Reconfiguring the Stock Management Policy for the Critical Products of a Non-Production Warehouse

Schaeffler Portugal's case study

Leonardo Pedro Ferreira Fidalgo Marcelino

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Supervisor: Prof. Inês Marques Proença

Examination Committee

Chairperson: Prof. Ana Paula Barbosa Póvoa

Supervisor: Prof. Inês Marques Proença

Member of the Committee: Prof. António Manuel da Nave Quintino

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Resumo

O desempenho das cadeias de abastecimento é altamente impactado pela eficiência das atividades dos seus armazéns. Como parte integrante das cadeias de abastecimento modernas, a gestão de armazéns pode ter um impacto significativo no custo das actividades logísticas das empresas. Para além do referido, a gestão de inventário referente a peças de manutenção aumenta substancialmente a complexidade do processo de gestão dos armazéns.

É neste contexto que o tema para a presente dissertação estudado na Schaeffler Portugal surge. A Schaeffler Portugal é um fabricante de componentes automotivos e industriais. A política seguida pelo armazém geral da empresa é revista de forma a adaptá-la à natureza intermitente da procura dos produtos que gere.

Assim, de forma a selecionar a melhor política para os artigos geridos por este armazém, modelos de gestão de inventários são analizados, bem como um algoritmo de redes neuronais recorrentes, de forma a prever a procura futura destes artigos. Os resultados demonstram que a politica de revisão de stocks (s, Q*) obtém melhores resultados. Finalmente, são retiradas conclusões das políticas analisadas bem como do impacto que a limitação de dados disponíveis tem no desempenho da rede neuronal recorrente.

Palavras-chave: Gestão de inventário de peças de manutenção; gestão de armazéns; algortimos de previsão; redes neuronais artificiais.

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.

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List of Abbreviations

ANN – Artificial Neural Network

CEO – Chief Executive Officer

DC – Distribution Center

DMAIC – Define, Measure, Analyze, Improve, Control

ECP – European Consolidation Point

ERP – Enterprise Resource Planning

FAG – *Fischers Aktien-Gesellschaft*

FIFO – First In First Out

KPI – Key Performance Indicator

MRO – Maintenance, Repair and Operating

MRP – Manufacturing Resource Planning

OEM – Original Equipment Manufacturing

SC – Supply Chain

SDC – Satellite Distribution Center

SKU – Stock Keeping Unit

1. Introduction

The current chapter presents the context in which the problem being studied arises, highlighting both the objectives and structure of the master's dissertation. Section 1.1 provides a brief contextualization of the problem. Section 1.2 presents the purpose and objectives of the dissertation. Finally, the methodology of the problem is specified in section 1.3 and the structure and outline of the document are described in section 1.4.

1.1 – Problem Contextualization

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). In recent years, the strategic role of this industry in the socio-economic development of countries has been emphasized, especially regarding mobility solutions: it ensures an adequate and sustainable means of transportation for passengers, generates wealth and economic prosperity, significantly contributes to the world's competitiveness and promotes the creation and development of new companies, consequently generating highly qualified employment (World Economic Forum, 2013).

The highly complex supply chain that characterizes the sector is continuously pushed to perform better by the day, not only due to high demand service levels from customers but also due to the highly competitive environment of the industry. Moreover, it represents a significant portion of non-value adding costs that are being transferred to the customer.

Within the 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. On the other hand, its operations represent the use of intensive labor as well as capital whose performance impacts not only the operational costs of the warehouse as well as the costs of the whole supply chain.

Automotive suppliers intend to reduce costs, enhance productivity and quality as well as increase operations flexibility. In this context, the present dissertation arises in collaboration with Schaeffler Portugal in order to study the warehousing operations of the non-production activities in the company. It is intended to advise Schaeffler Portugal's decision, regarding the stock management models applied to the products managed by the referred warehouse. Schaeffler Portugal is a subsidiary of the Schaeffler Group, a global automotive and industrial components supplier.

1.2 – Master's Dissertation Purpose and Objectives

The problem the current dissertation addresses is the evaluation of the current policy being adopted by the non-production warehouse of Schaeffler Portugal and the proposition of 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.

As such, the intermediate objectives are presented in order to accomplish the purpose mentioned previously:

- To provide a characterization of the Schaeffler Group's supply chain and all its actors, including a detailed overview of Schaeffler Portugal's processes and warehousing policies, as well as the policy current constraints;
- To demonstrate the solutions being applied across several industries to manage highly complex supply chains and warehouses, with a focus on non-production parts which are characterized by a high variability of demand;
- To develop and validate a methodology suitable for the solution of the present problem;
- To collect, discuss and segregate data, including the considered assumptions, in order to implement it in the problem under study;
- To apply the methodology discussed along the dissertation to the present problem and consider different future scenarios and possibilities;
- To analyze the results obtained from the methodology discussed along the dissertation and identify significant insights that can provide guidance in the proposed management policies.

1.3 – Master's Dissertation Methodology

The methodology followed along the current dissertation to solve the abovementioned problem is now presented. It includes seven steps which are represented in figure 1.

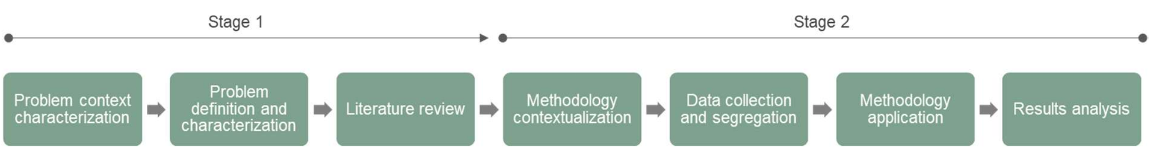

Figure 1. **Dissertation methodology - seven steps**

1. **Problem context characterization**

   The first step fully describes the problem's context. In this phase, the Schaeffler Group and Schaeffler Portugal's organization are described, including the structure of the group's supply chain and a brief context of the company's processes.

2. **Problem definition and characterization**

   The second step defines and characterizes the problem under study, aiming to produce a comprehensive understanding and analysis of the problem within the previously presented context. The problem's characterization is presented including the policy currently followed by Schaeffler Portugal. It is possible to pinpoint the current challenges met by the company and the opportunities that arise the latter.

3. **Literature review**

   The third step is intended at conducting a revision of the available academic work developed in the field of warehouse management policies, in order to guide the process of selecting a methodology to address the problem. The warehouse and inventory management policies of relevant articles in literature are studied, as well as forecasting methods, with a special emphasis on Artificial Neural Networks models.

4. **Methodology contextualization**

   The fourth step aims at introducing the methodology used during the remaining steps of the dissertation, ensuring the suitability of the designated framework to reach the desired solution.

5. **Data collection and segregation**

   The fifth step is dedicated at collecting and treating the available data present at the company and to segregate it into relevant groups that can be fitted into the stock management policies introduced in the following section.

6. **Methodology application**

   The sixth step aims at applying the best policies to the groups of products managed by the warehouse as well as estimating the parameters of latter policies.

7. **Results analysis**

   The seventh and final step analyses the results obtained previously. A comparison between the different policies is drawn and different solutions are analyzed and discussed. The improvement opportunities are identified as well as control plan to review the studied policies.

1.4 – Master's Dissertation Structure

This dissertation is structured according to the following chapters:

- **Chapter 1 – Introduction**

  Represents the current chapter, in which the subject of the dissertation is briefly introduced. It encompasses the context of the problem at hand, the defined goals as well as the methodology and structure of the entire dissertation.

- **Chapter 2 – Case study**

  The Schaeffler Group is concisely introduced as a global automotive and industrial parts supplier, with a special emphasis in its subsidiary Schaeffler Portugal, where the case study is taking place. Both the supply chains are analyzed from a holistic point of view as well as Schaeffler Portugal's non-production warehousing policies. Finally, the case study is introduced and the problem at hands is characterized.

- **Chapter 3 – Literature Review**

  A theoretical and scientific context is presented in this chapter. Firstly, the design, operations and performance measures are introduced. Spare parts inventory management is the focus of the remaining of the chapter with a focus on artificial neural networks as a forecasting algorithm.

- **Chapter 4 – Data collection and solution approach**

  A methodology framework is proposed to be used during the development of the future dissertation based on the DMAIC (Do-Measure-Analyze-Improve-Control) methodology. Products' data is collected and analyzed in order to be segmented to the next chapters.

- **Chapter 5 – Case Study Resolution**

Stock management policies are introduced based on the segmentation performed in the previous chapter. Artificial neural networks are introduced to analyze the reliability of this tool to determine the stock management parameters of high uncertainty demand items. Conclusions are drawn from applying the stock management policies.

- **Chapter 6 – Final remarks and future work**

  The chapter presents the main conclusions from the present dissertation, identifying key points that are relevant for the case study at hands. Considerations for future work are also drawn.

