for the abnormally high values of the returns rate indicator early in the current season. These alerts could eventually lead to a cessation of product marketing or a product line. Thus, we identified the need to develop a predictive tool allowing learning from what threshold value of the returns rate and in how many weeks it will be possible to have a reliable prediction of returns for every sale week.

Some problems like data imprecision and incompleteness in the industrial area justify the additional complexity of real industrial problems compared to theoretical problems. Whereas we have such problems in our case of study, we have managed so far to develop, following the analysis of components and constraints of reverse logistics, a predictive tool for the adapted returns to the field of distance selling sector. The deployment of this tool is very simple as it can be adapted to other areas presenting the problem of reverse logistics as the after sale service and re-production.

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