Reconfiguring the Stock Management Policy for the Critical Products of a Non-Production Warehouse
Schaeffler Portugal's case study

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ABSTRACT

The efficiency of the activities of a warehouse highly impact the performance of its supply chain. As a key-component of modern supply chains, warehouses can have a significant weight in the total cost of the logistics activities. Moreover, spare parts inventory management highly increases the complexity of the warehouse management process.
It is in this context that the present dissertation proposed by Schaeffler Portugal, arises. Schaeffler Portugal is an automotive and industrial components manufacturer. The current non-production warehouse management policy is reviewed, in order to adapt it to the high intermittent demand nature of the products it manages.
In order to select the best management policies for the considered items, stock management models are analyzed as well as a recurrent neural network algorithm to predict future demand, based on the DMAIC methodology. The results conclude that the (s, Q*) review policy provides the best overall results. Conclusions are drawn from the current policies as well as the impact that the limited available data proves to have in the performance of the machine learning algorithm.

Keywords: Spare parts inventory management; warehouse management; forecasting algorithms; recurrent neural networks

1. INTRODUCTION

The automotive-supplier industry presents a crucial role for Europe's growth, amounting for 4% of the European Union's gross domestic product. The sector represents the largest private investor in research and development in the European Union (European Comission, 2019).
Within this industry's supply chain, warehousing is responsible for managing the flow of intermediary stocks, providing the means for a high service level by stabilizing variability along the chain caused by elements such as seasonality of demand. Its operations represent the use of intensive labor as well as capital whose performance impacts the operational costs of the warehouse and the costs of the whole supply chain. Automotive suppliers intend to reduce costs, enhance productivity and quality as well as increase their operations flexibility. In this context, the present work arises in collaboration with Schaeffler Portugal in order to study the warehousing operations of the non-production activities of the company in order to advise Schaeffler Portugal's decision, regarding the stock management models applied to the products managed by the referred warehouse.
The purpose of the current paper is to evaluate the current policy being adopted by the referred warehouse and to propose an alternative policy for the critical products of that warehouse, namely through the development of a methodology that intends to improve the overall stock levels of the warehouse.
The remainder of the paper is organized as follows. Section 2 presents the problem under study. Section 3 introduces the literature review.

Section 4 describes the data collection and solution approach to the problem. Section 5 presents the case study resolution and, section 6 details the paper's conclusions and lines for future research.

2. CASE STUDY

2.1 – The Schaeffler Group overview

The Schaeffler Group is a global automotive and industrial components supplier whose mission and vision underlie the company's basis for success: the innovative spirit, top-quality and outstanding technology of its developed solutions (Schaeffler Group, 2018).

The company is one of the world's largest family-owned businesses, having generated roughly €14 billion in sales in 2017. Currently, the company is present in more than 50 countries, in approximately 170 locations worldwide employing more than 90 000 people (Schaeffler Group, 2018).

The Schaeffler Group's organizational structure follows a three-dimensional organizational structure, characterized by the different divisional, functional and regional units. Regarding the divisional organization, the Schaeffler Group is managed in terms of Automotive Original Equipment Manufacturing (OEM), Automotive Aftermarket (MRO) and Industrial divisions. In terms of functions, the organizational model includes the Chief Executive Officer function, technology, operations, finance and human resources. Finally, respecting the third dimension, the Group is divided into four regions: Europe, Americas, Greater China and Asia/Pacific. Schaeffler Portugal integrates the industrial, automotive OEM and MRO divisions and operations function of the European region. It manufactures uniquely ball-bearing. The structure was disclosed in an article posted on the company's intranet (personal communication, July 12, 2018).

This project arises in collaboration with the Master Planning and Logistics Department of Schaeffler Portugal in an effort to improve the stock management policies of the non-production warehouse of the company. Therefore, the warehouse overview is presented in the next sub-section 2.2.

2.3.4.1 – Non-Production Warehouse

The main function of a warehouse is to assure there is enough stock to meet its customers' demand. In the case of Schaeffler Portugal's non-production warehouse, its customers include the maintenance, production as well as most support and quality, cost and delivery departments. Warehouse management includes three main branches: material flow, information flow and warehouse physical specific characteristics, described below.