2. Case Study

The purpose of the present chapter is to characterize Schaeffler Portugal's non-production warehouse stock management policy. The Schaeffler Group and Schaeffler Portugal main activities are firstly analyzed in section 2.1, as well as their organizational structure. In section 2.2, the company Schaeffler Portugal is framed in the Schaeffler Group's supply chain. The Master Planning and Logistics Department of the company is reviewed on section 2.3, which is the department at focus on the present thesis. The company's stock management policy problem is then analyzed in section 2.4 and finally section 2.5 presents the chapter's main conclusions.

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, including manufacturing sites, research and development facilities as well as sales companies. It employs more than 90 000 people (Schaeffler Group, 2018).

The Schaeffler Group sets its foundation in 1946 in Herzogenaurach, Germany, by brothers Dr. Wilhelm Schaeffler and Dr. Georg Schaeffler. The company began its rise in 1949 with the invention of the cage-guided needle bearing, which was produced in considerable quantities for the German automobile industry under the brand *Industrie NAdellager* . In the following years the company grew organically and sustainably on a global scale. The growth of the company increased upon the acquisitions of *Lamellen und Kupplungsbau GmbH* – a clutch manufacturer – in 1998 and of *Fischers Aktien-Gesellschaft* (FAG) – a roller bearing manufacturer – in 2001 (Schaeffler Group, 2018). Schaeffler Portugal (previously *Rol – Rolamentos Portugueses*) was part of FAG. Nowadays it is a wholly-owned subsidiary and produces ball bearings for both INA and FAG brands.

The acquisition of *Continental Aktiengesellschaft* (Continental AG) in 2008 represents another milestone in the company's history. Continental AG is a global tire and auto parts supplier. In 2015, the Schaeffler Group successfully launched an initial public offering to refinance itself (Bower, 2015).

The introduction of the "Mobility for tomorrow" strategic concept in 2014 in the Group was based on four impactful megatrends[1] that are likely to shape Schaeffler Group's business in the future: climate change, urbanization, globalization and digitalization. To tackle these megatrends, given the number of industries supplied by the Group, four focus areas are defined as the basis for Schaeffler's strategic orientation: eco-friendly drives, urban mobility, interurban mobility and energy chain. It is based on these focus areas that the company is shaping its initiatives and direction for the future (Schaeffler AG, 2016).The Schaeffler Group's organizational structure presented in figure 2 follows a three-dimensional organizational structure, characterized by the different divisional, functional and regional units.

[1] Megatrend - an important shift in the progress of a society or of any other particular field or activity (2019 Oxford University Press, 2019).

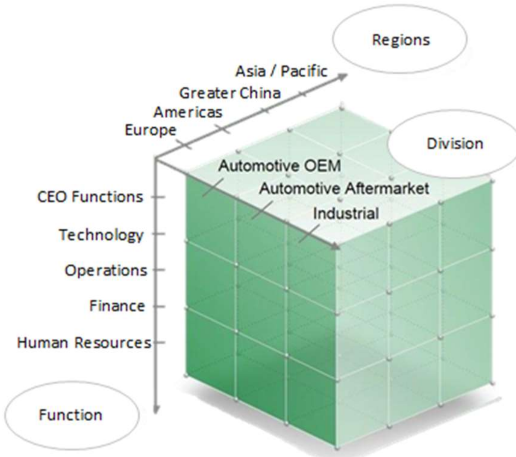

Figure 2. **The Schaeffler Group three-dimensional structure**

Regarding the divisional organization, the Schaeffler Group is managed in terms of Automotive Original Equipment Manufacturing (OEM), Automotive Aftermarket (Maintenance, Repair and Operating, MRO) and Industrial divisions. In terms of functions, the organizational model includes the Chief Executive Officer function (CEO 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, each managed by a regional CEO.

Schaeffler Portugal integrates the industrial, automotive OEM and MRO divisions and operations function of the European region. The company where the project is taking place is a ball bearing manufacturer and it is organized according to the organizational chart presented in figure 3. The structure was disclosed in an article posted on the company's intranet (personal communication, July 12, 2018).

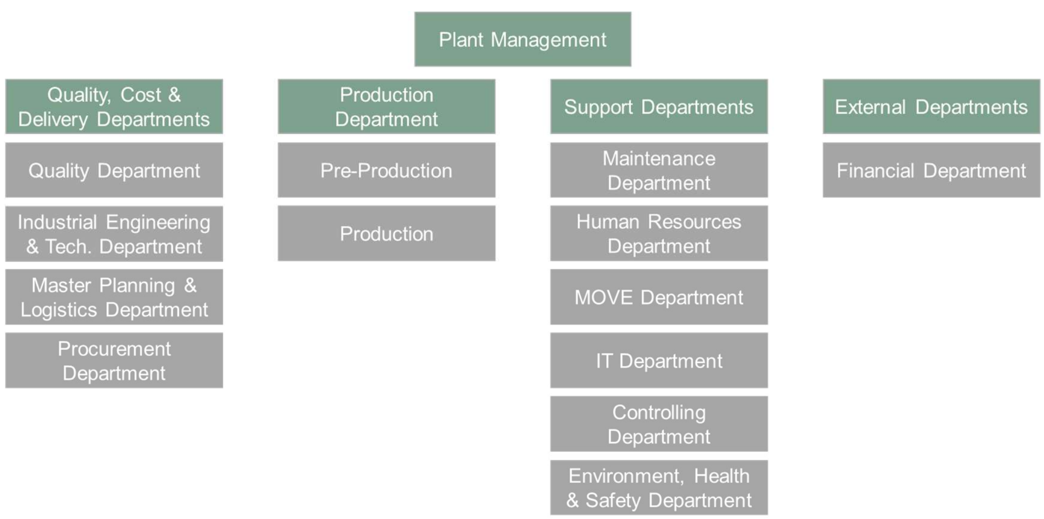

Figure 3. **Schaeffler Portugal organizational chart**

Tables 1 to 4 briefly describe the departments presented in the organizational chart.

Table 1. **Production Department Description**

Production Department	Description
Pre-Production	Responsible for running the operations in the Pre-Production facility;
Production	Responsible for running the operations in the Production facility.

Table 2. **Support Departments Description**

Support Departments	Description
Maintenance	Responsible for all the preventive maintenance activities, mechanical and electrical repairs as well as for all the required production line setups;
Human Resources	Responsible for managing the workforce of the company;
MOVE	Responsible for the implementation of the continuous improvement methodologies in the factory;
Information Technology	Responsible for supporting both the shop floor control system (MES) and the Material Resource Planning software (SAP);
Controlling	Responsible for the production of reporting instruments of the plant to provide a basis for the control of the organization to the top management;
Environment, Health and Safety	Responsible for ensuring the Environmental, Health and Safety norms are duly respected in the company.

Table 3**. External Departments Description**

External Departments	Description
Financial	Responsible for managing the organization's cash flow and ensure the company's liquidity, as well as to manage the company's accounting of the company;

Table 4. **Quality, Cost & Control Departments Descriptions**

Quality, Cost & Delivery Departments	Description
Quality	Responsible for guarantying that the quality standards of the materials used are met, conducting regular audits along the shop floor stages;
Industrial Engineering and Technology	Responsible for covering the entire process from factory layout planning to the definition of methods and standards for manufacturing planning, production logistics, maintenance and investment;
Master Planning and Logistics	Responsible for planning the production in the plant, including resource allocation with regard to the demand and capacities of the factory; It is

	responsible for all the intralogistics operations of the company, including the management of all the warehouses
Procurement	Responsible for handling the materials requests and acquiring goods from external suppliers;

The responsibilities of each department were disclosed in an article posted on the company's intranet (personal communication, July 13, 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 company. Therefore, it is useful to understand the existing interactions among the supply chain members – Schaeffler Portugal and its suppliers and customers – as well as their functions and specific characteristics.

2.2 – Schaeffler Portugal Supply Chain Structure

Schaeffler Portugal integrates the industrial division and operations function of the European region. This division and function have its own distinct supply chain (SC) within the Schaeffler Group, represented in Figure 4. Schaeffler Portugal is part of the Production level of the SC. Backward in the SC, the suppliers are responsible for sourcing of the raw materials and components needed for the production of the final product.

