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# SALES STRUCTURE AND ITS IMPACT ON ACCURACY OF SHORT-TERM SALES FORECASTING IN MANUFACTURING COMPANIES

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The article deals with the issue of the hierarchical sales forecasting in manufacturing companies and focuses on the specifics of those companies whose customers are mainly intermediaries operating on B2C markets. The article proposes a hierarchical forecasting models while determining their accuracy in short-term sales forecasting in a selected company of chemical industry. Through the forecasting model accuracy analysis, the impact of aggregation level of sales on the forecasting accuracy was studied.

#### Introduction

The law of supply and demand forecasting are an integral part of corporate planning in every manufacturing company. Its primary goal is to estimate as accurately as possible the size of future customer demand depending on the level

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of its marketing efforts as well as on the business environment. The final sales forecast should serve as the basis for the majority of decisions by the management, in strategic and tactical-operational terms. More accurate forecast will allow company better preparation on real demand and quick response on customers' requirements. Ability to react quickly to customers' requirements is one of these factors which result in reinforcing of relationships with customers and in their increased loyalty [1].

The success rate of utilization of forecasting in the corporate management does not only depend on the choice of accurate forecasting methods. The aim of forecasting is always to support decision-making at different time levels, but also at different stages of aggregation of production and sales segments. For the forecast to be meaningfully usable in other business processes, the "sales structure" must meet the needs and requirements of the processes. Hierarchical forecasting is an approach to sales forecasting that takes into account the possibility of merging forecasted items into related groups according to selected aggregate variables. The result is a system of matched forecasts at different levels of aggregation with regard to the different needs of the various functional areas of the company [2]. The issue of hierarchical forecasting also includes possibilities of forecasting sales that are created at a different level of aggregation than the desired level of aggregation of the target forecasts. This is used in particular in cases where the sales forecasting at the desired level of aggregation shows a high error of forecasts, or these sales are difficult to forecast, for example because of high production of forecasts (see, e.g., Refs [3-5]).

For short-term planning of sales, production and purchase in a manufacturing company, managers use short-term forecasts with a low level of aggregation of sales according to the product type, but they usually do not require detailed idea about to which customers the output produced will be distributed. Therefore, in traditional sales forecasting we do not take into consideration the affiliation of the sales to a particular customer or customer segment. Hence, this paper focuses on studying the impact of the level of customer aggregation on the accuracy of short-term forecasts of sales in manufacturing companies, whose customers are mainly intermediaries operating on B2C markets (wholesale, retail, etc.). Sales made by intermediaries are in fact affected not only by the nature of demand in the operated final consumer segment, but also by purchasing behaviour of the intermediaries that may be specific instance (e.g., order fulfilment, inventory systems). We could improve the forecasting accuracy in the structure required by the company by selecting a suitable hierarchical model.

This article aims to analyze the impact of customer aggregation of sales in the short-term forecasting accuracy of the selected chemical industry company. To achieve this goal, the paper designed hierarchical forecasting models that use forecasting at different levels of sales aggregation according to their affiliation to clients of the company. By comparing the accuracy of the proposed forecast models, we can infer the importance of the studied impact.

## Research Background and Methodology

Characteristics of the Company under Study

The company, in which the research was conducted, is a Czech company with a long tradition in the production of speciality chemicals for B2B and B2C markets. The main pillar of the studied company's business is the manufacture of products for home care, disinfection, materials for treatment of metals and specialty chemicals. The strongest product line includes a group of cleaning and disinfecting products that are specific for their focus, target group and export territory. These are special cleaning products for household, toilet cleaners, bleaching agents and stain removers, universal disinfectants and cleaners, anti-mildew solutions and drain cleaners. It is mainly households that are the end consumers of the products from the monitored product lines. Key customers, therefore, include wholesalers, retail chains with grocery and drugstore products and other independent retail stores (drugstores, speciality stores). Detergents and disinfectants designed for professional use are distributed to industrial and food businesses, hospitals, schools, spas and hotels through distribution companies and wholesale of cleaning agents.

