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DEMAND FORECASTING IN AN ENTERPRISE – THE FORECASTED VARIABLE SELECTION PROBLEM

Abstract: Forecasting process efficiency depends – to a large extent – on the correct determination of the forecasted variable. Therefore, companies should use for sales forecasting, the variables that reflect actual consumer demand. However in practice, since demand is usually not directly observable, many operational measures of demand are used. In the manufacturing and retail enterprises, the most often used variables are historical orders, shipments, and billed sales volumes. The purpose of this paper is to characterise the effects of using as the predicted variable, different operational measures of consumer demand. Theoretical discussion is illustrated by an attempt to estimate errors in demand forecasts for Avon Cosmetics' products that are related to changes in data used for forecasting.

Keywords: demand, demand forecasting, operational measures of demand.

1. Introduction

Forecasting is a prediction of future events, and its aim is to reduce risk in the decision-making process. In the case of manufacturing and retail enterprises, the most frequently performed and also the most important forecast is usually the demand forecast [Dittmann 2003].

For business planning purposes, the demand is commonly defined as "what customers want" – sometimes with an additional condition, "with the price they are willing to pay, along with all other products they wish to buy at any given time" [Chockalingam 2009]. However, demand defined in such a way is generally unobservable. Therefore, in commercial practice, various operational measures of demand – various predicted variables – are used. The selection of forecasted variable depends mainly on the aim of the created forecast and results in the selection of an appropriate data source [Dittmann et al. 2011]. On the other hand, the available data sources necessary for the construction of the forecast may also, to some degree, determine the choice of the forecasted variable. Hence, in practice, relations between the forecasted variable and the accessible data sources may be bilateral.

The purpose of this article is to point out the possible results of choosing the most common operational measures of consumer demand. The consequences of this choice are presented using the example of demand forecasts for one of the Avon Cosmetics Corporation products.

2. Forecasting data sources in the enterprise and operational measures of demand

Over the past few years, there have been significant advances made in the field of collecting and storing data in electronic form. Storage costs dropped so significantly that now many companies are able to collect information on the level of individual stock keeping units (SKUs). As a result, companies beginning their forecasting process can choose not only between the levels of forecast aggregation, but also between operational measures of demand and data sources containing information on this demand. Currently, the most commonly used operational measures of consumer demand are historical customer orders, shipments volumes, and billed sales volumes [Chase 2009]. Meanwhile, the source of forecast data is usually the relevant marketing information system of the company.

In an ideal situation, all these measures of demand should lead to the creation of identical predictions. However, in practice, few companies serve their customers perfectly by executing all the orders in full and exactly on time. Therefore, forecasting processes based on retrospective data about orders, shipments and billed sales volumes may actually lead to different predictions.

2.1. Historical customer orders

In manufacturing and retail enterprises, the customer order fill rate usually does not reach 100% and therefore orders might be subject to various political gamesmanship between the company and its clients. Consider three cases related to the situation of product stock out:

1. If customers' orders cannot be fulfilled, and customers move (or repeat) their orders in subsequent periods.
2. If customers predict the occurrence of product stock out and refrain from placing orders to take advantage of competitive manufacturers' or suppliers' offer, or to order alternative products.
3. If customers predict the occurrence of product stock out and artificially inflate their orders to get greater part of allocation from the available pool of goods at a given time [Gilliland 2010].

In the first case, the unhandled orders appear again in the period following the time when actual consumer demand existed. Moving unfulfilled orders results in overstating the consumer demand. Orders are recorded both in the initial period and in the future periods as long as they are not executed or cancelled.

In the second case, due to chronic shortages of the goods resulting from problems in the supply chain, or much larger orders than initially expected, customers choose the services of competitive enterprises. Even if in fact there is a demand for the company's product, it is not reflected in the orders' history, because they have not been placed. Orders are frequently perceived in business practice as, by definition, greater than or equal to consumer demand. However, this example shows that, in theory, orders can also be lower than the actual demand.

In the third case, the consumer (or sales representative) has in advance, knowledge about anticipated shortages of the product and predefined rules of allocation for available volume. If orders are fulfilled according to some deterministic rules, such as "realize 90% of all orders" or similar, the customer can simply order more than he/she actually needs and hope, that as a result of orders reduction, he/she will finally get the desired amount of the product.