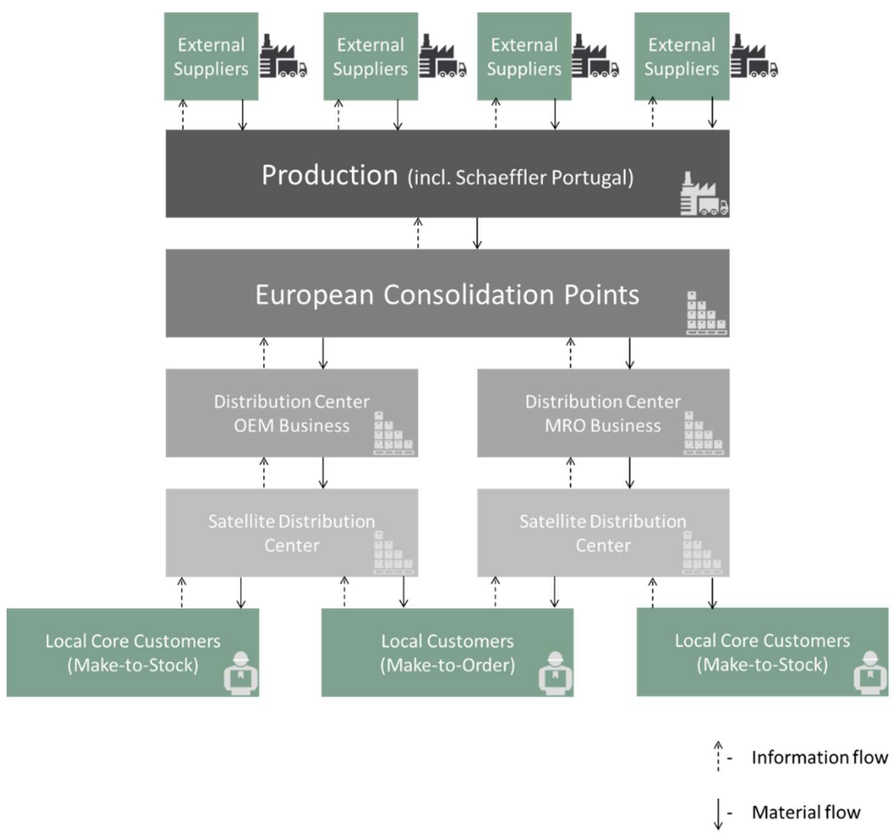

Figure 4. **The Schaeffler Group Supply Chain**

Forward in the SC, the European Consolidation Points (ECPs) represent Schaeffler Portugal's customers. Both ECPs are located in Germany and are responsible for bundling the demands of the remaining SC – the Distribution Centers (DCs) – which can be distinguished between Original Equipment Manufacturing (OEM) and Maintenance, Repair and Operating (MRO). Distribution Centers supply the Satellite Distribution Centers (SDCs), whereas SDCs supply the Local Core Customers as well as the Local Make-to-Order Customers. The difference between these two is explained next.

Both the OEM and MRO Businesses belong to the Core Program (which represents the catalog products), for which a Make-to-Stock strategy is defined. The Core Program can be divided into the Regional Core Program (relative to DCs) and into the Local Core Program (relative to the SDCs). Customers benefit from immediate availability if their required products belong to both Local and Regional Core Programs. If the required products only belong to the Regional Core Program, customers can expect immediate availability except for the transit time between the DC and the SDC. The Core Program can differ from region to region due to the different areas of main application (for example the strong agricultural industry located in the south of Europe and the strong food industry in the Netherlands originate different supply needs in these regions). If the products do not belong to neither of the Core Programs, a Make-to-Order strategy is defined. The analysis focuses on the Make-to-Stock Strategy Supply Chain since Schaeffler Portugal's main activities are directed towards this strategy. The structure of the Supply Chain was disclosed in a brochure posted on the company's intranet (personal communication, July 13, 2018).

In the following sub-sections, each intervenient of the Schaeffler Portugal Supply Chain is individually analyzed:

2.2.1 – External Suppliers

The components needed for the production of a ball bearing include an outer ring, a cage, bearing balls, an inner ring and two shields (see figure 5).

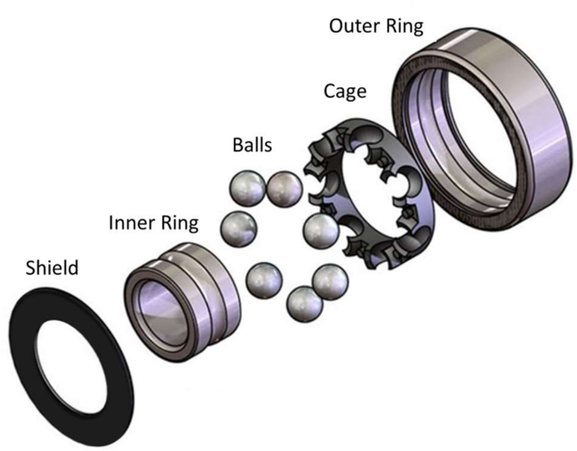

Figure 5. **Ball bearing components**

These components are supplied from external entities to Schaeffler Portugal, located in different regions of the globe. Although some components are fed directly to the assembly stage – the cage, balls and shield – the outer and inner rings suffer transformations along the production stage. These transformations are further explored in the next sub-section.

2.2.2 – Production

Schaeffler Portugal is part of the Production level in the Schaeffler Group's supply chain. The Production level is responsible for the manufacturing of the final products – ball bearings, in the case of Schaeffler Portugal. The operation encompasses several processes in order to achieve the final product and can be broken into three main stages (see figure 6): Pre-Production, Production - Grinding and Production - Assembly. The manufacturing site contains two facilities. The Pre-Production stage is performed in a separate facility from the Production stages. Due to the different capacities of each stage, the Production - Grinding stage operates seven days a week and the remaining stages five days per week. Each day is divided into three shifts, with a total duration of eight hours per shift. The three operations are detailed in sections 2.2.2.1 – 2.2.2.3.

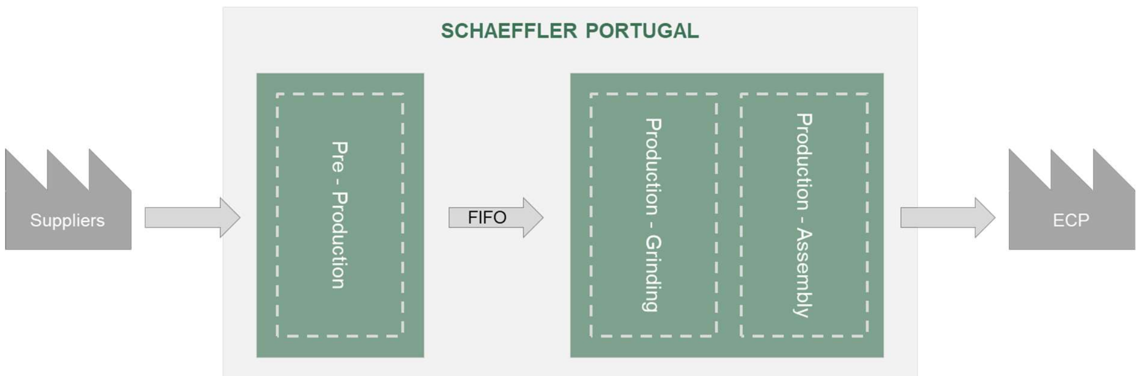

Figure 6. **Production stages at Schaeffler Portugal**

2.2.2.1 – Pre-Production

The process starts with the arrival and unloading of the trucks carrying the outer and inner rings from the suppliers in containers which are unloaded into the materials warehouse. As orders are released, the outer and inner rings are placed in a First In First Out Lane (FIFO-Lane) – a physical lane where containers are placed according to a planned schedule – in order to start the process. In parallel, steel pipes suffer a turning operation that turns them into rings that are also placed in a FIFO-lane. This last process is only made for small, special orders. An order either uses the rings that arrived directly from the rings manufacturer or uses the rings produced from the steel pipes. Next, the rings are washed to initiate the thermal treatment. When the thermal treatment finishes, the plain surface of the rings is grinded into the desired dimensions in one of the plain surface grinding lines. To finish the Pre-Production stage, the external diameter of the outer rings (and of some inner rings) is grinded to the desired dimensions in one of the external diameter grinding lines. The rings are then placed in a FIFO-

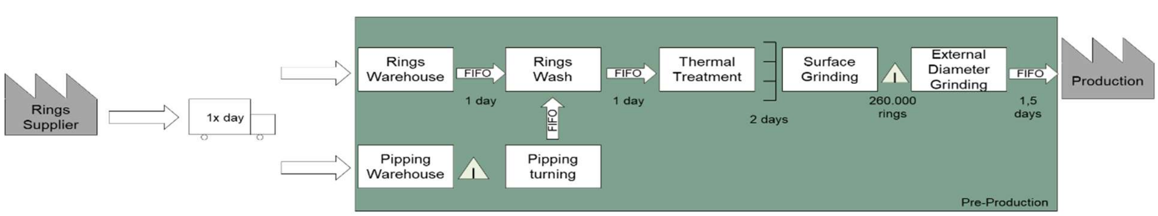

Figure 7. **Pre-production stage**

lane and are ready to enter the Production Stage. Figure 7 illustrates the described process. Note that inner and outer rings are always separated along the processes.

2.2.2.2 – Production – Grinding

The Production stage is comprised by 36 grinding production lines – 18 for inner rings and 18 for outer rings. It also includes seven production cells, i.e. a production system that includes both the grinding and the assembly stages without physically separating them.