As with most manufacturers of consumer products in the current market environment, competitiveness of the company depends on the speed of response to changing demand for products of the company. However, this requires creating accurate sales forecasts on the tactical-operational level, which would provide the necessary data for the creation of short-term business plans, optimum utilization of production capacities and labour, as well as for the creation of low stock levels in the company. The structure of sales forecasts, usable for short-term planning of sales, production and purchasing, has been identified as a *monthly forecast of the total number of individual products* regardless of the customer to whom the product will be distributed (complete aggregation of sales by customer).

During the research, there were designed three types of hierarchical models for forecasting sales in the structure required by the company (Aggregate Model, Disaggregate Model and Semi-Aggregate Model). These models were used for creating partial sales forecasts at different levels of aggregation, depending on the kind of customer for which the sales are carried out.

# Aggregate Model

The principle of the Aggregate Model is the creation of a single sales forecast in the structure required by the company (i.e., the full aggregation of sales by customer). It is, therefore, a traditional approach to sales forecasting, which is also used in the company under study.

#### Disaggregate Model

The time series of aggregated sales completely blur any differences in the purchasing behaviour of the company's customers. Sales forecasting at individual customer level could increase the accuracy of the resulting forecasts in the structure required by the company. The Disaggregate Model principle lies in forecasting the sales of the item for each customer separately and their subsequent sum for all customers. Assuming that the item in the observed period was purchased by *n*-customers, the model can be defined by the following formula

$$F = \sum_{i=1}^{n} f_i \tag{1}$$

where F is the final sales forecast in the structure of the desired by the company and  $f_i$  is a partial sales forecast, completed with the customer i.

## Semi-Aggregate Model

The Semi-Aggregate Model uses partial aggregation of sales with customers with intermittent demand. The exponential smoothing methods to balance these sales are not very suitable, because the resulting forecast is distorted by the presence of zero values in the smoothed time series of sales. The principle of the model lies in creating partial sales forecasts only for customers who realized at least one order in all periods of the observed time series. Sales of other customers (lost customers, customers with intermittent demand) are aggregated into a single time series for which a single partial sales forecast has been created. Assuming that the item was purchased in the observed period by *n*-customers of which *o*-customers contained at least one zero value in the previous periods of the time series, the model can be defined by the following formula

$$F = f_{SA} + \sum_{i=1}^{n-o} f_i \qquad \text{for } n \neq 0$$
 (2)

where F is the final forecast sales in the structure required by the company,  $f_{SA}$  is a partial sales forecast for the aggregated time series of sales of all customers who have made no order for that item in at least one period of the observed time series of sales, and  $f_i$  is a partial forecast sales realized by the i-th customer who realized at least one order for the item in all the observed periods of the time series of sales.

## Characteristics of Data Selected for Analysis

For the purpose of the analysis, the company provided data on sales for the calendar year January 2012-May 2013. The period of time series of sales in 2012

was used to set and optimize parameters of the forecasting models. The accuracy of forecasting models was determined *ex post* during the test period January 2013-May 2013. Owing to the wide product portfolio in the observed product line (about 80 products), only a group of 15 key products was selected for the analysis, whose volume of sales in 2012 accounted for almost 80 % of the total sales for products from the monitored product line (measured in SKU). Time series of sales for all 15 items were, prior to the analysis, purged of the effect of promotions.

## Selecting Forecasting Methods

In short-term sales forecasting, most applied in practice are the exponential smoothing methods that do not require storage of large amounts of data, and due to their natural adaptability they can relatively quickly respond to changes in the development of short-term sales [6]. Other advantages of these methods include simplicity, the speed associated with it, low costs [7] and easy automation of the forecasting process [8]. Consequently, the exponential smoothing methods were used in making forecasts in the proposed models.

