DEMAND PREDICTIVE MODEL FOR SMALL METALLURGICAL COMPANIES

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Abstract

The typical problems facing with small metallurgical companies are prediction errors, because their markets are volatile and difficult to predict. For that reason, the ability to develop accurate demand predictions is critical in the industry. The paper presents a hierarchical middle-term predictive model for small metallurgical companies. The model is built by top-down predictive approach and verified by means of a case study in the company producing the special rolled sections. Weaknesses of the model are identified during discussion of the acquired results. A Generalized concept of ANN predictive model is designed for elimination these weaknesses.

Keywords: Metallurgical company, demand predictive model, top-down approach, special rolled sections.

1. INTRODUCTION

Small metallurgical enterprises face many specific problems related with logistics management (see e.g. [1], [2], [3], [4]). The typical factor causing these problems is very difficult demand prediction, because their markets are volatile and difficult to predict. For that reason, the ability to develop accurate demand predictions is critical in the industry. The aim of the paper is to design a hierarchical middle-term predictive model for small metallurgical companies and its verification in special rolled sections branch.

2. METHODOLOGICAL BASE

Most companies deal with multiple levels of aggregation and require consistent predictions at all levels. Hierarchical predicting, a family-based predictive methodology, is a centralized predictive approach capable of satisfying the variety of prediction information requirements [5]. Predictions of item and family demands in the process are produced using two approaches - “top-down” and “bottom-up”, or a combination of the two (sometimes called “middle-out” approach). The top-down approach entails predicting the completely aggregated series, and then disaggregating the predictions based on historical proportions [6]. These proportions may be accomplished in various ways as demonstrated by Gross and Sohl [7]. The top-down approach is recommended for strategic and tactic plans and budgets [8]. Thus, this approach will be used in designed demand predictive model.

3. HIERARCHICAL DEMAND PREDICTIVE MODEL DESIGN

The following demand predictive model was created on the base of literature review in the area of prediction theory for the purpose of middle-term predictions in small metallurgical companies. Middle-term predictions look ahead between three months and a year, and they are mostly used for Sales and Operations Planning (S&OP) process [9]. Base for utilization of top-down prediction approach in S&OP was defined by Lapide [10]. The prediction model is based on applying six main stages:

1) Prediction structure determination - determination of prediction levels, families at any level (parents) and children within any family.

2) Time dimensions identification - identification of the length and periodicity of the prediction.

3) Data collection and manipulation - accessing and assembling appropriate data for each child and family, their getting into a form that is required for using the intended prediction techniques.

4) Generating direct forecasts - determination of direct and independent child and family forecasts which can include time series analysis, prediction techniques selection, partial models building and evaluation, models implementation, and prediction combination (if it is appropriate).

5) Top-down process application - determination of derived child predictions from the top level family with the following proration procedure [5]:

- Ratios calculation - calculation of the ratio of the direct child prediction and the sum of the direct child predictions comprising its family:

$$r_i = \frac{DCF_i}{\sum_{i=1}^{n} DCF_i} \tag{2}$$

r_i - ratio of i-th child, DCF_i - direct prediction of i-th child, n - number of children in its family, i = 1, 2, ..., n

- Final predictions derivation - multiplication of the final parent prediction by this ratio:

$$FCF_i = FPF \cdot r_i \tag{3}$$

FCF_i - final prediction of i-th child, FPF final parent prediction

6) Tracking results - continuous tracking of how well the predictions compare with the actual values observed during the prediction horizon. Over time, even the best of techniques and models are likely to deteriorate in terms of accuracy and need to be respecified or replaced with an alternative method [11].

4. CASE STUDY

The possible utilization of the designed demand predictive model was verified in a company producing the special rolled sections. An overwhelming majority of production is intended for automotive industry. Thus, the case study is focused on this branch.

4.1. Prediction structure determination

In middle-term horizon, the demand is predicted on three levels (see **Fig. 1**). The top level includes the total demand of the plant. These are divided into two branch families - automotive and other branches.