The Production stage is fed through a Milk-Run system: when the stock of rings (inner or outer) in the beginning of the production lines reaches a re-order level, a Kanban card is placed in the beginning of the Production - Grinding. When the tugger train drives by the production lines to deliver the required rings, it gathers the Kanbans. That way the driver of the tugger train becomes informed of the required materials it needs to bring in the next lap. The inter-lap time is constant and the tugger train follows a pre-determined route that goes through all grinding production lines as well as through the Pre-Production facility's final FIFO-lanes.

The inner and outer rings both undergo two separate transformations:

- The outer rings start the process by the grinding of the raceway. As the precision of this process is not enough to meet the quality standards, the outer rings are subject to a raceway honing process which ensures the components meet the desired quality standards, i.e., the bearing balls will not suffer abrasion from a rough finish of the raceway surface and in order to extend the bearing's expected lifetime.
- The inner rings undergo through a similar process to the outer rings. The process starts by the raceway grinding process. Then, the rings have to be checked for thickness control to ensure they have the right dimensions. The hole's grinding is the next operation to be performed, followed by an inspection to its dimensions. The raceway honing is the last operation to be performed to the inner rings.

The rings are then ready to be assembled in the assembly lines. In order to transfer the rings to the assembly lines, the rings are placed either into trolleys or trays, for outer or inner rings respectively. The process described above is represented in figure 8.

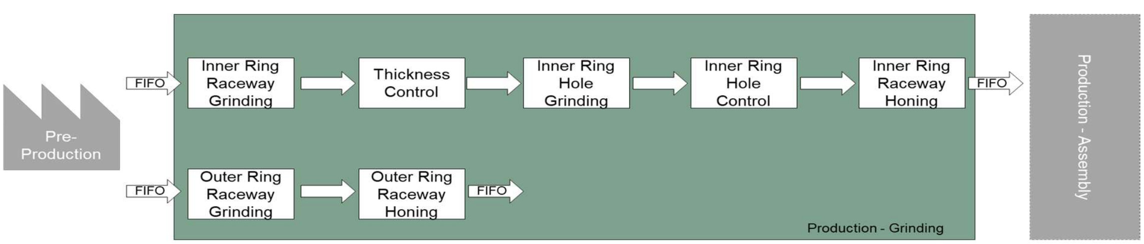

Figure 8. **Production Stage**

2.2.2.3 – Production - Assembly

Schaeffler Portugal currently has 12 assembly lines, 8 of which are dedicated lines – only produces a specific a reference. These lines are located inside of an atmospheric controlled room.

The assembly process starts off by demagnetizing and washing the inner and outer rings. The rings are then paired and the bearing balls are inserted. The balls are then spread evenly in order to assemble the cage over the balls. The bearings are greased and the shields are placed between the rings. Along the process, bearings suffer a noise control process and a weight control process. The bearings are laser labeled and packaged in the end of the production line. It is important to outline that this is a general description of the process – different bearings references suffer different processes according to their specifications (e.g. open bearings do not have shields). The process Production - Assembly is represented in figure 9.

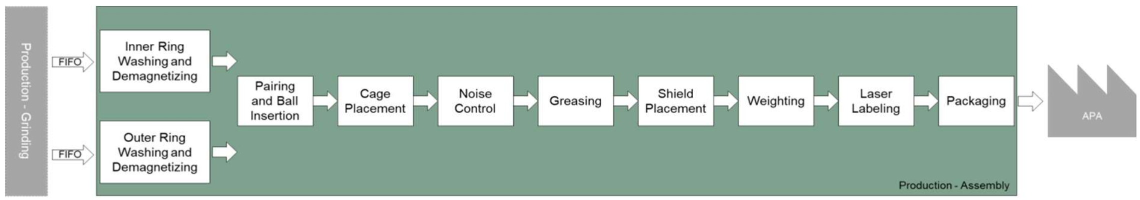

Figure 9. **Assembly stage**

When the assembly stage is completed, the packaged bearings are carried to the final products' warehouse, ready to be transported to the European Consolidation Point.

2.2.3 – European Consolidation Point

The European Consolidation Points (ECPs) are responsible for coupling the demand of the OEM and MRO Businesses Distribution Centers, in order to create larger lot sizes for Production. A frozen zone in which orders cannot be changed, of four to eight weeks is aligned between the ECPs and the Production stages in order to guarantee a stable production plan. The lot size between Production and the ECPs is defined twice a week. From the Production point of view, the ECPs are its only customers, meaning that the ECPs make the orders and collect the final products to forward to Distribution Centers.

2.2.4 – Distribution Center

The Distribution Centers (DCs) are organized into both the OEM and MRO Businesses. From the Production point of view, there is no distinction between these two businesses. The DCs ensure the required Make-to-Stock orders are available for all sub-regions. The lot size is defined monthly for the replenishment by the EDC.

2.2.5 – Satellite Distribution Center

Satellite Distribution Centers are where Local Make-to-Stock (Local Core) as well as Make-to-Order customers order their products. The SDCs are able to decrease the delivery time to end customers and increase the service level of the supply network. The lot size between DCs and SDCs is defined weekly to increase transportation and warehouse handling efficiency.

2.3 – Master Planning and Logistics Department Overview

The Master Planning and Logistics Department is encompassed by the Quality, Cost and Delivery Departments of Schaeffler Portugal, which support the Production activities. The department is responsible for receiving the orders from customers, arranging the production schedules for all production stages, ordering the required supplies for production and for handling the internal logistics of the factory, including the management of both the production warehouses and the non-production warehouses. These activities are further explored in sub-sections 2.3.1 to 2.3.4.

2.3.1 – Order Receiving

The orders are automatically placed to Schaeffler Portugal by the ECPs through SAP. The orders result from the bundling of the demand from the OEM and MRO divisions. The orders are placed in the company with an expected lead time that varies for the different products. The allocation of the orders within the Group is made in order to reduce the lead time. The portfolio of products offered by the ECPs is manufactured in different facilities across the globe. Some facilities, such as Schaeffler Portugal, have a set of unique product references that are not manufactured in any other production site. Other product references can be manufactured in a set of different locations.

The orders are then accepted or denied according to the availability of the production schedules of the lines by the department's allocation responsibles. This topic is further explored in next sub-section 2.3.2.

2.3.2 – Production Schedules

The Production Schedules are developed for each different production stage. The goal is to process the orders according to a pull strategy, which means that the first production schedule to be developed is the assembly's stage, with regard to the orders of the customers and the respective delivery dates. The second production schedule to be made is the grinding's stage, which is aligned with the assembly's stage production schedule. Finally, the Pre-Production schedule is developed in order to properly respond to the grinding's stage production schedule. These records are then made available to the remaining departments. The Maintenance department uses the schedules to prepare the necessary setups in the production lines. The logistics personnel of the department use the schedule to efficiently deliver the required supplies to the feeding streams of the production lines. Finally, the Production Department uses this information to coordinate the production personnel and to effectively monitor the production.

2.3.3 – Supplies Ordering

The supplies ordering policies follow a twofold approach: on the one hand, the material planners of the Master Planning and Logistics Department are responsible for ordering all the components necessary to build the bearings, including the rings. The ordering of the supplies is based on the various production schedules so that the components arrive to the production site respecting a *just-in-time* policy. Although a just-in-time policy might prove to be beneficial in terms of lower inventory levels and, consequently, lower holding costs, it carries the risk of delays in the receiving of the components (Investopedia, 2015). This often forces changes in the production schedules creating undesired backlog of orders.

On the other hand, the spare parts warehouse is responsible for bundling and ordering the supplies necessary for the maintenance of the production equipment, based on the requests of the maintenance department. Moreover, non-production equipment that does not encompass the components of the bearings are also managed by this warehouse, such as cleaning products, office supplies and disposable production items. The purchase orders of the spare parts warehouse must always be approved by the purchasing department.

2.3.4 – Internal Logistics and Warehousing

The logistics segment of the department has the role of managing the material flows within the factory. This includes: unloading the rings and remaining components from the suppliers' trucks; organizing the materials in the respective warehouses; feeding the production lines with the required rings and components according to the production schedule; transferring the rings from the Pre-Production facility to the Production facility; transferring the finished bearings from the end of the assembly stage to the finished goods warehouse; and arranging the expedition of the bearings.

The internal logistics segment of the department is deeply connected with the warehousing functions. The segment is responsible for the transportation of the raw materials and components to the feeding streams of the production lines of the plant, including the rings from the pre-production facilities to the production facilities as well as the remaining components from the components warehouse directly to the assembly lines.

Warehousing takes on an important role in the management of Schaeffler Portugal's supply chain, namely the management of the company's four warehouses. A brief description of each is presented in table 5

Table 5. **Warehouses description**

Warehouse	Description
Non-production Warehouse	Responsible for ordering, receiving, controlling the inventory, storing and dispatching of non-production Stock Keeping Units (SKUs) such as spare parts and office supplies;
Raw Materials Warehouse	Responsible for receiving, controlling the inventory, storing, picking and dispatching the inner and outer rings for pre-production;
Components Warehouse	Responsible for receiving, controlling the inventory, storing, picking, sorting and dispatching the spheres, cages, shields and grease for the assembly stage of production;
Finished Products Warehouse	Responsible for receiving, controlling the inventory, storing, picking, sorting and dispatching the finished bearings for the plant's customers.