2.2. Shipments

As in the case of orders, the use of information on recorded shipments of goods as a proxy for data concerning actual consumer demand may lead to certain consequences. Shipments are usually perceived as equal to, or as less than, the actual demand and therefore serving together with completed orders as lower and upper limits of demand. However, according to the conclusions of the first of the discussed cases, shipments may be actually higher than the real demand for a particular product at a given time. Such a situation occurs when orders are not fulfilled in a timely manner, and must be processed in subsequent periods. Shipments are then recorded later than actual consumer need and overstate the demand for a given period of time.

Therefore, it must be noted that all operational measures of demand based on shipments of goods should use gross shipments, instead of net shipments (shipments without returns). Returns express an overestimation of demand at a time when the order was fulfilled. To get the actual demand value, returns need to be subtracted from the recorded shipments of goods from the past period. However, there is a fundamental question – from what period? If, for the purposes of obtaining operational measure of demand, the returned volumes are subtracted from the orders in the period when the company received a return, then the assessment of consumer demand in this period is probably underestimated [Chase 2009].

Of course, it is proper to correct billed sales and shipments volumes by recorded returns for accounting purposes. Nonetheless, this type of adjustment is neither necessary nor appropriate when we aim to estimate the actual demand to be used in the company's forecasting process.

2.3. Billed sales volume

The billed sales volume is probably the most commonly used operational measure of consumer demand. However, sometimes sales do not correspond to the actual demand. In practice, there are temporal discrepancies and shifts between billed sales and demand that are analogous to the ones described in the previous examples of historical orders and recorded shipments of the goods.

2.4. Other operational measures of demand

In addition to the previously discussed relatively simple operational measures of consumer demand, there are in practice also more complex measures based on combinations of orders and shipments, as well as information about product stock outs. As examples the following measures may be given:

1) the arithmetic mean of customer orders and shipments during a particular period,

2) recorded shipments incremented by known stock outs,

3) recorded shipments incremented by last stock outs.

However, these operational measures of demand do not solve either all the problems discussed before. The first is based on the assumption that customer orders are exaggerated, as often the company experiences product shortages. The second and third enable, in varying degrees, to avoid the risk of underestimating the demand but can as a result lead to its overestimation [Gilliland 2003].

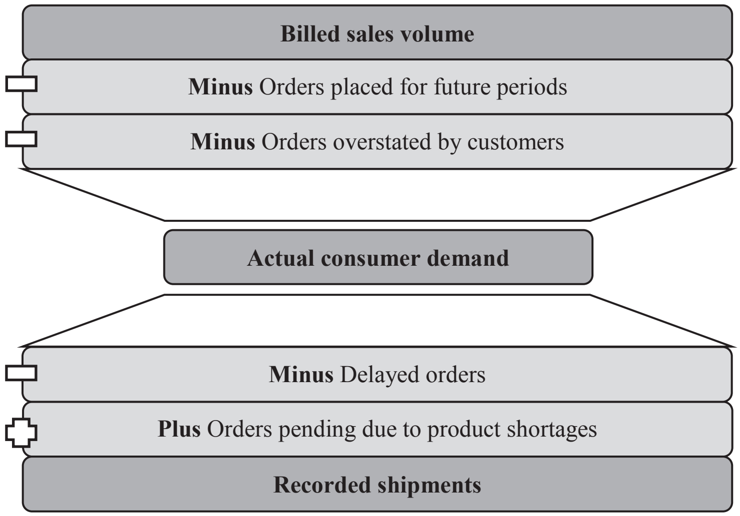

Figure 1. Differences between billed sales volume, recorded shipments, and consumer demand

Source: own study based on [Chockalingam 2009].

A more comprehensive operational measure of actual consumer demand should incorporate information on the differences between recorded shipments and billed sales volumes. Differences come from future orders, orders overstated by the customers, or on the other hand orders that are pending due to either logistic reasons or product shortages. An illustration of the operational measure of demand that takes into account all the mentioned above considerations is presented in Figure 1.

To summarize the theoretical considerations, we may therefore conclude that the development of accurate operational measure of consumer demand for the forecasting and planning business can be a difficult task – in many cases even impossible – due to the lack of reliable data sources on customers' expectations concerning the production capacity of the company. Nonetheless, this task is important from a practical point of view, because as we will show in the empirical example, using different operational measures of demand may yield a significant difference in the created forecasts.

3. Empirical example

An analysis of the differences coming from the application of various operational measures of consumer demand has been carried out on the example of forecasts for one of the products of Avon Cosmetics Corporation. The data used came from the company's own marketing information systems and covered the years 2008–2010 at the Central European region level[1].