Due to the length of the analyzed time series, only 4 of the methods of exponential smoothing without seasonal component (simple exponential smoothing, Holt's exponential smoothing, Brown's exponential smoothing and Exponential smoothing with damped trend) were used for smoothing and development thereof. Smoothing constants of the forecasting methods were optimized by a numerical method with a criterion function to minimize residual variance of the smoothed time series. Also, in the analysis, the Expert Modeller function (available in IBM SPSS Statistics software) was used, which automatically collects the most suitable method of exponential smoothing. The standard Bayesian Information Criterion (BIC) software was used as a selection criterion, which can be defined as follows

$$BIC = \ln(MSE) + k \frac{\ln n}{n} \tag{3}$$

where MSE is the Mean Square Error of the forecasting method, k is the number of parameters of the forecasting method and n is the number of periods of the time series that was smoothed by the forecasting method.

# Methods of Data Processing and Evaluation

Selected statistical procedures and methods of time series analysis were used in the quantitative data analysis. Sales data were processed and analyzed using IBM SPSS Statistics software (Version 19.0). The accuracy of forecasts was evaluated using Mean Absolute Percentage Error (MAPE) indicator. This characteristic is not dependent on the scale of the data and, therefore, it can be used for comparing the accuracy of models across all of the analyzed products.

#### **Results and Discussion**

Comparisons of the obtained MAPE values depending on the type of the forecasting model and product analyzed are featured in Tables I-III. The mean error of the aggregate model in the group of 15 analyzed products was in a relatively broad range of 19-103 %. The optical assessment of the MAPE values clearly showed that the accuracy of aggregate models depends on the type of the forecasted product and the type of the exponential smoothing method used.

Tables I-III also show that the choice of an appropriate hierarchical model can reduce the forecast errors, made at the aggregate level, with selected products.

Table I Mean Absolute Percentage Error (MAPE) of Forecasts by Using Aggregate Model

|         | MAPE, % |      |       |        |                    |  |
|---------|---------|------|-------|--------|--------------------|--|
| Product | Simple  | Holt | Brown | Damped | Expert<br>Modeller |  |
| 1       | 47.4    | 49   | 51.6  | 49     | 47.4               |  |
| 2       | 32.6    | 34.2 | 37.8  | 33.7   | 35.1               |  |
| 3       | 25.2    | 27.2 | 26.9  | 24.3   | 26.9               |  |
| 4       | 32.3    | 34   | 35.9  | 34.3   | 34.4               |  |
| 5       | 29.6    | 31   | 30.3  | 33.1   | 29.6               |  |
| 6       | 29      | 32.1 | 29.1  | 35     | 29                 |  |
| 7       | 62.4    | 80.2 | 69    | 77.6   | 60.4               |  |
| 8       | 90.9    | 96.7 | 102.8 | 985.6  | 101.2              |  |
| 9       | 72.7    | 95.4 | 98.5  | 84.4   | 97.7               |  |
| 10      | 43.7    | 48.2 | 56.1  | 45.8   | 44.4               |  |
| 11      | 30      | 33.8 | 31.4  | 35.3   | 33.7               |  |
| 12      | 39.3    | 37.4 | 37    | 38.3   | 39.3               |  |
| 13      | 19.3    | 26.3 | 27.3  | 23.4   | 19.7               |  |
| 14      | 36.9    | 39.6 | 40.7  | 39.1   | 36                 |  |
| 15      | 27.6    | 30   | 27.6  | 30.8   | 26.7               |  |

This reduction is roughly in units of percent, but a few of them show much greater decreases in forecast errors. With the Semi-Aggregate Model, the error of the exponential smoothing methods used can be decreased in particular for the product No. 7 (MAPE reduction by 9.8 to 28.5 %) and product No. 10 (MAPE reduction by 13.9 to 20.9 %). The Disaggregate Model can be considered successful, because by using this model we achieve a significant reduction of errors in product No. 1 (MAPE reduction by 10.6 to 17.4 %), product No. 2 (MAPE reduction by 7.7 to 11.2 %), product No. 7 (MAPE reduction of 9.3 to 22.3 %), product No. 9 (MAPE reduction by 22.6 to 47.6 %) and product No. 10 (MAPE reduction by 6.1 to 9.3 %).