- Material flow – management of the spare parts of the maintenance department;
- Information flow – central to the warehouse management process, it displays, at each moment, the availability and needs of the items at the warehouse. Nonetheless the system is not being used to its full potential since automatic re-orders are not being placed, resulting in an extra effort from the warehouse staff confirming the orders to the suppliers;
- Warehouse physical specific characteristics – The general warehouse has a total area of 210 m^2, holding two automatic product dispensers with 46 shelves each as well as 252 shelves. Each shelve has a total capacity of 152 liters. A truck dock is located nearby the warehouse entrance, where a maximum of one truck can unload products. Currently a total stock of 485 000 € is present at the warehouse, including maintenance parts, lubricants and office supplies.

2.4 – Problem Characterization

The current paper arises from the Schaeffler Portugal's need to analyze if restructuring the information flow in the non-production warehouse, namely defining order quantities and safety stocks for its critical products, increases the efficiency of the processes, particularly in terms of decreasing time spent controlling stocks and ordering products as well as reducing the total quantity of products present in the warehouse at study.

Therefore, the company intends to analyze a scenario where items are segmented according to their demand profile, in order to be managed automatically through the implemented Enterprise Resource Planning system, SAP.

To summarize, the objective of the present paper is to review the stock management policy of the non-production warehouse of Schaeffler Portugal, indicating the most adequate method to manage the different categories of products present in the warehouse.

3. LITERATURE REVIEW

3.1 – Warehouse Management

The allocation of operating costs in a typical warehouse is primarily assigned to labor costs (60%), followed by the occupation of space (25%) and equipment (15%).

Gu, Goetschalckx & McGinnis (2010) propose a methodology to analyze warehouse operations related to their four major functions, i.e., order receiving, item storage, order picking and shipping and suggest the analysis to be divided into three categories: warehouse design, warehouse operations and warehouse performance measures.

3.2 – Warehouse Performance Measures

Performance measures (or Key Performance Indicators – KPIs) are a fundamental principle of management since they identify and register the difference between the current and target values of an indicator and provide an overview of the previous progress (Peterson, 2005).

3.3 – Inventory Management Models

Regarding inventory control, the periodic and continuous review approaches are introduced. The parameters used to define the policies are the re-order point or minimum stock (*s*), safety stock (Q_{safety}), maximum stock (*S*), order quantity (Q*) and the review period (*T*) (Silver, Pyke, & Peterson, 1998).

The continuous review policy (*s, Q**) is the basis of the present paper, where the stock level is kept under constant observation and a re-order is set every time the stock level reaches a reference re-order point. As the intended level of stock after the re-order is known (order-up-to-level), a fixed number of items is ordered when stock reaches the re-order. This policy is generally adopted when managing independent demand items.

According to Silver, Pyke and Peterson (1998) the (*s,Q**) model, according to normal distribution, is defined according to expressions (1) to (5):

$$Q_{safety} = k \times \sigma_{DL} \quad (1)$$

$$s = \mu_{DL} + Q_{safety} \quad (2)$$

$$Q^* = \sqrt{\frac{2 \times \mu_{DL} \times C_a}{c}} \quad (3)$$

$$\sigma_{DL} = \sqrt{(\mu_L \times \sigma_D^2) + (\mu_D^2 \times \sigma_L^2)} \quad (4)$$

$$\mu_{DL} = \mu_D \times \mu_L \quad (5)$$

where:

μ_{DL} – average demand during the supply period; μ_D – average demand; μ_L – average replenishment time; Q_{safety} – safety stock quantity; *k* – safety factor; σ_{DL} – demand standard deviation during the supply period; *s* – minimum stock or re-order quantity; μ_{DL} – average demand during the supply period; Q_{safety} – safety stock quantity; *Q** - order quantity; μ_{DL} – average demand during the supply period; C_a – cost of processing an order; I – Cost of maintaining the items in the warehouse; *c* – acquisition cost; σ_{DL} – demand standard deviation during the supply period; μ_L – average replenishment time; σ_D – demand standard deviation; μ_D – average demand; σ_L – replenishment time standard deviation;

3.4 – Spare Parts Inventory Management

Spare parts inventory management is greatly different from other manufacturing inventories management. The intermittent demand patterns are the factor that mostly differentiates spare part inventory management from any other. The patterns are characterized by sequences of zero demand interpolated with occasional demands different from zero. Several distributions have been studied in literature to represent these patterns, even though empirical evidence is inexistent (Lengu, Syntetos, & Babai, 2014).