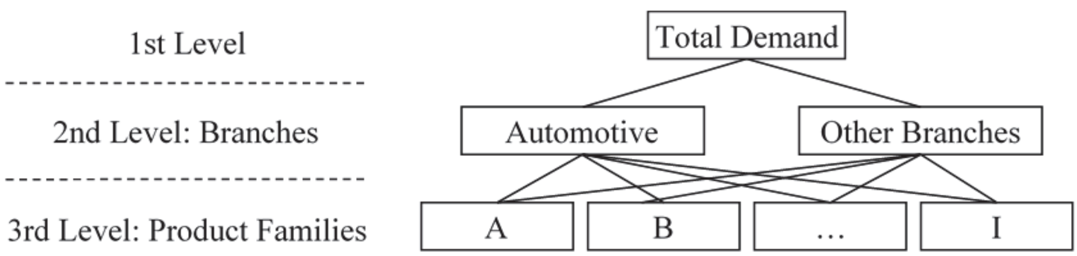

Fig. 1 Scheme of the plant prediction structure

Each of them is divided into nine product families according to the sections rolling mill operating capacity (see **Fig. 2**, kg/h) - from A to I. Products for automotive branch plays a key role (80% of the production).

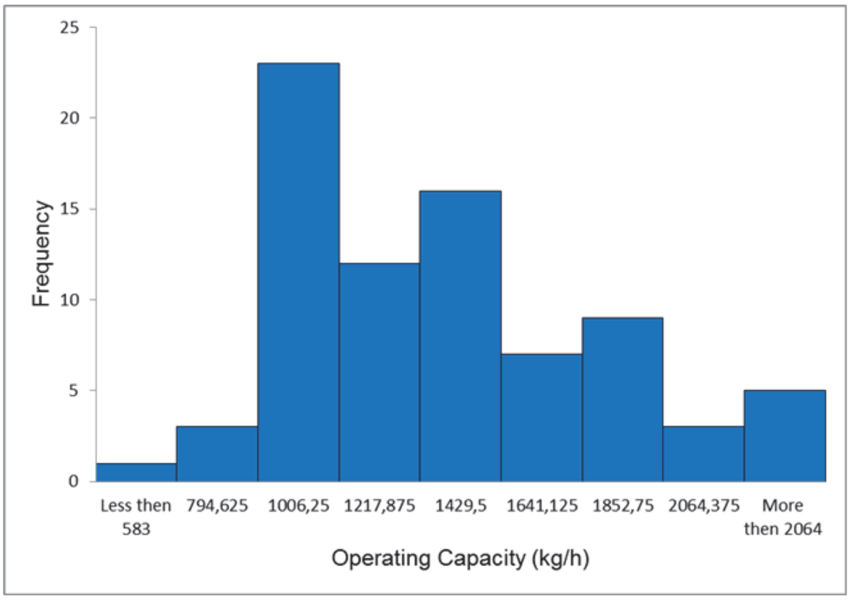

Fig. 2 Operating capacity of product families

4.2. Times dimensions identification

The prediction is carried out on a monthly basis. The length of the prediction horizon is one year (from 1 January to 31 December), i.e. 12 months.

4.3. Data collection and manipulation

Company demand is characterized by relatively significant seasonal fluctuations. The lower demand periods are at the middle and end of the year. The situation is related to holiday months in the automotive industry. Particularly prediction of demand is performed for the purpose of S&OP. Thus, the predictions are carried out in kg. Demand of product families intended for automotive industry during the period of 36 month are demonstrated in **Fig. 3**.