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 (Teo & Shu, 2004). 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 (layout, capacity, etc.).

- Material flow – management of the spare parts of the maintenance department can prove to be a challenge due to the high unpredictability of the machines' components failure. A process workflow describing this activity is represented in appendix 1.
- Information flow – central to the warehouse management process, the information management of the general warehouse is still not fully operational after its installation in 2016. It displays, at each moment, the availability and needs of the SKUs 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 all 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 dissertation 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 (ERP) system, SAP. This scenario is analyzed throughout the following chapters in order to understand if the efficiency of the overall automatic re-order process increases when compared to the current process of not having any automatic re-ordering operation in practice.

To summarize, the objective of the present dissertation 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.

2.5 – Chapter Considerations

Schaeffler Portugal is part of the Industrial, Automotive OEM and MRO divisions of the European region and is at the Production stage within its supply chain, assuming a key role in the production of ball bearings in the Schaeffler Group. The European Consolidation Points are the Schaeffler Portugal's only customer. As they are located in Germany, the company exports all of its production.

The raw materials needed to produce one ball bearing are the inner and outer rings, the balls, a cage and two shields. These materials are supplied by external suppliers of the company which are located in different regions of the globe.

Currently, the production process is divided into three different stages at Schaeffler Portugal – Pre-production, Production – grinding and Production – assembly. The current project aims to analyze the operations of the non-production warehouse of the company, namely regarding the definition of adequate re-order quantities for the critical products as well as defining suitable safety stocks for same products. The introduction of this operation aims at decreasing the total amount of time the warehouse supervisor spends at manually re-ordering spare parts as well as increasing the availability rate for critical products.

Since the implementation of this project requires the analysis of several warehouse management strategies, a literature review on warehouse management systems is carried out in order to examine the approaches and methods already developed for this topic and their main conclusions. To frame the project in this theoretical and scientific context, a literature review is presented in chapter 3.

3. Literature Review

The purpose of the current chapter is to frame the dissertation in a theoretical and scientific context that will serve as a supportive basis to approach the problem under study. Therefore, in section 3.1 it is first presented the general concepts of warehouse management, namely in terms of design, operations and performance measures. In section 3.2, inventory management is introduced to provide an overview of the available inventory management models, more specifically regarding spare parts. The available item classification strategies are presented in the same sub-chapter. Section 3.3 focuses on forecasting methods due to the demand variability associated with spare parts demand. A special emphasis is put on Artificial Neural Networks as a forecasting tool. Finally, section 3.4 ends the chapter with the main conclusions drawn from the literature review.

The search from the literature review was conducted through search engines such as Google Scholar and Google. These search engines would redirect to scientific databases such as ScienceDirect, ResearchGate, IEEExplore and SpringerLink. The search was administered during February and March of 2019 using keywords like: warehouses; warehouse design; warehouse operations; inventory management; spare parts inventory; spare parts warehouse; forecasting methods and combinations and synonyms of these keywords, leading to the referenced articles present in the chapter.

3.1 – Warehouse Management

A warehouse plays an important role within a supply chain (Frazelle, 2002). On the one hand, it adds value to the supply chain by 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. On the other hand, its operations represent the use of intensive labor as well as capital whose performance impacts not only the operational costs of the warehouse as well as the costs of the whole supply chain (Gu, Goetschalckx, & McGinnis, 2007; Poon, et al., 2009; Singh, Chaudhary, & Saxena, 2018).

According to A. T. Kearney (2017), capital and operating costs of warehouses in the U.S.A. represent around 30% of total logistics costs of companies. 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%) (Emmett, 2005). Nonetheless, Lambert, Stock and Ellram (1998) justify the high cost of warehousing due to the functionality it adds to the supply chain, such as:

- Economies of scale in transportation activities;
- Economies of scale in production activities;
- Lower prices due to higher lot sizes;
- Higher response rate to customer requests;
- Guaranteeing just-in-time policies in production;

As warehouses represent the primary connections between goods and customers in the supply chain, warehouse management must have into account the necessary short response and high uncertainty it is under, which leads to the importance of having reliable forecasts in their operations (Krittanathip, Cha-um, Suwandee, Rakkarn, & Ratanamaneichat, 2013). The reliability of the forecasts takes a special role

in cross-docking facilities, since the amount of stock present in these premises is kept to a minimum (Bienert, Kornfeld, & Kara, 2017).
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. Each of the three mentioned topics is further analyzed in sections 3.1.1 to 3.1.3.

3.1.1 – Warehouse Design

Warehouse design decisions fall into the strategic and tactical segments of a warehouse project (infrequent decisions with long lasting impacts). Gu, Goetschalckx and McGinnis (2010) suggest five focus areas while designing a warehouse (see figure 10): Overall structure; Sizing and Dimensioning; Department Layout; Equipment Selection and Operation Strategy. These areas are further analyzed from sections 3.1.1.1 to 3.1.1.5.

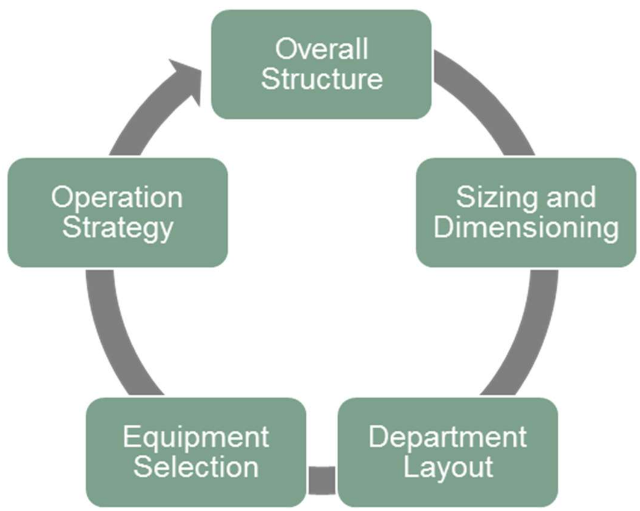

Figure 10. **Warehouse project structure**

3.1.1.1 – Overall Structure

The overall structure of a warehouse is determined by the projected material flows, the desired functional sections as well as the flow among these sections. The selection of functional sections should be justified by the required number of sections, the employed technology and the requests processing procedures (Peerlinck, Govaert, & Landeghem, 2010; Baker & Canessa, 2009; Gu, Goetschalckx, & McGinnis, 2010). Mukherjee and Dey (2008) and Gu, Goetschalckx and McGinnis (2010) defend that the goal of this design stage is to define which are the warehousing requirements that need to be fulfilled as well as minimizing the total investment costs and future operational costs.

3.1.1.2 – Sizing and Dimensioning

The dimensioning stage of a warehouse is impacted mainly by two factors: the required capacity and the necessary functional area for its requirements to be fulfilled (Gu, Goetschalckx, & McGinnis, 2010).

Relatively to the required capacity, assuming the warehouse can manage its inventory policy, factors such as construction, maintenance, inventory replenishment and material handling have a high impact in its dimensioning stage. Lowe, Francis and Reinhardt (1979) propose a network flow algorithm to determine the in-plant versus the outsourcing allocation of storage of a plant given the inventory policy allows for variable requirements of capacity.

To determine the necessary functional area, construction and operational costs must be considered when modelling a warehouse. Moreover, Berg and Zijm (1999) refer that the tradeoffs in the total size of a warehouse and its respective sections should be considered since it has an impact in the efficiency of the operations.

3.1.1.3 – Department Layout

A well-organized warehouse layout can increase productivity, improve product flow, reduce costs, enhance customer service and provide better working conditions. Gu, Goetschalckx and McGinnis (2010) classify warehouse layout related problems according to three groups: pallet block-stacking pattern; storage department layout and; automated storage/retrieval system configuration.