3.5 – Items Classification

ABC inventory classification is an inventory planning and control instrument that allows to properly discriminate SKUs according to the required level of attention of each item in the inventory, giving a homogenous service level to items in the same class (Zheng, Fu, Lai, & Liang, 2017).

Depending on the required objective, a different set of models can be used to segment the items. Two models based in different criteria – economic value and demand pattern – are analyzed in the next sections.

3.5.1 – Economic Value

The ABC classification allows classifying items according to three categories: A, B and C. Category A corresponds to the most relevant items, category B to the intermediate relevance items and category C to the least relevant items. It follows the Pareto principle that indicates that few items in the inventory amount for most of the inventory costs, whereas a large amount of items only amount for a relatively low share of the total inventory costs.

3.5.2 – Demand Type

The demand patterns of the items become especially relevant in a non-production warehouse, since the segmentation of the items can help to identify the inventory management model that best suits the different groups of materials.

Syntetos, Boylan and Croston (2005) classified demand according to two criteria: demand variability and average time between demand. The demand of each item can be classified as erratic, lumpy, smooth or intermittent (see figure 1).

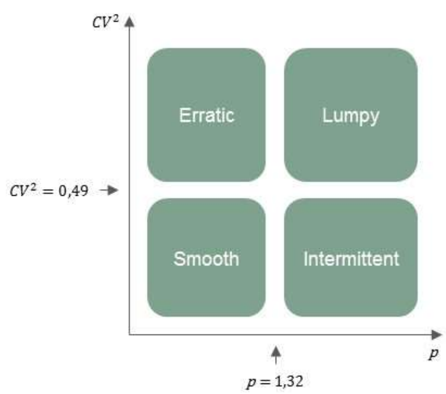

Figure 1. **Demand type segmentation**

The demand variability is a dimensionless variable that measures the predictability of the demanded quantity. The variable is expressed as the variation coefficient CV^2, given by the expression 6. The lower the variation coefficient, the lower the unpredictability.

$$CV^2 = \left(\frac{\sigma}{\mu}\right)^2 \tag{6}$$

where:

σ is the demand standard deviation; μ is the average demand.

The average time between demand is measured in time units and corresponds to the average between two successive requests of the same item (see expression 7).

$$\begin{aligned} &\mathit{Average\ time\ between\ demand} = \\ &= \frac{\mathit{Total\ number\ of\ periods}}{\mathit{Number\ of\ demand\ buckets}} \end{aligned} \tag{7}$$

Each quadrant of figure 1 corresponds to a demand type identified above, and the values p = 1,32 and CV^2 = 0,49 were proposed by the authors.

3.6 – Forecasting methods

The reliability of the demand forecasting becomes especially relevant in the spare parts inventory management context due to the intermittent nature of spare parts demand. An effective management of resources makes use of demand forecasts to anticipate future needs.

3.6.1 – Artificial Neural Networks as a forecasting method

Artificial Neural Networks (ANNs) are a technique designed to emulate the human pattern recognition using the processing of several inputs and inferring. Several authors concluded ANNs outperform conventional time series models when applied to spare parts forecasting (Gutierrez, Solis, & Mukhopadhyay, 2008). Furthermore, Recurrent Neural Networks (RNNs) are better suited for modelling sequential data for sequence recognition and prediction. RNNs are ANNs that present recurrent connections, which allow them to store and select memory based on previous states, enabling the processing of past complex signals for long time periods.

3.6.2 – Artificial Neural Network forecasting model design

An ANN is composed of three main components: the input layer, the hidden layer and the output layer. Both of the hidden and output layers are composed of a subset of neurons, which are the processing units of the data present in the input neurons (the subset of data present in the input layer). The three layers are interconnected by a set of weights which together with the architecture of the network store the knowledge of the network.