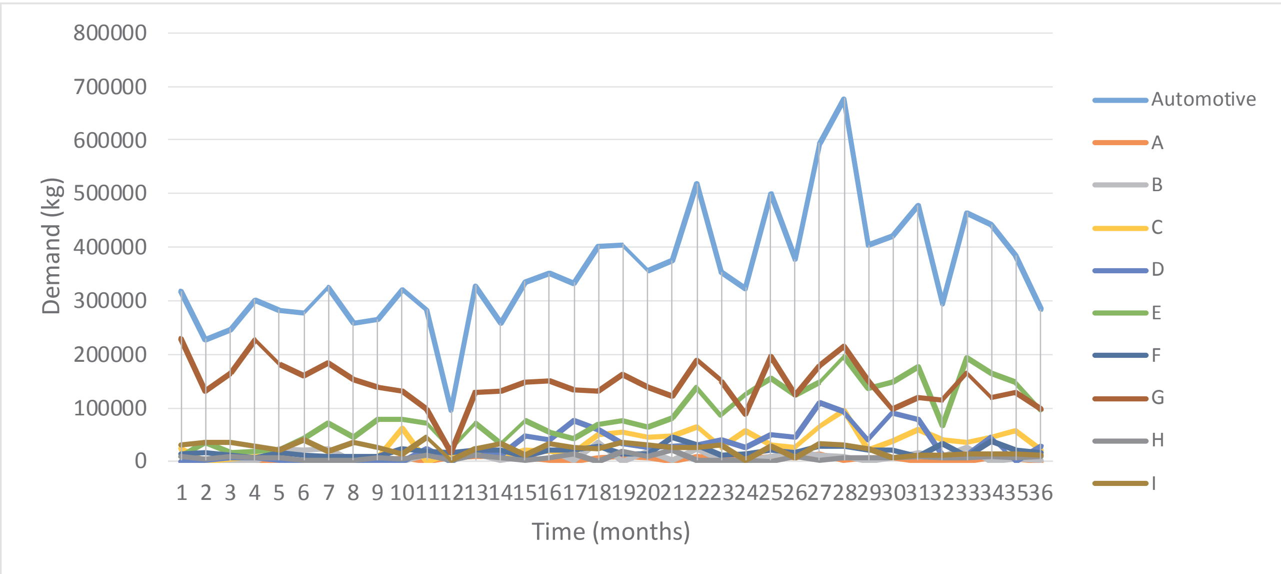

Fig. 3 Time series plot for demand from automotive industry

With regards to the sensitive nature of information, the monthly demand data were modified. **Fig. 3** clearly shows the gradual increase of demand from automotive industry caused especially by recovery of the automotive markets.

4.4. Generating direct predictions

Using the descriptive and time series analysis in statistical software STATGRAPHIC Plus 5.0, relatively significant seasonal component were identified in automotive time series and in C, D, and E product families time series. Other product families' time series have only random component with/without trend component. With regards to this fact, different prediction techniques were used for direct demand predictions. Models were built and evaluated using the statistical software STATGRAPHIC Plus 5.0. The most accurate prediction models for each time series can be seen in **Table 1**. The direct predictions are presented in **Fig. 4**.

Table 1 The most accurate prediction models

Branch/Product Families	Prediction Technique	Prediction Model
Automotive	SARIMA	(1,1,1)x(2,1,0)12 with constant
A	Simple exponential smoothing	α = 0.2937
B	Constant mean	9 908
C	SARIMA	(1,1,0)x(2,1,2)12 with constant
D	SARIMA	(2,1,0)x(2,1,2)12 with constant
E	SARIMA	(1,1,1)x(2,1,0)12 with constant
F	Linear trend	13 209 + 312 t
G	Constant mean	144 390
H	Constant mean	6 738
I	Linear trend =	32978 - 513 t

