INVENTORY MANAGEMENT SYSTEM FOR PRODUCTS WITH HIGH DEMAND VOLATILITY

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Abstract

Inventory management is a central task of the logistics area. The success of an efficiently operating system is determined by the selection of an appropriate method of replenishment of stocks based on the adopted control parameters. The inventory management process becomes extremely difficult in cases where the company has a very extensive range of products or when the market demand for individual products is characterized by high volatility. In a situation where both factors occur simultaneously, inventory management becomes a real challenge for the company. The decision-making process in this case depends to a large extent on a properly functioning calculation algorithm, which will take into account the specifics of the sector served and the occurring variability of demand. The purpose of the article is to present the results of research obtained under the project, whose end result was the development of an algorithm supporting the inventory control system in the selected enterprise. The company has clients from various sectors of the economy: automotive, household appliances, furniture industry, maintenance services. Therefore, the specificity of requirements regarding the availability of goods from stock is also varied. The article presents the results of the risk analysis resulting from the specifics of the enterprise's operation and describes the proposed algorithm for calculating the demand.

Keywords: Inventory management, demand volatility, algorithm

1. INTRODUCTION

Logistics system support for the company's core processes plays a key role in building the company's competitive position [9]. An important task of this system is proper inventory management, in particular finished goods inventory [5,11]. The adopted management model depends on the material flow strategy in the enterprise, the industry served, customer requirements and the availability of information about future demand.

Currently, we can distinguish two approaches to the theory of finished goods inventory. The classic and conventional inventory management theory emphasizes the importance of a hedge against demand uncertainty [2]. An increase in sales leads to an increase in inventory, the purpose of which is to mediate the trade-off between holding cost and uncertain demand. Thus, one of the major goals of this inventory theory is minimizing holding cost by reducing inventory level across an entire supply chain. Many studies have shown evidence of a significant relationship between inventory levels and several independent variables (including inventory holding costs, lead time, demand uncertainty, etc.), thereby implying the benefits of reducing inventory levels [8,3]. However, de Leeuw et al. [6] rightly point out that the complexity of supply chains means traditional inventory models often ignore important practical considerations. The contemporary inventory management theory focuses on the concept that high inventories can not only increase service level but also stimulate demand. For example, high inventories can increase product visibility, signal a popular product, provide customers an assurance of high service levels and future availability [1]. This dilemma between cost minimization and high inventory levels, especially in periods of demand volatility, has become a common theme in inventory management [4].

Therefore, enterprises are currently facing a huge challenge. The efficiency approach forces managers to constantly reduce inventory levels, which should lead to lower logistics costs. At the same time, the market approach forces high availability of products from stock in the warehouse. Only in this way can an enterprise provide a high level of service to its clients and maintain a highly competitive position. The inventory management process becomes particularly difficult when the market demand for delivered products is characterized by high volatility. The decision-making process in this case depends to a large extent on a properly functioning IT tool that supports the actions of managers [12]. The type of data collected and the algorithms used for calculations by the ERP system acquires significant importance [10,7,13].

The aim of the article is to present the results of research obtained under the project whose end result was the development of an algorithm that supports the inventory management system for products with high sales variability. Therefore, the current stock replenishment system, which operates in the company, has been characterized. The results of the risk analysis were also presented. They indicate the effects of the current algorithm. Then the model of the new demand calculation was presented. The proposed algorithm takes into account the coefficient of variation for individual products in the calculations. The level of logistics service offered was dependent on this coefficient. Finally, the most important conclusions from the research are presented.

2. CURRENT INVENTORY MANAGEMENT SYSTEM

The studied organization is a production and commercial company that operates in the pneumatic sector. The company supplies its products to recipients from various sectors of the economy, primarily maintenance teams, automotive, household appliances and furniture. The analysis of historical sales data has shown that the specifics of product sales are characterized by high volatility - **Figure 1**. This variability causes that standard tools for managing inventory do not fulfill their role. This is due to the fact that these tools are largely based on the assumption of statistical repeatability of sales. Meanwhile, in the case of analyzed products, such repeatability does not occur. Even in relation to warehouse items, which are considered cyclically renewable and therefore are continuously stored in a warehouse, the analysis of historical data indicates that these products are characterized by high volatility rates. These indicators exceed the permissible standards for which it can be concluded that in the observed time series one is dealing with statistical repeatability.