- The first group of problems, related to pallet block-stacking problem, deals mainly with the lane depth determination, in order to balance the tradeoff between space utilization and task execution in the warehouse (Shah & Khanzode, 2015; Derhami, Smith, & Gue, 2017). Goetschalckx and Ratliff (1991) developed a heuristic procedure to maximize space utilization by assigning shipments to a pool of different available lane depths and later, Nishi and Konishi (2010) proposed heuristics to optimize the honeycombing[2] effect that typically affects block stacking systems.
- The second group of problems, related to the storage department layout, considers the aisle structure of a storage department to minimize construction and handling costs including decisions related to the number, orientation, width and length of the aisles (Pohl, Meller, & Gue, 2009; Roodbergen & Vis, 2006); Roodbergen and Vis (2006) have presented an approach to minimize the expected length of a picking tour by selecting the optimum number and length of aisles in a depot location.
- The third group of problems, that considers automated storage/retrieval system configuration, deals with the dimensioning of an automated system where the number shelves, aisles and cranes must be determined in order to minimize construction, maintenance and operational costs, or to maximize the equipment utilization (Karasawa, Nakayama, & Dohi, 1980; Cox, 1986; Heragu, Cai, Krishnamurthy, & Malmborg, 2011).
-

3.1.1.4 – Equipment Selection

The equipment selection process in a warehouse is a strategic decision which highly impacts the overall costs of its infrastructure. This process intends to determine the level of automation and the storing and

[2] Honeycombing is defined as the effect that creates unusable space for storage until a lane is totally filled (Gu, Goetschalckx, & McGinnis, 2010).

handling systems to employ in a warehouse project. This task can sometimes be underestimated in the design stage and is mostly accomplished using the designers and managers personal experience, since literature on the topic is scarce (Gu, Goetschalckx, & McGinnis, 2010; Berg & Zijm, 1999; Roodbergen & Vis, 2009). The main disadvantages of automated warehouse equipment are the inflexibility of the equipment to accommodate different items as well as the complex and lengthy implementation process of the equipment combined with a high risk of disruption in the early stages of use. Nonetheless, with an adequate implementation, it proves both to increase the service level as well as to be a cost-efficient solution (Baker & Halim, 2007; Hompel & Schmidt, 2007).

3.1.1.5 - Operation Strategy

The operation strategy is a comprehensive topic that has important implications in the daily operations of a warehouse. Gu, Goetschalckx and McGinnis (2010) consider that the operational strategy can be assigned mainly to two different sub-strategies: storage and picking strategies.

- Authors consider four different storage strategies: random, dedicated, class-based and Duration-of-Stay based storage (Graves, Hausman, & Schwarz, 1977; Van Den Berg, 1999; Chan & Chan, 2011). The selection of strategy is based on the minimization of travelling time and costs.
- Three picking strategies are typically considered: wave, batch and zone picking (De Koster, Le-Duc, & Roodbergen, 2007; Parikh & Meller, 2008; Hwang & Cho, 2006). The strategy should be chosen based on the characteristics of the received orders (type of products, transportation method, expedition time, among others) so that the efficiency of the picking process is maximum.

Baker and Canessa (2009) conclude that although there appears to be a general consensus regarding the overall approach for the warehouse design process, there is some debate concerning the sequence of steps to adopt in the process, since it generally has an iterative instead of sequential nature.

3.1.2 – Warehouse Operations

The warehousing operations encompass several activities from the arrival of the products into the warehouse, until their exit. Karásek (2013) and Gu, Goetschalckx and McGinnis (2007) consider four main operations respecting the planning and control of warehouse operations (see figure 11): receiving, storage, order picking and shipping.

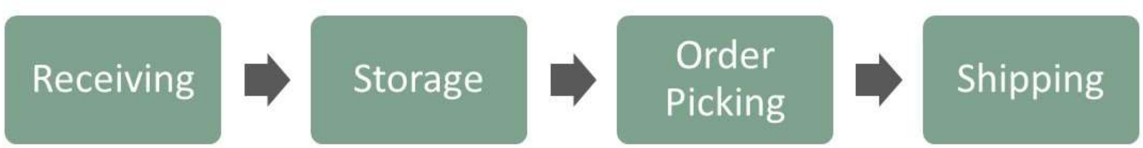

Figure 11. **Warehouse operations**

Each of the previous activities is independently analyzed in the following sub-sections 3.1.2.1 to 3.1.2.3.

3.1.2.1 – Receiving and Shipping

Both receiving and shipping operations represent the articulation of the material flows between the warehouse and its environment. In order to perform them, handling resources must be available as well as information regarding arrival and dispatching times (through, for example, the analysis of the demand patterns) (Gu, Goetschalckx, & McGinnis, 2007). Little literature is dedicated to these operations regarding standard warehouses and is mostly dedicated to cross-docking facilities.

3.1.2.2 – Storage

Storage is an important warehousing activity which objectives are to organize products with the most efficient space allocation and handling policies possible (Reyes, Solano-Charris, & Montoya-Torres, 2018). Three major decisions must be defined in the storing function (Gu, Goetschalckx, & McGinnis, 2007):

- How much inventory of each SKU should be kept in the warehouse;
- How often should the inventory of an SKU be replenished;
- Where should an SKU be stored in the warehouse;

The first two decisions belong to the traditional inventory control area: the first is concerned with the lot sizing problem and the second with the staggering problem. Both these topics are analyzed in detail in section 3.2.1. The third decision involves a strategic resolution respecting storage strategies introduced in section 3.1.1.5 (Maxwell, 1964; Gallego, Shaw, & Simchi-Levi, 1992). Kulturel, Ozdemirel, Sepil and Bozkurt (1999) compare class-based and Duration-Of-Stay strategies through simulation and conclude that the former consistently outperforms the latter.

3.1.2.3 – Order Picking

The picking operation is the most expensive operation in most warehouses, and is estimated to represent 55% of the total operational warehousing costs (De Koster, Le-Duc, & Roodbergen, 2007; Van Den Berg, 1999; Coyle, Bardi, & Langley, 1996). It is an important operation in warehouse management and three strategies are generally employed: wave, batch and zone picking (De Koster, Le-Duc, & Roodbergen, 2007; Parikh & Meller, 2008; Hwang & Cho, 2006).

Wave picking fractions orders according to a time interval and destination (for example, if an order is prepared for a given carrier departing at a certain time). In batch picking, the picker aggregates orders with the same items so that it collects them according to a batch. In zone picking, each picker is allocated to a dedicated zone and is responsible for the picking in that area of the warehouse. Zone picking can either be sequential or simultaneous. If it is sequential, a cart attributed to an order is handed to a zone picker which will collect the designed SKUs and hand it over to the next zone picker. If it is simultaneous, the zone pickers collect the items in each zone and deliver them to be combined according to the orders (II, 2000; Petersen & Aase, 2004; Petersen C. G., 2002).

Furthermore, Gu, Goetschalckx and McGinnis (2010) mention that the organization of the picking process should be defined in terms of SKU movement. In a picker-to-part policy, the picker reaches the collection area to remove the SKU from the storing area. In a part-to-picker policy, the SKU is transported to the picker.

Petersen & Aase (2004) evaluate the effect of picking, routing and storage on a manual order picking operation. The authors concluded that batching has the largest impact when reducing total fulfillment time, particularly in small order sizes.

3.1.3 – 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 (Weber & Thomas, 2005; Peterson, 2005). Parker (2000) identifies the reasons companies should use KPIs to measure their progress. The author defends that the KPIs identify the success of every process as well as if the customer's requirements are being satisfied.

Kersten, Blecker and Ringle (2014) define a set of operational KPIs used in the warehousing industry, summarized in table 6 with the respecting formula.

Table 6. **KPIs for the warehousing industry**

KPI	Formula
Warehouse utilization	$Warehouse\ utilization\ (\%) = \frac{Number\ of\ stored\ SKUs}{Warehouse\ Capacity}$
Number of SKUs dispatched per hour	$Number\ of\ SKUs\ dispatched\ per\ hour = \frac{Number\ of\ outgoing\ SKUs\ in\ a\ day}{Number\ of\ working\ hours\ in\ a\ day}$
Inventory Turnover	$Inventory\ Turnover = \frac{Number\ of\ outgoing\ SKUs}{Average\ number\ of\ SKUs\ in\ stock}$
% of on time deliveries	$\%\ of\ on\ time\ deliveries = \frac{Number\ of\ on\ time\ deliveries}{Total\ number\ of\ deliveries}$
% of incorrect deliveries	$\%\ of\ incorrect\ deliveries = \frac{Number\ of\ incorrect\ deliveries}{Total\ number\ of\ deliveries}$
Total warehouse flow time	$Total\ Warehouse\ flow\ time = \frac{Average\ number\ of\ SKUs\ in\ Stock}{Average\ number\ of\ outgoing\ SKUs\ per\ day}$

Frazelle (2002) goes further and identifies four major areas of performance evaluation used in logistics: financial, productivity, quality and cycle time measurements. Nonetheless, none of these performance measures seems appropriate for Schaeffler Portugal's non-production warehouse case.

3.2 – Inventory Management

In the field of inventory management, a firm's decisions are a compromise between limiting risk of having a large inventory and restricting the costs of inventory (Michalski, 2008). According to Stevenson (1999) the two major tasks of inventory management are both maintaining a record of the items in stock and deciding the quantity and time to order the items. Moreover, an effective inventory policy must have access to:

- A system to keep a record of the existing and ordered stock;
- Reliable demand forecasts;
- Lead time and corresponding variability;
- Reliable estimates of keeping, ordering and stocking-out costs of items;
- Stock classification system.

Stock costs can be grouped into three types: i) cost of keeping the stock, including interest, insurance, depreciation, obsolescence, deterioration, robbery, failing and maintenance costs; ii) ordering costs; iii) stocking-out costs when the demand exceeds the level of stock (Frazelle, 2002; Olayinka, 2010; Ackerman, 2012).