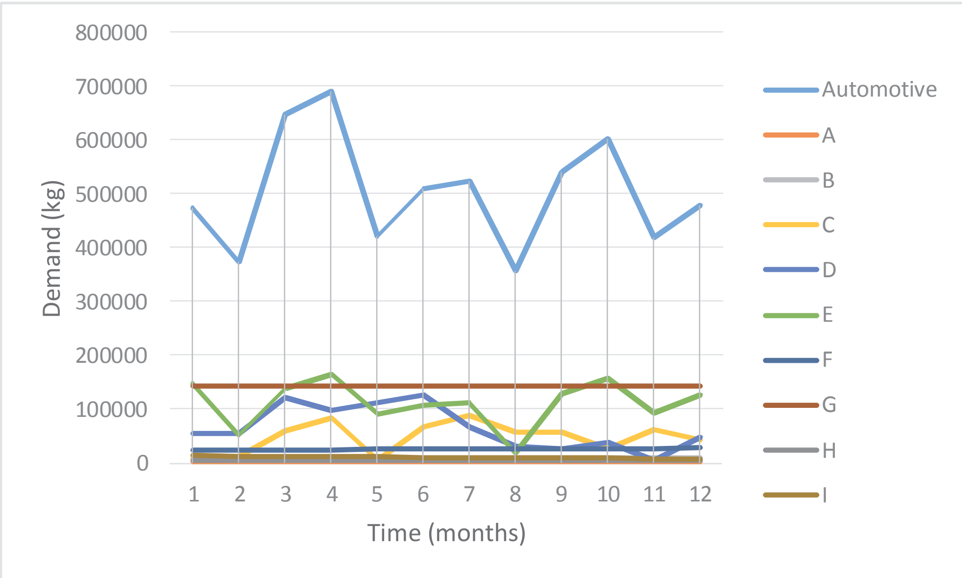

Fig. 4 Direct automotive demand prediction

4.5. Top-down process application

The final predictions used with the proration procedure (top-down process) are presented in **Fig. 5**. The predictions acquired on the product families' level are consistent with the automotive demand prediction.

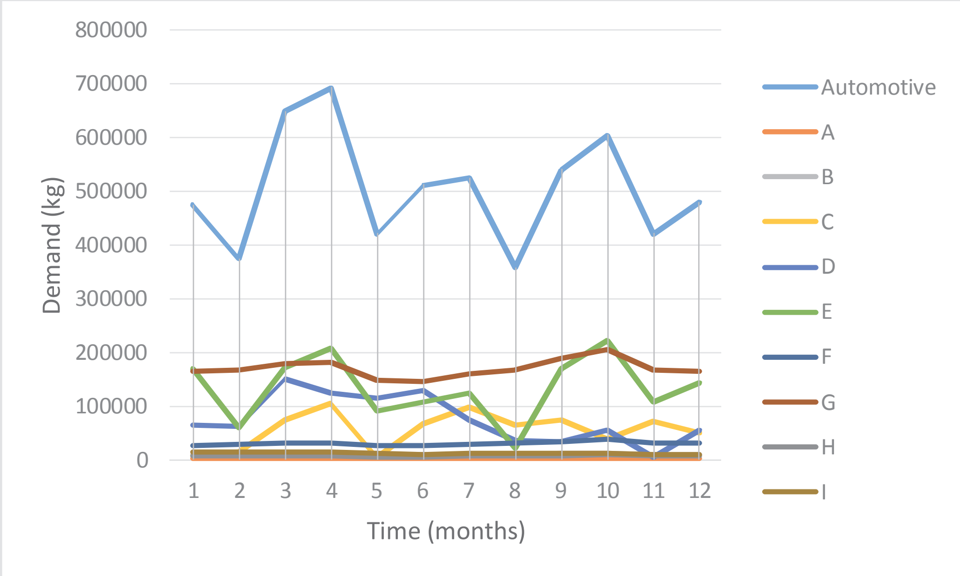

Fig. 5 Final automotive demand prediction

5. DISCUSSION OF RESULTS

Despite the fact that the time series analysis currently provides a number of very high quality tools for demand predictions, their application in special rolled sections branch is limited. The main reason is the fact that the use of historical data for the purpose of prediction doesn't take into account other, in many cases absolutely essential factors, influencing the future demand. This factors are demand development in automotive and metallurgical markets, strategic plans of the company, and trade negotiations with key customers.

That is why it is necessary to look for such tools of hierarchical predicting in this branch that make it possible to include not only the historical data concerning demand but also other factors having essential impact on the prediction quality. Suitable tools to be applied in this sphere may include the artificial neural networks (ANNs). These models can be exposed to large amounts of data and discover patterns and relationships within them [14]. The generalized concept illustrated in **Fig. 6** can be used for demand predicting in the single levels of hierarchy in the special rolled sections branch.