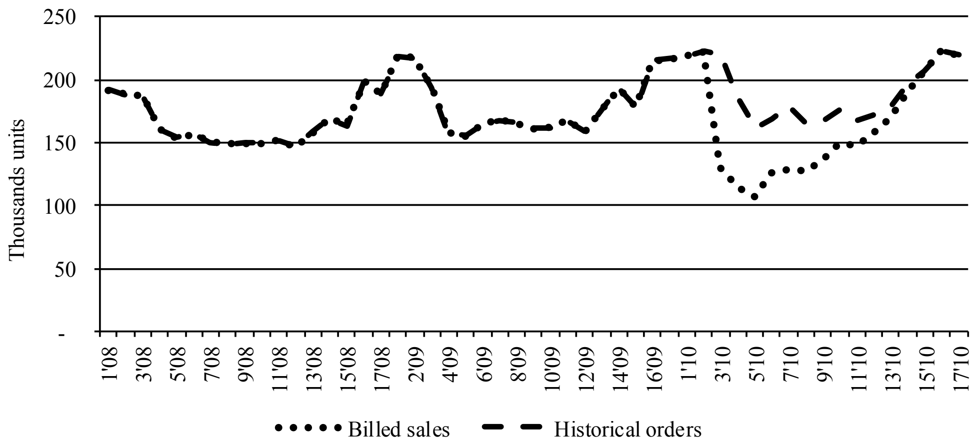

Figure 2. Billed sales and historical orders in 2008–2010

Source: own computation based on company internal data source.

[1] Avon Cosmetics is a company operating on the direct selling principle. Avon sells its products through catalogues distributed to sales representatives. In the past few years the number of catalogues distributed in Central Europe was on the level of 17 editions per year.

Changes in the number of customer orders and billed sales volumes are presented in Figure 2. On this basis, we can state that in the period of 2008–2009, the sales volume was virtually equal to the order volumes. The values of both operational measures of demand were growing steadily and were subject to regular fluctuations. As confirmed by the analysis of variance, the results of which are given in Table 1, in the period 2008–2009 there was trend and seasonality in both the company's sales and orders.

Table 1. Analysis of variance

Source of variance	*SS*	*Df*	*MS*	*F*	*P*-value	Test *F*
Catalogues	1.34E+10	16	8.36E+08	20.2071	1.17E-07	2.333484
Years	1.92E+09	1	1.92E+09	46.52879	4.11E-06	4.493998
Error	6.62E+08	16	41348316			
Sum	1.6E+10	33				

Source: own computation based on company internal data source.

In Figure 2 there are also visible significant differences between the actual billed sales volumes and orders placed in the second part of 2010. The existence of differences between these two measures of demand used in the company enables us to conduct a comparative analysis of forecasts based on them. For this purpose, using data from 2008–2009 (catalogues 1–34) for both operational measures of demand we estimated Winters models with linear trend. Then we created rolling forecasts for the year 2010 (catalogues 35–51) for horizons of one, two, three, four and five periods. The results are shown in Figures 3–12.

Forecasts for horizon of one catalogue

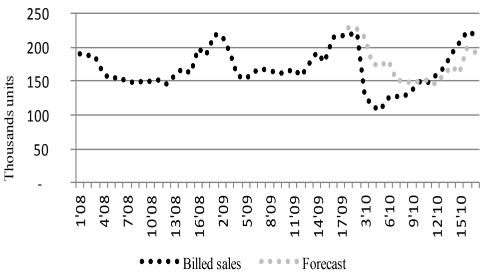

Figure 3. Company's billed sales forecasts

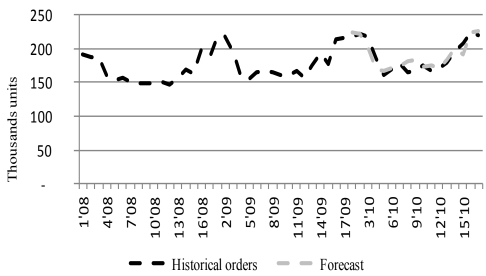

Figure 4. Customers' orders forecast

To assess the impact of switching between different operational measures of demand we calculated *ex post* forecast errors. The Mean Absolute Percentage Errors (MAPEs) are shown in Table 2. Meanwhile, the Mean Percentage Errors (MPEs) are presented in Table 3. By comparing errors of forecasts based on customer orders and errors of forecasts based on company billed sales volumes, we can conclude that in