Managing inventories is a very complex and demanding problem because its planning needs to consider several factors such as supply chain structures, levels of coordination among actors and information sharing processes (Fattahi, Mahootchi, Moattar Husseini, Keyvanshokooh, & Alborzi, 2015). The inventory management policy adopted by each entity in the supply chain is an important factor, since it directly affects the replenishment of the downstream entity.

3.2.1 – Inventory Management Models

Regarding inventory control, Mahadevan, Pyke, Fleischmann (2003) differentiate between the periodic and the continuous review approaches. 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 dissertation, 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 point (Bischak, Robb, Silver, & Blackburn, 2014). This policy is generally adopted when managing independent demand items, i.e. when managing items that are only a function of market demand and do not depend on the production process.

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

$$Q_{safety} = k \times \sigma_{DL} \tag{1}$$

where:

Q_{safety} – safety stock quantity;

k – safety factor;

σ_{DL} – demand standard deviation during the supply period.

$$s = \mu_{DL} + Q_{safety} \tag{2}$$

where:

s – minimum stock or re-order quantity;

μ_{DL} – average demand during the supply period;

Q_{safety} – safety stock quantity.

$$Q^* = \sqrt{\frac{2 \times \mu_{DL} \times C_a}{I * c}} \tag{3}$$

where:

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.

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

where:

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.

$$\mu_{DL} = \mu_D \times \mu_L \tag{5}$$

where:

μ_{DL} – average demand during the supply period;

μ_D – average demand;

μ_L – average replenishment time.

3.2.2 – Spare Parts Inventory Management

Spare parts inventory management is greatly different from other manufacturing inventories management. On the one hand, companies endure finished products inventory to deliver a certain service level to customers. Spare parts inventory exists to support the maintenance department of companies with the right components in order for the production department to have as least downtime as possible. On the other hand, work-in-process and finished products inventories can be changed by increasing/decreasing production rates, reducing lead times, etc. Spare parts inventory can vary based on the choices the maintenance department does on its policies. For instance, if a routine maintenance indicates that an item is in decay, a policy might be to reduce the use of the item. Those types of options are not available for product inventories (Kennedy, Patterson, & Fredendall, 2002; Costantino, Di Gravio, & Tronci, 2013).

In case any machine breakdown occurs, spare parts have the role of reducing production's downtime as much as possible, since the occurrence may have a high cost for the company. The trade-off between the cost of the part and the cost of having a production line interrupted due to the lack of that part needs to be considered, since generally these parts represent a significant investment to have as inventory

(Syntetos, Keyes, & Babai, 2009; Bošnjaković, 2010). Moreover, the high variety of different SKUs in a typical spare parts warehouse, the intermittent demand patterns, the need of a fast response rate due to the high cost of downtime and the obsolescence risk turn the spare parts inventory management into a high complexity issue (Murthy, Solem, & Roren, 2004; Cohen, Agrawal, & Agrawal, 2006; Boylan & Syntetos, 2010; Jouni, Huiskonen, & Pirttilä, 2011).

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. Furthermore, the demanded quantity is highly variable. Several distributions have been studied in literature to represent these patterns, even though empirical evidence is inexistent (Lengu, Syntetos, & Babai, 2014).

Wahba, Galal and El-Kilany (2012) highlight that there is a high number of models that have been applied to spare parts categorization, however, the most popular is still the ABC analysis which uses the Pareto principle and certain criteria for the criticality evaluation of the parts. This methodology is further detailed in the next sub-chapter 3.2.3.

3.2.3 – Items Classification

Possibly thousands of SKUs might be kept in inventory for maintenance operations, but only a small share of them should be under close attention and accurate control of management (Braglia, Grassi, & Montanari, 2004). 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 (Teunter, Babai, & Syntetos, 2010; Zheng, Fu, Lai, & Liang, 2017).

Depending on the required objective, a different set of models can be used to segment the items (Torabi, Hatefi, & Pay, 2012). In sections 3.2.3.1 and 3.2.3.2 two models based in different criteria – economic value and demand pattern – are analyzed.

3.2.3.1 – 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 (Teunter, Babai, & Syntetos, 2010). 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 (Millstein, Yang, & Li, 2014).

This principle is also known as the 80:20 rule, which suggests that 20% of items amount for 80% of total costs. Therefore, category A represents 20% of the items with approximately 80% of total costs; Category B represents 30% of the items with approximately 15% of total costs and; Category C represents 50% of the items with approximately 5% of total costs (Millstein, Yang, & Li, 2014).

Empirical evidence demonstrates that after the analysis is performed and the three categories are established, concentrating the management's attention in inventory effectiveness on the category A items is a reasonable rule for allocating scarce managerial time (Flores & Whybark, 1985).

However, spare parts inventory management needs a differentiated ABC classification policy in order to enhance the accuracy of the selected items as well as to consider other factors such as response time demanded by the customer, the importance to the normal operations of the machine, norms or special items, monthly demand, delivery dates, etc. (Guvenir & Erel, 1998; Teixeira, Lopes, & Figueiredo, 2017). Huiskonen (2001) considers the ABC analysis as an insufficient control tool since the shortage of a critical part might be a multiple of its commercial value. The author suggests introducing criticality as a factor to adjust the correct value of items for this analysis, by introducing the downtime costs.

3.2.3.2 – Demand Type

Item segmentation can be applied with different criteria. 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, 2001).

The classification of the items by demand type can either be mono or multi-criteria, depending on the number of criteria used to classify the items. In a mono-criteria classification system, items are classified according to a single criterion, whereas in a multi-criteria system, items are classified according to more than one criterion which allows to a deeper, more segmented treatment of information (Bacchetti, Plebani, Saccani, & Syntetos, 2010; Ladhari, Babai, & Lajili, 2015). Celebi, Bayraktar and Ozturkcan (2008) suggest using a multi-criteria ABC classification with criteria such as item criticality, lead time, obsolescence or commonality.

The current dissertation employs a double dimension model. Syntetos, Boylan and Croston (2005) classified demand according to two criteria: demand variability and average time between demand. The authors considered employing the lead time variability as a criterion, nonetheless the added complexity does not translate a more correct classification of the items. Moreover, the demand of the items is defined within the company boundary, whereas the lead time does not depend on the internal performance of the company, but on an external entity – the suppliers.

The demand of each item can be classified as erratic, lumpy, smooth or intermittent according to two dimensions – demand variability and average time between demand (see figure 12) (Varghese & Rossetti, 2008).

According to Kocer (2013) the average time between demand measures the average number of time periods between two consecutive item demands. Expression 6 indicates how the variable is calculated.

$$Average\ time\ between\ demand = \frac{Total\ number\ of\ periods}{Number\ of\ demand\ buckets} \tag{6}$$

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 7 (Ghobbar & Friend, 2002). The lower the variation coefficient, the lower the unpredictability.

$$CV^2 = \left(\frac{\sigma}{\mu}\right)^2 \tag{7}$$

where:

σ is the demand standard deviation;

μ is the average demand.

Each quadrant of figure 12 corresponds to a demand type identified above, and the values p = 1,32 and CV^2 = 0,49 were proposed by the authors through the analysis of different articles (Syntetos, Boylan, & Croston, 2005).

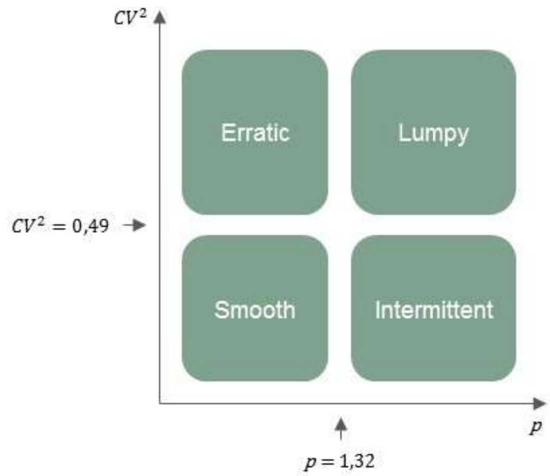

Figure 12. **Demand variability and interval between demands**

3.3 – 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 and avoid larger losses.

In the next sub-sections, a brief introduction to a few forecasting methods is presented, along with a few error measures to evaluate the accuracy of the methods.

3.3.1 – Forecasting Procedures

Forecasting allows to extrapolate predictions based on past data. Since there is a wide domain of applications for forecasting, which are generally related to a time scale and type of demand pattern, applying a method for all cases is not a valid alternative (Hyndman & Athanasopoulos, 2018).

According to Hoshmand (2009) the implementation of a structured forecasting study should follow a group of five steps (see figure 13):

Figure 13. **Five steps of a forecasting study**

- **Problem Characterization:** Often the most difficult step of the implementation process. This point requires a previous study of the available forecasting methods and its applications;

- **Information Collection:** Data collection requires the collection of both numerical and key stakeholders input;
- **Preliminary Analysis:** The analysis includes plotting the data to evaluate any possible trend; Statistical data is calculated and analysis is performed to pick any seasonality or cycles; Atypical data should also be identified;
- **Selection of Forecasting Method:** A horizon should be defined (short, medium or long term); A forecasting method should be chosen based on previous analysis;
- **Forecasting Method Evaluation:** An evaluation of the obtained results should be performed and compared to real data; It is recommended that the person who applied the previous steps, is the same evaluating the performance of the method, to be able to identify any inconsistency in the results.