The development of an ANN can be broken down into eight fundamental steps (Kaastra & Boyd, 1996): Variable selection; Data collection; Data pre-processing; Training, testing and validation sets; Neural network paradigms;

Evaluation criteria; Neural network training; and Implementation.

3.6.3 – Recurrent Neural Networks

RNNs are a sub-class of ANNs and present an architecture with high dimensional hidden states and non-linear dynamics. The hidden states work as the memory of the neural network and are conditioned by their previous states, allowing these structures to be more suited to collect, recall and process past signals for more extended periods of time.

4. DATA COLLECTION AND SOLUTION APPROACH

4.1 – DMAIC methodology outline

The framework utilized to answer the company's current situation is the DMAIC methodology. This is an efficient and effective implementation approach which serves as a basis for problem solving in a continuous improvement environment.

4.2 – Defining stage

The objective of the first stage of the methodology is to fully define the scope of the policy review project for the non-production warehouse. The detailed scope is presented considering the three phases of the defining stage: i) team definition; ii) problem definition; and iii) targets definition. These phases are explained below.

i) Team definition

The project team is defined according to the required areas of intervention of the project, namely the teams concerned with the non-production warehouse management, stock management and maintenance management.

ii) Problem definition

After a brainstorming with the project team to develop the "5W&1H (*What-Who-When-Where-Why-How*)" methodology application, the scope of the project became clearly defined,

iii) Targets definition

Based on previous project implementations and on global targets defined for the plant, the project team defined that a target stock value reduction of 5% for the non-production warehouse would be acceptable for the project.

4.3 – Measuring Stage

4.3.1 – Data collection

Once the problem is characterized, data is collected and categorized according to the following groups: amount of stock in the non-production warehouse and respective price in April 2019; and demand record of products between January 2018 and April 2019.

The files are collected using SAP, where all the movements of the products are kept in a record. In April 2019, a total of 2 646 different products was registered in the company's database, accounting for 68 019 products, which represented 465 000 € in stock. Considering the different number of products registered in the warehouse in April 2019, a demand of 1 235 different products in 2018, approximately 47% of the number of different products, reflects either there are several obsolete products in stock, or high safety margins. During the first quarter of 2019 this percentage drops to 21%. Nonetheless, according to the products records a moderate percentage of items can be considered obsolete, representing an inefficiency in terms of poorly occupied space and investment.

4.3.2 – Data screening

A comparison between the 2 646 different products that were in the warehouse in April 2019 and the products that had been picked between January 2018 and April 2019 reveals that 1 167 products (44%) had no recorded demand during that period (see table 1).

These products are further explored in section 4.4.2 and are classified as "Group of products without demand between 2018 and 2019".

Table 1. **Existing product groups**

Group description	Total price
Products in stock in April 2019	465 000 €
Products with demand between 2018 and 2019	293 000 €
Products without demand between 2018 and 2019	172 000 €
Critical products selected by the warehouse manager	75 500 €

4.4 – Analyzing Stage

4.4.1 – Group of products with demand between 2018 and 2019

In this section, the products with a recorded demand between 2018 and 2019 are segmented according to their economic value and recorded demand during the referred period.

Economic Value Analysis

To identify the SKUs that have the highest economic importance in the warehouse, a categorization according to an ABC analysis is performed. The price being considered is the purchase price of the item, excluding the value added tax. Considering the typical values used in literature for item segmentation in the ABC analysis, as well as the data presented previously for the items with demand during the 2018 and 2019 period, the items of the warehouse are divided into three classes as summarized in table 1.

Table 2. **ABC analysis segmentation**

Class	% of products	% of product price	Accumulated % of product price
A	20	77	77
B	30	18	95
C	50	5	100

It is possible to verify that although class A only represents 20% of products, it amounts for 77% of the accumulated products price. These products should be under a more effective and efficient control from management. A total of 296 articles are included in class A, and the first 10 products account for more than 20% of the total accumulated products price.

Class B is composed of 444 products and class C of 739 products. As expected, class C only accounts for 5% of the accumulated product price and amounts for 50% of products present in the warehouse.

Demand Type Analysis

In addition to economic value, the products demand type is an extremely useful characterization technique. Demand can be characterized according to two variables: average time between demand and demand variability.