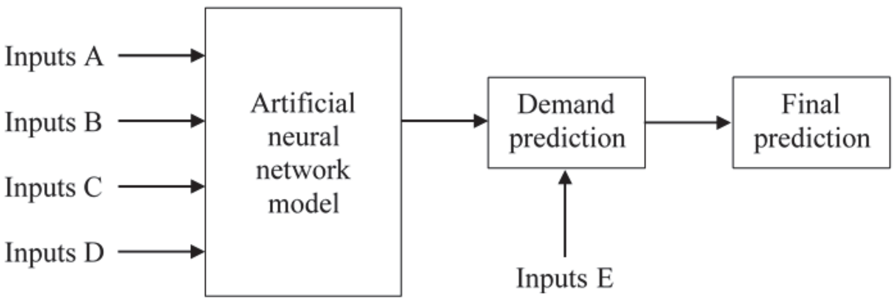

Fig. 6 Generalized concept of ANN prediction model

Inputs for an ANN prediction model can be divided into five groups:

1) Inputs A - historical data regarding demand of the metallurgical company.
2) Inputs B - data taking into account the automotive market development (e.g. in form of automotive market indexes).
3) Inputs C - data taking into account the metallurgical market development (e.g. in form of metallurgical market indexes).

4) Inputs D - data expressing the success of metallurgical company in negotiations with key customers (e.g. as a ratio of inquired and really ordered quantity).
5) Inputs E - correction of demand predictions acquired by ANN prediction model related to the strategic plans of the company (e.g. modernization of equipment, introduction of new products).

6. CONCLUSION

The current situation on small metallurgical companies' markets is characterized by high fluctuations of customer demand. This makes the predictive process in various company levels more and more difficult, especially from the point of view of quality predictions used in S&OP. In many small metallurgical companies, this process runs almost purely on the basis of experience of the company managers. That is why the complex hierarchical demand predictive system, based on top-down prediction approach and use of prediction techniques which would make it possible to include not only the historical data concerning demand progress but also other factors having essential impact on the prediction quality, should be designed and applied.

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REFERENCES

[1] SANIUK S., SAMOLEJOVÁ A., SANIUK A., LENORT R. Benefits and barriers of participation in production networks in a metallurgical cluster - research results. Metalurgija, Vol. 54, No. 3, 2015, pp. 567-570.

[2] KRAMARZ M., KRAMARZ W. The identification of zones of amplification of disruptions in network supply chains of metallurgic products. Metalurgija, Vol. 54, No. 1, 2015, pp. 279-282.

[3] VILAMOVÁ Š., MIKLOŠIK A., KOZEL R., SAMOLEJOVÁ A., PIECHA M., WEISS E., JANOVSKÁ K. Regression analysis as an objective tool of economic management of rolling mill. Metalurgija, Vol. 54, No. 3, 2015, pp. 594-596.

[4] SPISAK J., LISUCH J., ROHACOVA A. Technological logistics - tool of optimalization of heat treatment processes of raw materials. In Metal 2011: 20th Anniversary International Conference on Metallurgy and Materials, Ostrava: Tanger, pp. 1169-1176.

[5] FLIEDNER G. Hierarchical forecasting: issues and use guidelines. Management and Data Systems, Vol. 101, No. 1, 2001, pp. 5-12.

[6] HYNDMAN R. J., AHMED R. A., ATHANASOPOULOS G., SHANG H. L. Optimal combination forecasts for hierarchical time series. Computational Statistics and Data Analysis, Vol. 55, No. 9, 2011, pp. 2579-2589.

[7] GROSS C. W., SOHL J. E. Disaggregation methods to expedite product line forecasting, Journal of Forecasting, Vol. 9, No. 3, 1990, pp. 233-254.

[8] KAHN K. B. Revisiting top-down versus botton-up forecasting. The Journal of Business Forecasting, Vol. 17, No. 2, 1998, pp. 14-19.

[9] TAKALA J., MALINDŽÁK D., STRAKA M. et al. Manufacturing Strategy - Applying the Logistics Models, Vaasa: Vaasan yliopisto - University of Vaasa, 2007.

[10] LAPIDE L. Top-down & bottom-up forecasting in S&OP. The Journal of Business Forecasting, Vol. 25, No. 2, 2006, pp. 14-16.

[11] LEVENBACH H., CLEARY J. P. Forecasting: Practice and Process for Demand Management. Duxbury, 2006.