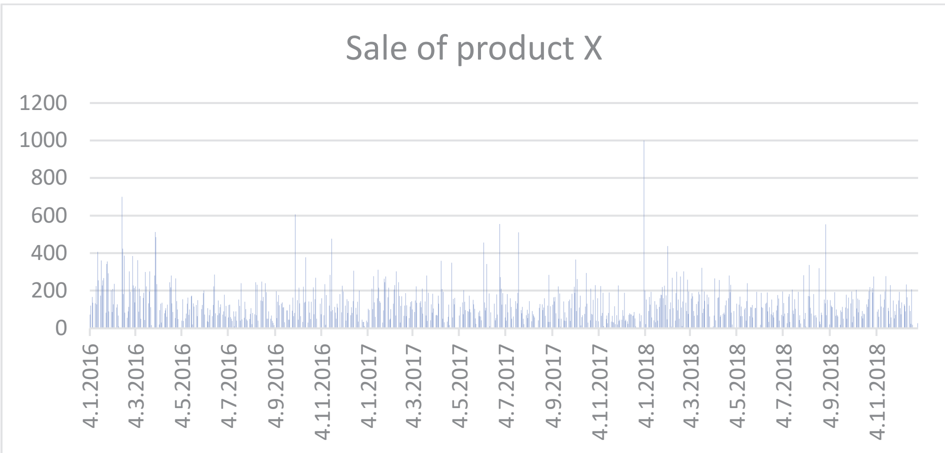

Figure 1 Sales variation of the selected product

The current inventory management system, which is the basis for demand reporting in the ERP system, was created based on quantitative models described in the literature. The algorithm was built on the concept of cyclical replenishment of inventories based on two control parameters (T - optimal inventory renewal cycle and S - maximum inventory level). Parameter S in the algorithm used reflects the anticipated demand determined on the basis of the average sales volume registered over the last 12 sales cycles, while the cycle length corresponds to the adopted parameter T. Cyclical products are usually ordered in 1-, 2- or 4-week cycles. The cycle depends on the product group and supplier's conditions. This means that the algorithm uses "too historical" data for products with a long inventory renewal cycle. In order to calculate the current demand for these products, the algorithm takes into account sales that were registered 6-10 months ago. This stiffens the reported demand and limits the flexible response to changing sales trends on the market.

Parameter S also takes into account the delivery time. This period includes the time of order processing at the supplier's (lead time) and the time needed to enter the delivery to the warehouse (including all input operations related to the receipt, control, recording and placing of goods in the warehouse). Due to multi-assortment deliveries received from selected suppliers, the time of entering the delivery to the warehouse can last even several days. The algorithm also has the option of introducing a safety stock in the event of disturbances occurring in deliveries from a given source (e.g. delay or lack of complete delivery). The safety stock is expressed in the form of an additional number of weeks for which the delivered goods should be sufficient.

The maximum stock level S is reduced by the current stock level on the day of placing the order. High sales fluctuations and, above all, periodically occurring sales peaks cause significant threats to determine the correct inventory. The conducted risk analysis showed that for the event "*reporting excessive demand by the system*" the risk indicator reached a level not accepted by the Management Board. This is due to the high frequency of this event occurrence and the accompanying effects. The most important result is too large inventory level, which causes excessive freezing of capital. At the same time, however, it should be noted that the system does not provide comprehensive information that allows logistics employees to make current decisions automatically. People responsible for purchases must actively participate in the reported volumes of demand, which requires their current knowledge of suppliers, products and customers. This makes it difficult to standardize work and employee substitution in case of holidays or sick leave occurrence. Therefore, the company's management decided to modify the current demand calculation algorithm in the ERP system.

3. INVENTORY MANAGEMENT MODEL, THAT TAKES INTO ACCOUNT HIGH SALES VOLATILITY

The proposed inventory management model is to be based on the forecasted amounts of future demand. For the preparation of the forecast, the method is to be selected that will have the smallest errors for the ex post forecast. The forecast deviation from actual sales will be estimated using two types of errors:

Mean absolute deviation MAD:

$$MAD = \frac{\sum_{i=1}^{n} |y_i - p_i|}{n} \tag{1}$$

Thiel coefficient:

$$\mathrm{I}^2 = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \mathrm{p_i})^2}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{y_i^2}} \tag{2}$$

where:

y_i - registered sales in week *i*; p_i - sales forecast for the week *i*

Analysis of historical data indicates that the high volatility of registered sales limits the effectiveness of quantitative forecasting methods to determine future demand. Therefore, it was decided to purge (smooth) historical data that is the basis for calculating forecast sales for future periods. In this way, the time series adopted for prognostic analysis will be devoid of extreme values, which may significantly affect the overstatement or understatement of the adopted sales forecast, which is the basis for the determined demand in future periods.