A total of 351 items with a single demand over the 2018 and 2019 period have been identified. It is not possible to calculate any of the referred dimensions of the single demand SKUs since they do not present neither of the referred dimensions. Regarding the items with more than a single demand over the referenced period, a total of 1 128 SKUs meet these conditions. These items are subject to a segmentation regarding the demand type.

According to the Schaeffler Portugal's warehouse management team, an item with an average interval between demands higher than three months is immediately considered a lumpy or intermittent item. Moreover, an item with a demand variability higher than one is automatically considered as an erratic or lumpy demand item.

From the 1 128 SKUs identified as having more than a single demand, 727 belong to the uncertainty region categorized by an average interval between demands lower than three months and with a demand variability lower than one. According to Syntetos, Boylan and Croston (2005) the region can be segmented when the average interval between demands and the demand variability are 1,32 and 0,49 respectively. Figure 2 represents the 727 items segmented across the four regions – erratic, lumpy, smooth and intermittent.

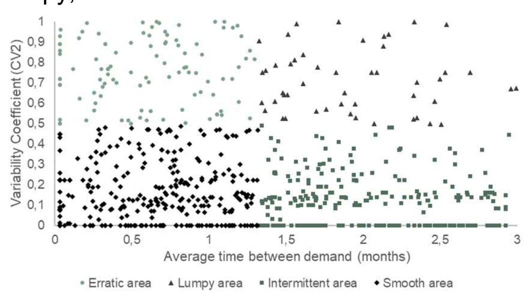

Figure 2. **Four regions of demand type segregation**

Examining the plot, it is possible to conclude that the intermittent nature category of products represents 32% of the SKUs present in the warehouse, amounting for a total of 33% of the total value present in the warehouse.

Items in the smooth demand category represent more than a fifth of the total products in the warehouse (21%).

SKUs in the erratic and lumpy demand categories represent 14% and 9% of the total number of products present in the warehouse respectively.

4.4.2 – Group of products without demand between 2018 and 2019

The group of products without demand between 2018 and 2019 holds 1 167 different items in these conditions amounting for 34 634 items with a total of 172 000€. The identified SKUs represent occupied space in the warehouse that could be used for other purposes as well as an investment that could be redirected for other operations. Nonetheless, the exclusion of the items should be carefully examined. Moreover, the analysis only covers one year and four months of records, which might not have enough representativeness when considering the exclusion of high cost spare parts.

4.4.3 – Group of critical products selected by the warehouse manager

Since there are 2 646 different products in the warehouse, a group of items considered critical for the normal operations of the plant is selected by the warehouse manager to be the focus of the implementing and control stages. All items with a recorded demand that are selected belong to class A of the ABC analysis performed previously.

5. CASE STUDY RESOLUTION

5.1 – Improving Stage

5.1.1 – Warehouse stock management

SAP offers a range of stock management models to apply in the configuration of each item. Three types of models are currently being applied by the warehouse management team: MRP ZV, characterized by a manual reorder of items once a reorder point is reached; MRP ZT, where materials according to a planned schedule; and MRP ND where there is no item requirement generation when an item reaches a low stock level.

The characterization performed above is not inflexible. If warehouse employees experience an MRP management model suits a certain item best, then its application should also be considered. Next, items classified as intermittent or smooth are assigned to the MRP ZV class due to the low variability nature of the items.

5.1.1.2 – Parameters determination

MRP ZV parameters determination

The MRP ZV stock management model follows the (s, Q*) review policy.

Since the cost of processing an order (C_a) and the cost of maintaining a product in the warehouse annually (I) are not available at Schaeffler Portugal, the following values are assumed for each variable respectively: 0,50€, 1€ and 2€ as well as 3%, 5% and 7%. Combining the previous values, 9 scenarios can be considered for each item, regarding the optimal order quantity.