Table II Mean Absolute Percentage Error (MAPE) of Forecasts by Using Semi-Aggregate Model

|         | MAPE, % |       |       |        |                    |  |
|---------|---------|-------|-------|--------|--------------------|--|
| Product | Simple  | Holt  | Brown | Damped | Expert<br>Modeller |  |
| 1       | 46.1    | 50.3  | 48.3  | 49.4   | 46.8               |  |
| 2       | 31.1    | 33.9  | 36.8  | 33.6   | 35                 |  |
| 3       | 25.6    | 27.4  | 27.7  | 28.1   | 26.7               |  |
| 4       | 33.7    | 35.4  | 45.4  | 36     | 45.6               |  |
| 5       | 28.8    | 29    | 30    | 32.1   | 29.3               |  |
| 6       | 28.1    | 35.6  | 28.9  | 33.7   | 28                 |  |
| 7       | 49.7    | 51.7  | 58.1  | 54.6   | 50.6               |  |
| 8       | 90.9    | 96.7  | 102.8 | 95.6   | 101.2              |  |
| 9       | 72.3    | 101.6 | 103.2 | 90.3   | 102.5              |  |
| 10      | 28.5    | 34.1  | 35.2  | 31.9   | 29.6               |  |
| 11      | 28.9    | 33.4  | 37.6  | 34.9   | 33.3               |  |
| 12      | 35.2    | 36.5  | 37.8  | 36.1   | 39.9               |  |
| 13      | 19.8    | 27.6  | 25.4  | 27.8   | 19.1               |  |
| 14      | 37.4    | 39.3  | 40.7  | 39     | 36.4               |  |
| 15      | 26.5    | 30.7  | 30.1  | 30.3   | 24                 |  |

By comparing the mean error of the models in the observed group of products, it can be stated that there was a reduction in the mean error of the aggregated model using both hierarchical models (see Table IV). The forecasts

Table III Mean Absolute Percentage Error (MAPE) of Forecasts by Using Disaggregate Model

|         | MAPE, % |       |       |        |                    |  |
|---------|---------|-------|-------|--------|--------------------|--|
| Product | Simple  | Holt  | Brown | Damped | Expert<br>Modeller |  |
| 1       | 36.8    | 35.7  | 34.2  | 37.7   | 36.4               |  |
| 2       | 23.6    | 25.6  | 27.4  | 26     | 23.9               |  |
| 3       | 28      | 31.8  | 34.8  | 31.1   | 28.8               |  |
| 4       | 30.5    | 37.9  | 45.3  | 35.4   | 41.3               |  |
| 5       | 29.1    | 32.9  | 34.6  | 30.8   | 32.6               |  |
| 6       | 25      | 29.5  | 34    | 27.3   | 27.5               |  |
| 7       | 47.9    | 57.9  | 59.6  | 57.5   | 49.7               |  |
| 8       | 77.4    | 108.5 | 103.5 | 107.7  | 91.6               |  |
| 9       | 45.3    | 58.3  | 61    | 57.7   | 50.1               |  |
| 10      | 37.4    | 38.9  | 49.8  | 39.3   | 38.3               |  |
| 11      | 32.1    | 44.1  | 48.6  | 44.7   | 35.8               |  |
| 12      | 29      | 41.6  | 41.6  | 39.7   | 35.2               |  |
| 13      | 20.8    | 27.3  | 27.5  | 26.3   | 22.5               |  |
| 14      | 36.5    | 38.9  | 40.5  | 38.9   | 38.8               |  |
| 15      | 26.7    | 29.4  | 32.3  | 29.1   | 23.8               |  |

Table IV Mean Absolute Percentage Error (MAPE) of Forecasting Models

| Forecasting model  | MAPE, % |      |       |        |                    |
|--------------------|---------|------|-------|--------|--------------------|
|                    | Simple  | Holt | Brown | Damped | Expert<br>Modeller |
| Aggregate          | 41.3    | 46.3 | 46.8  | 45.3   | 44.1               |
| Semi-<br>aggregate | 38.8    | 44.2 | 45.9  | 43.6   | 43.2               |
| Disaggregate       | 35.1    | 42.6 | 45    | 41.9   | 38.4               |

with the highest accuracy can be obtained by applying a simple exponential smoothing. In this case, it was possible to reduce the mean error of the Aggregate Model (MAPE = 41.3%) using the Disaggregate Model (MAPE = 35.1%). The

observed difference (MAPE reduction by 6.2%) is the only significant difference of those observed at the 0.05 level (tested by the Paired-Samples t-test).