In order to select the appropriate smoothing criterion for the registered time series, a multi-variant analysis of possible options was performed. Finally, a time series smoothing procedure was adopted based on the average registered sales and standard deviation of the population calculated using the rolling method from the last 52 weeks preceding the moment of the analysis. Smoothing the time series in the developed algorithm will be carried out according to the principle expressed by the formula (3) and (4):

$$If\ y_i > M + \partial, then\ y_i = M + \partial \tag{3}$$

$$If\ \ y_i < M - \partial, then\ y_i = M - \partial \tag{4}$$

where:

y_i - registered sales in week *i*; M - arithmetic average of the last 52 weeks; ∂ - population standard deviation from the last 52 weeks.

The analysis of historical sales data by the simple regression method proved that the upward and downward trends appearing in the examined periods are short-term, and the indicator of the calculated trend is insignificant. Additionally, cost-benefit analyzes based on the analysis of the volume of registered errors have shown that the use of advanced sales forecasting methods is unjustified due to the slight differences in registered forecast errors. For this reason, the algorithm uses simple forecasting methods. Three forecast variants were adopted for verification. For all analyzed representatives, the 12-element rolling average method allowed to determine the forecasts with the smallest error, both MAD and THIEL for the analyzed period (2016-2018).

The sales forecast is created based on the cleaned time series. As a result, the variability of the demand assumed for calculations was limited. The reference period is one week regardless of the optimal renewal cycle. This prevents the receipt of multi-month historical data for calculating current demand. The prepared sales forecast is a rolling type. This means that it is updated each time on the day of placing the order, based on current sales data on a weekly basis.

Based on the sales forecast determined in this way, the maximum level of stock in the warehouse is determined. The second basic control parameter is the optimal renewal cycle, which, similarly to the original algorithm, results from the standard of service offered by the supplier and the specifics of selling the product itself. Also the time of order processing includes both the time of delivery by the supplier and the time of taking the goods to the warehouse. The algorithm also includes a safety reserve expressed in weeks, which takes into account the occurrence of possible disturbances. New parameter included on the proposed approach is the ratio of logistics services. This ratio depends on the coefficient of variation, which is calculated and updated for the sale of a given product each time an order is placed. The coefficient of variation for individual products will be reported in set time intervals, as its nature is dynamic due to changing sales levels. This report will support managers' decisions regarding the qualification of the product to the appropriate group. The manager assigns a product to class X, Y or Z on the basis of the current value of its coefficient of variation.

$$If\ Wzm_k < \alpha, then\ OL = X \tag{5}$$

$$If\ \alpha \leq Wzm_k \leq \beta, then\ OL = Y \tag{6}$$

$$If\ Wzm_k > \beta, then\ OL = Z \tag{7}$$

Where:

Wzm_k - coefficient of variation of product *k*; *OL* - ratio of logistics services.

Indicator limits (α and β) are the basis for assigning the product to individual classes. Limit values are manually controlled by the manager. The X class has the lowest volatility index, these are the leading products in the company's constant sales. These products should never be missing from the store shelf, therefore the logistic service for them is set at the highest level (close to 100 %). The Z class consists of products with the highest coefficient of variation. These are products that are largely sold on individual customer orders. Therefore, the amount of their stock in the warehouse should be limited, because their sale does not require providing such a high level of logistics service as it is in the case with class X. The level of logistics service will be assigned by managers responsible for product management.

Finally, the new algorithm will calculate the demand for individual products according to formula (8).

$$D_k = \left(\widehat{V_k} \times (T + L + ZB)\right) \times OL \tag{8}$$

Where:

D_k - demand for the product k; $\widehat{V_k}$ - forecast weekly sales of the product k; T - optimal weekly ordering cycle; L - order processing time specified in weeks; ZB - safety stock expressed in weeks; OL - logistic service indicator assigned in accordance with the reported coefficient of variation.

4. CONCLUSION

Enterprise logistics systems are currently facing a major challenge. The market requires high availability of products for enterprises. At the same time, managers are evaluated for the effectiveness of their activities. The combination of both these goals is extremely difficult, especially when products supplied to the market are characterized by high demand volatility. In this situation, IT tools support is important. The reporting system and methods of calculating future demand should support the decision-making processes of managers.

The article presents the results of the project implemented jointly with an enterprise whose products are characterized by high demand variability. For this reason, a modification of the currently functioning algorithm for determining future demand has been proposed. An important modification was the shortening of the time horizon of data used to determine the forecast, smoothing the time series used and making the level of logistic service dependent on the current coefficient of variation, which groups products into three classes. The presented algorithm is currently implemented in the ERP system, which supports material flows in the enterprise. The first phase of the tests indicated its high efficiency compared to the current solution.

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