Considering the worst-case scenario (C_a = €0,50; I = 3%) the recommended order quantity is 4 units. The minimum stock currently defined for the item is 12 units. Applying expressions (1) to (5) for a service level of 95%, this value should be 14 units. Performing a similar analysis to the remaining items characterized by low variability demand, figure 3 shows that 14 SKUs have excessive stock, 2 SKUs have the recommended amount of stock and 1 SKU has less than the recommended amount of stock. This amounts for an extra 56 600 € in stock that could be reduced, amounting for a 12,2%

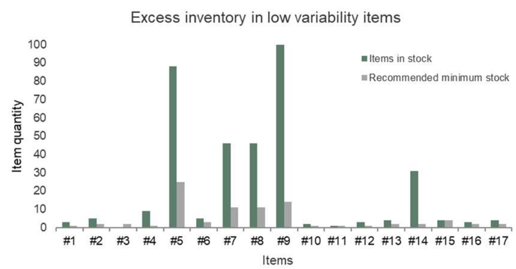

Figure 3. **Excess inventory in low variability items**

improvement in the overall stock of the warehouse.

Considering the limited available records of demand, it is recommended that this analysis is revised in a yearly period, since a broader record allows a more effective determination of parameters and ultimately for a more effective inventory management.

Forecasting with Artificial Neural Networks

Classic inventory management models do not produce reliable results with high demand variability items. Instead, forecasting algorithms such as artificial neural networks are applied, producing more trustworthy results. The analysis is designed and performed according to the framework suggested by Kaastra and Boyd (1996) (section 3.6.2). Erratic and lumpy demand items within the critical products group are considered for the current analysis. Item 058645900 is used as an example for the application of the method. The analysis performed to this item is then replicated for the remaining two items. For simplification purposes, item 058645900 is referred as item A, item 063988470 as item B and item 222781246 as item C.

The network is trained by supplying a dataset of input-target pairs and minimizing the loss functions. The latter is minimized by optimizing the weights of the network through a backpropagation algorithm to reduce the difference between the output of the algorithm and target values supplied to the network.

Empirical results

The predicted demand set of each analyzed item is compared with the target values for the considered period.

For the models' results evaluation, the resulting values of the predictions should be used, as well as a performance measure, the correlation coefficient.

The predicted demand for item A has the same value of the real demand (4 units) in February 2019 (figure 4). Moreover, in March 2019 the algorithm does not perform so well, returning a prediction of approximately 1 unit, whereas the real demand is 4 units. The correlation coefficient between the real and predicted values for the sample is 0,6636, indicating a fairly poor performance of the model. A cost analysis is performed later in table 3 for all the considered products.

Figure 4. **Real and predicted demands - item A**

In this case, the algorithm performed reasonably well for item B, following the trend of the real demand. On the one hand, for January and February 2019, the predicted demands differ a maximum of 2 units from the real demands. On the other hand, for March 2019 the predicted and real demands diverge to a moderate degree, not only in terms of unitary value, but also in terms of trend. The correlation coefficient between the real and predicted values for the considered sample is 0,876, indicating a good performance of the model.

Finally, for item C, the algorithm has performed fairly well in predicting the rising and declining demand trends for January and February 2019 respectively, although it is more conservative than the real demand values. This discrepancy can be explained by the testing set demand values, which never reach the magnitude of the demand presented in January and February of 2019. In March 2019, the predicted and real demand values were the same. The correlation coefficient between the real and predicted values for the considered sample is 0,799, indicating a reasonable performance of the model.

Taking into consideration that the average replenishment time for the analyzed items is lower than one month, it is possible to simulate how the neural networks would have performed for the given period in predicting the stock requirements. Moreover, it is possible to quantify what would be the level of stock for the considered items, if the results of the network would have been used to order the items from January 2019 to April 2019.

The prediction would have caused a stock out in the plant during the analyzed periods in case there was no available extra stock. The predictions in all three cases, considered results that did not match the real demand of the periods. A possible cause can be the lack of a robust set of historical data, which brought about the test generalization capability and the reliability of the resulting data to underperform under the considered conditions.

Due to the poor performance of the algorithm, regarding the considered items, it is important to analyze how, the previously studied policy (MRP ZV) that considers the (s, Q*) review policy, performs comparing to the neural network, using the same approach of section 5.1.1.2. Both, the cost of holding extra stock of the considered products in the warehouse as well as the cost of stockout, produced by using the developed network should be considered to decide the best policy for the considered products.