The results of the model accuracy analysis points out for some products that the increasing aggregation of sales by customers also increases the forecast error in the structure required by the company. However, this cannot be generalized for all products, because the differences in the mean accuracy of models are not significant in most cases at the 0.05 level. However, in selected cases the use of the Disaggregate Model proved to be a better way of forecasting sales compared with the traditional approach to sales forecasting with the full aggregation by customers.

The advantage of the Disaggregate Model is that it provides an individual approach to forecasting for each customer, which is probably the main reason for reducing errors of the resulting forecasts. The main drawback of the Disaggregate Model is a potential distortion of forecasts for customers of intermittent demand. This weakness of the model would be manifested especially in the case of using exponential smoothing methods with a seasonal component. It is because the zero values in the time series of sales for individual customers cannot be actually considered seasonal variations, if they arise as a result of the chosen method of inventory control on the part of the customers.

It is necessary to mention the fact that the number of partial forecasts in the models with a low degree of aggregation of sales increases in direct proportion to the number of customers of the forecasted item, which significantly increases the demands of the model application. In comparison with the Aggregate Model, in which a single forecast is formed, the hierarchical models required a formation of about hundreds of partial forecasts. At present, when the availability of information technology with high-speed data processing is a commonplace, this problem has been losing its importance.

#### **Conclusion**

By applying a suitable hierarchical model we can improve the accuracy of forecasts that are made in the manufacturing company with full aggregation of sales by customer. The success rate of the proposed hierarchical models is very individual, depending on the type of the forecasted product. The highest forecasting accuracy was achieved using the Disaggregate Model in which sales are forecasted at the lowest level of aggregation (i.e., sales transacted for individual customers). This method, however, involves a number of risks and disadvantages associated with the formation of a large number of corporate forecasting and forecasting of intermittent demand.

When designing hierarchical models, we used only the option of varying degrees of aggregation of sales by the number of customers. Theoretically,

however, other aggregate variables could be applied as well that would be based on, for example, typical features of individual customers (type of the intermediary, sales area, etc.) or the characteristics of time series of sales of individual customers (average monthly sales, variability of the time series, etc.). This could ultimately help to obtain more accurate forecasts not only in the thus identified segments, but also at other levels of aggregation required by the company's management. The subject of further research will therefore be the study of accuracy of hierarchical models based on these alternative aggregate variables.

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#### References

- [1] Lošťáková H.: Creation of the Customer's Value within the Value Network of Products Determined for Production Consumption, In Proceedings of the 20<sup>th</sup> Anniversary International Conference on Metallurgy and Materials "Metal 2011", Brno, 2011.
- [2] Fliedner G.: Industrial Management & Data Systems 101, 5 (2001).
- [3] Strijbosch L.W.G., Moors J.J.A.: IMA Journal of Management Mathematics **21**, 194 (2010).
- [4] Babai M.Z., Ali M.M., Nikopoulos K.: Omega 40, 719 (2012).
- [5] Zotteri G., Kalchsmidt M.: Journal of Production Economics 108, 77 (2007).
- [6] Makrikardis S., Wheelwright S.C.; Hyndman R.J.: *Forecasting: Methods and applications*, 3<sup>rd</sup> edition, Sage Publications, Thousand Oaks, 1998.
- [7] Mentzer J.T.; Moon M.A.: Sales forecasting management: A demand management approach, 2<sup>nd</sup> edition, Sage Publications, Thousand Oaks, 2005.
- [8] Entrup M.L.: Advanced Planning in Fresh Food Industries: Integrating Shelf Life into Production Planning, Physica-Verlag, Heidelberg, 2005.