Forecasts for horizon of two catalogues

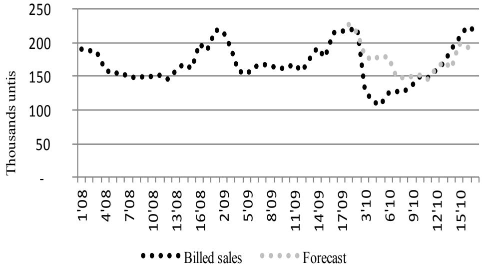

Figure 5. Company's billed sales forecasts

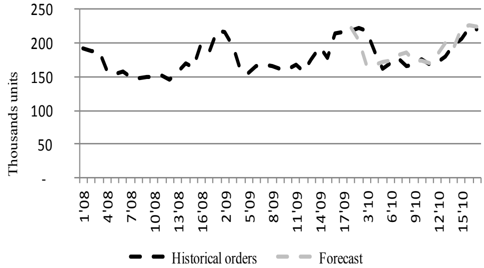

Figure 6. Customers' orders forecast

Forecasts for horizon of three catalogues

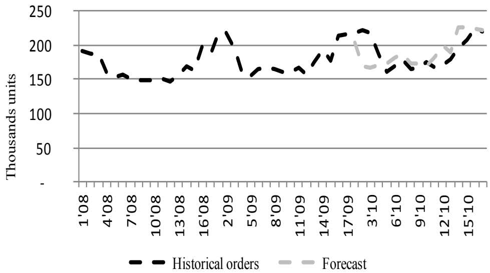

Figure 7. Company's billed sales forecasts

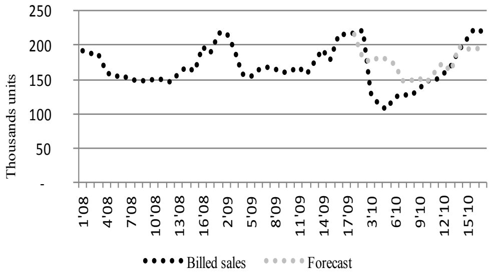

Figure 8. Customers' orders forecast

Forecasts for horizon of four catalogues

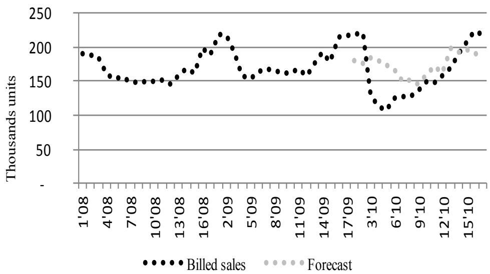

Figure 9. Company's billed sales forecasts

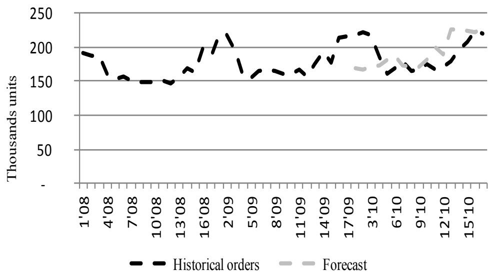

Figure 10. Customers' orders forecast

all cases forecast accuracy decreased when the horizon of forecast was extended. However, this relationship is less evident in the case of billed sales forecasts than in the case of customer orders forecasts. In addition, in each of the analyzed forecast horizons, orders forecasts were characterized by higher accuracy and significantly lower forecast bias than the billed sales forecasts.

Forecasts for horizon of five catalogues

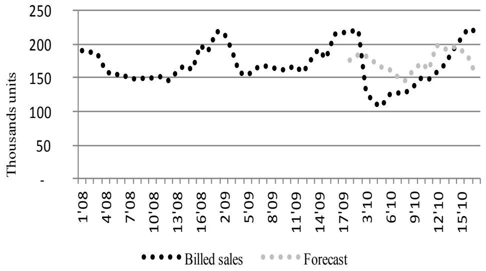

Figure 11. Company's billed sales forecasts

Source: own computation.

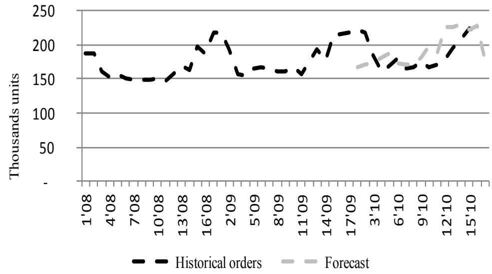

Figure 12. Customers' orders forecast

Source: own computation.