In order to analyze the performance of the proposed methodologies (forecasting using ANNs and MRP ZV) a comparison should be made using a unique performance measure. Therefore, by examining how the methods behave under a test scenario, it is possible to measure the actual costs of the company either by incurring in a stock out situation or by holding extra unnecessary stock. Since a stock out cost is not available at Schaeffler Portugal for the given parts, it is assumed that it is equal to the lost sales for a given month by having a production line stopped. Taking into account Schaeffler Portugal's operating income in 2018 is equal to 79.8 M€ (Sabi by Bureau van Dijk, 2019), and that a stock out would represent one of its 48 available production lines stopped, the stock out cost for one missing component is estimated according to expression 8.

$$Stock\ out\ cost/product/month = \frac{79\ 800\ 000}{12 \times 48} = 138\ 542\ € \qquad (8)$$

The methodology with the lowest cost for the given test is the MRP ZV model. Both scenarios are presented in Table 3. The real demand of products A, B and C is presented in the first column. The stock levels considering the two proposed methodologies are presented in the "test scenario stock level" columns, by subtracting to the stock quantity the real demand and adding the forecasted quantity to the following month. Moreover, the total stock out quantity for each product is then multiplied by the stock out cost per product per month used in expression 8.. Finally, the total cost per method is calculated by adding the total costs per product of each method. Even though the assumed stock out cost, represents a worst-case scenario, it is expected to off-balance any inventory holding cost. Therefore, a scenario where stock outs are present is always undesirable. Finally, taking into consideration the previous analysis, the recommended scenario is the MRP ZV model for the considered items.

5.2 – Controlling Stage

After implementing the recommended scenarios, the warehouse management team should continuously review the warehouse management policies, at least on a yearly period. Being the last stage of the DMAIC methodology, the controlling phase ensures the results of the previous stages are not forgotten.

Table 3. **Summary table**

Item	Real demand			Test scenario stock level with replenishment based on ANNs			Test scenario stock level with replenishment based on the MRP ZV model		
	A	B	C	A	B	C	A	B	C
January 2019	-	19	11	-	19	2	-	19	2
February 2019	4	10	7	7	9	-5	7	9	-5
March 2019	4	13	0	3	-4	0	10	5	7
Total stock out quantity	-	-	-	0	-4	-5	0	0	-5
Stock out cost (€)	-	-	-	0	554 168,00	692 710	0	0	692 710
Inventory holding cost (€)	-	-	-	4,50	14,00	1	8,50	16,50	4,50
Total Cost / product (€)	-	-	-	4,50	554 182	692 711	8,50	16,50	692 714,50
Total Cost / method (€)	-			**1 246 897,50**			**692 739,00**		

6. FINAL REMARKS AND FUTURE WORK

Warehousing is a fundamental activity within the supply chain management. Automotive suppliers, such as Schaeffler Portugal intend to reduce costs, enhance productivity and quality as well as increase their operations flexibility. In this context, the present paper is developed in collaboration with Schaeffler Portugal in order to study the warehousing operations of the non-production activities in the company. The DMAIC methodology is presented along with the data collection and segregation necessary to develop the case study. The segregation takes place according to both an economic and a demand analysis of the products. Lastly, a group of critical products is selected by the warehouse manager to represent the sample of products analyzed in the following section.

Following the segregation of the products, the application of the stock management models to the different groups of products takes place in the case study resolution chapter. On the one hand, items that present a smooth and intermittent demand are analyzed according a (s, Q*) review policy. On the other hand, items with erratic and lumpy demand patterns are subject to an analysis using ANNs to predict future demand patterns. However, restrictions on data availability resulted in unreliable results from the network and an (s, Q*) policy is also suggested to these items.

For the future development of the subject studied along the paper, some improvement and analysis opportunities were identified that should be taken into consideration:

Firstly, the company's non-production supply chains should be analyzed thoroughly, in order to identify possible advantages in centralizing high demand variability items for production plants that use similar technologies.

Secondly, a more extensive estimation and study of the demand is suggested, as it is a variable that depends on multiples factors. If explored correctly, the factors could provide meaningful insights which could lead to understand how is spare parts demand impacted by the different factors within an industrial environment.

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