Table 2. Mean absolute percentage forecasts errors

Forecast horizon	Mean absolute percentage errors		
	Sales forecast based on orders	Sales forecast based on sales	Orders forecast based on orders
1 catalogue	22.4	20.5	4.1
2 catalogues	22.4	17.9	6.4
3 catalogues	25.5	19.1	9.1
4 catalogues	28.9	21.0	11.6
5 catalogues	31.8	22.8	13.7

Source: own computation based on company internal data source.

On the basis of errors presented in both tables, we can also say that sales forecasts prepared on the historical orders data were less accurate than sales forecasts prepared on billed sales data. Their absolute errors were higher and they were more biased. In other words, in the analyzed company situation, using historical orders data to forecast future sales did not yield positive results.

Table 3. Mean percentage forecasts errors

Forecast horizon	Mean percentage errors		
	Sales forecast based on orders	Sales forecast based on sales	Orders forecast based on orders
1 catalogue	21.6	12.6	0.8
2 catalogues	21.4	12.2	1.0
3 catalogues	21.8	12.4	1.2
4 catalogues	23.2	12.3	2.3
5 catalogues	24.3	12.0	3.1

Source: own computation based on company internal data source.

Another fact worth stressing is that all three types of prepared forecasts were in most cases overestimated as indicated by the positive values of average errors presented in Table 3. With regard to forecasts based on historical orders, this may indicate that the company experienced the second from the previously described types of customer behavior in the stock out situation. Problems with the product availability persisted long enough to make customers expect further stock outs and to hold their orders to purchase from competitive producers or even refrain from any purchase.

To summarize the obtained results, it should be noted that the differences in the quality of forecasts prepared using different predicted variables that relate to different data sources and different operational measures of consumer demand were significant. Nonetheless, the results also indicate that the company would receive the most accurate forecast of the future sales if it proceeded in a standard way by forecasting sales solely on the basis of sales already billed.

4. Concluding remarks

This article discussed the implications of using different operational measures of demand for the purposes of business forecasting processes. The presented empirical example seems to confirm the existence of theoretically predicted discrepancies between forecasts constructed on the basis of billed sales volumes and forecasts prepared using data concerning historical customer orders.

When relating conclusions coming from the presented example to business practice, it should be noted that in the situation of persistent problems with products availability, customer orders may not be a better predictor of future sales than retrospective information about the billed sales volumes. In this case, future sales are more constrained by supply issues than by demand for the product. However, forecasting demand on the basis of variables that reflect customer orders, in conjunction with monitoring the volume of those orders, may allow to estimate losses in potential sales that are connected only to the customers moving away due to the stock out situations.

Such information might be useful in planning company operations. A key factor, when choosing operational measure of demand, and as a result the variable used in the forecasting process, remains the question about the purpose forecasting activity in the enterprise.

Furthermore, the magnitude of differences between the accuracy of particular predictions obtained in the presented empirical example leads to the next research question. Is the accuracy improvement which can be achieved by the use of different predicted variables significant in the context of the forecast errors obtained in business practice? (see [Jain 2003] and [Jain 2011]) The answer to this question requires a determination of costs that are associated with the collection of each data type that was analyzed in this study, as well as further works dedicated to the development of methodology for assessing the total cost of demand forecast errors in the enterprises.

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PROGNOZOWANIE POPYTU W PRZEDSIĘBIORSTWIE – PROBLEM WYBORU ZMIENNEJ PROGNOZOWANEJ

Streszczenie: Efektywność procesu prognozowania zależy w dużej mierze od poprawnego określenia zmiennej prognozowanej. Dlatego do prognozowania popytu przedsiębiorstwa powinny stosować zmienne, które odzwierciedlają rzeczywisty popyt konsumencki. Jednak popyt zazwyczaj nie jest bezpośrednio obserwowalny, więc w praktyce używane są różne zmienne prognozowane odpowiadające różnym operacyjnym miarom popytu. W przedsiębiorstwach produkcyjnych i handlowych są to najczęściej wielkość zamówień, wielkość wysłanych towarów lub wielkość zaksięgowanej sprzedaży. Celem artykułu jest scharakteryzowanie skutków stosowania jako zmiennych prognozowanych różnych operacyjnych miar popytu. Ilustrację rozważań teoretycznych stanowi próba oszacowania błędów prognozy popytu na jeden z produktów przedsiębiorstwa Avon Cosmetics Polska związanych z różnymi zmiennymi prognozowanymi.

Słowa kluczowe: popyt, operacyjne miary popytu, prognozowanie popytu.