3.3.2 – Forecasting Methods Categories

The categorization of forecasting methods follows a twofold approach between qualitative and quantitative methods. Moreover, each of these approaches can be subdivided into several models, presented in figure 14 (Jacobs & Chase, 2008).

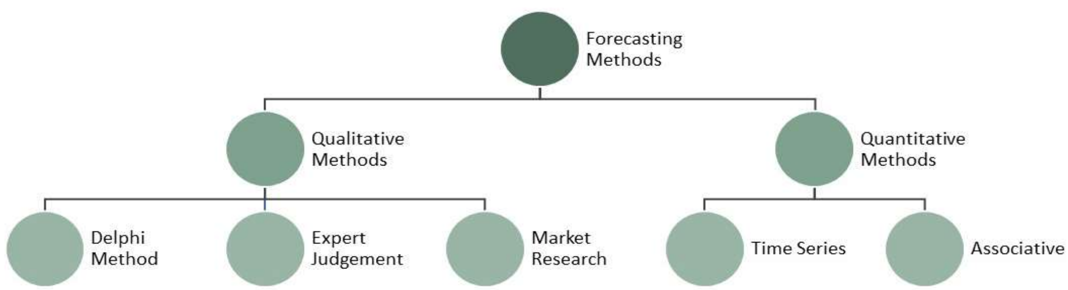

Figure 14. **Forecasting methods approaches**

In qualitative methods, forecasts estimates are based on expert and stakeholder's opinions and insights. Their use is recommended whenever there is no historical data or when data is not representative. Nonetheless, Goldstone (2008) recommends using whenever possible these methods simultaneously with quantitative methods so that both the results and predictions can be compared critically. The scope of qualitative methods is on the medium/long term forecasts. Winklhofer, Diamantopoulos and Witt (1996) classify qualitative methods according to several categories, from which it is possible to highlight the following:

- **Delphi Method:** A forecasting method based on several rounds of questionnaires where a panel of experts is asked to reply to a questionnaire. The results are then shared with the group after each round so that a consensus is reached by the end of the questionnaire.
- **Expert Judgement:** A simpler method in which the opinion of several experts is gathered in an individual way. It is prone to include a more diverse set of answers, inducing more variability to the model.
- **Market Research:** The consumer's behavior is analyzed to provide useful forecasts based on the market's responses. These methods are very sophisticated and are usually used to predict long term sales of new products.

Regarding the quantitative methods, these fall under the assumption that predictions can be based on past trends. An analysis is performed on historical data and any pattern is extrapolated into the future. The methods can be classified as either time series or associative/causal models (Zhang, Huang, & Zhao, 2013).

- **Time series models:** A time series analysis can be applied to identify any seasonality, cyclical patterns, trends and growth rates in the trends. They are used when data is available for several years and when relationships and trends are both relatively stable and clear. At its basis, lies the assumption that rates are either accelerating, stable or decelerating. Once the analysis is complete, several mathematical techniques can be used to extrapolate data from them (Brockwell, Davis, & Calder, 2002).
- **Associative/Causal models:** A causal model is the most sophisticated type of forecasting tool. It explicitly utilizes relevant causal relationships, such as economic forces, socioeconomic factors, related businesses data, promotions, competitive actions, strikes, among others, as well as incorporates time series models to construct a robust and reliable model. Data shows that causal models are the best predictive analysis to anticipate turning points as well as to prepare long-term forecasts (Witt & Martin, 1987).
-

3.3.3 – Types of Time Series Data

Anderson, Sweeney, Williams, Camm and Cochran (2012) classify time series according to four types of patterns: Seasonal, Trend, Cyclical or Random (see figure 15):

- **Seasonal:** Characterized by regular fluctuations. It can be observed with a trend pattern, indicating an increasing or decreasing seasonal fluctuation;
- **Trend:** Defined by an increasing or decreasing general variation during the time period;
- **Random:** Characterized by an irregular and unsystematic variation and random behavior;
- **Cyclical:** Defined by a stationary demand with values fluctuating around a constant mean value.

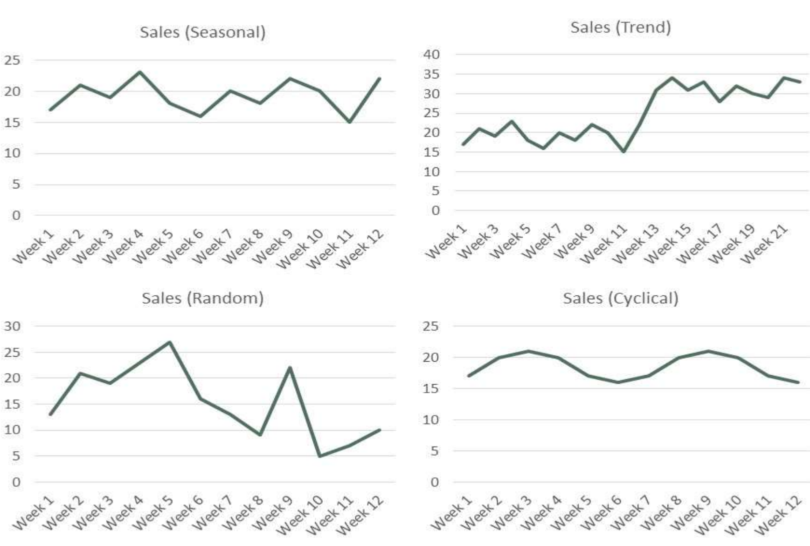

Figure 15. **Time series patterns**

3.3.4 – Artificial Neural Networks as a Forecasting Method

This subsection introduces the main forecasting methods present in literature related to inventory management, with special focus on Artificial Neural Networks (ANNs) and on Recurrent Neural Networks (RNNs). The existing research on forecasting sporadic demand data can be divided according to five categories (Sahin, Kizilaslan, & Demirel, 2013): Parametric monte-carlo simulation based methods; Nonparametric bootstrapping methods; Croston based methods; Artificial Neural Networks based methods; and support vector machine based methods. The first two methods focus on interval estimates of the demands whereas the remaining three methods focus on point estimates of the demand.

ANNs are an artificial intelligence based technique designed to emulate the human pattern recognition function using the processing of several inputs and inferring causal relationships between variables of data sets. The method has the advantage of being capable of detecting and extracting nonlinear relationships as well as interactions among predictor variables. Several authors concluded ANNs outperform conventional time series models when applied to spare parts forecasting (Hill, Marquez, O'Connor, & Remus, 1994; Amin-Naseri & Tabar, 2008; Gutierrez, Solis, & Mukhopadhyay, 2008). Furthermore, according to Barbounis et al. (2006) 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.

In the following subsection, the design of an ANN will be explored further. Later, RNNs are explored in section 3.3.4.2.

3.3.4.1 – 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 (Zhang, Patuwo, & Hu, 1998; Yeh, 1998). A representation of an ANN is presented in figure 16.

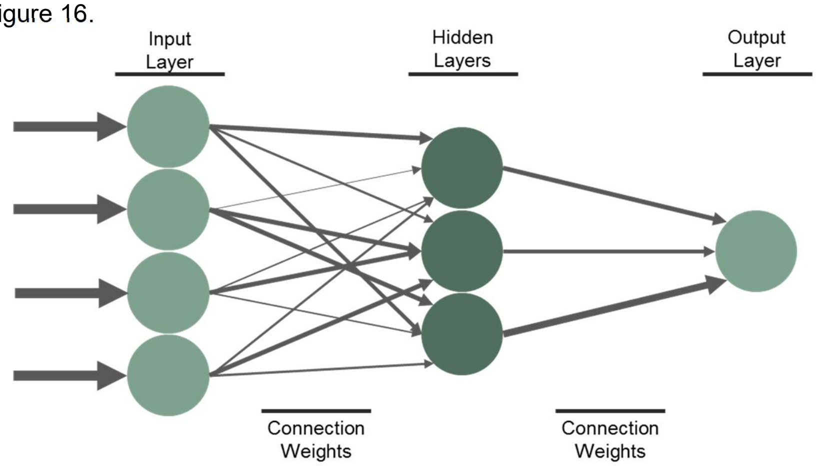

Figure 16. **Artificial neural networks structure**

The development of an ANN can be broken down into eight fundamental steps (Kaastra & Boyd, 1996):

1) Variable selection

A clear understanding of the problem is at the basis of a successful neural network design. Although the main purpose of a neural network is to identify complex nonlinear relationships, the selection of the right variables will improve the quality of the prediction. The available raw data is at the basis of the inputs of the model (Swingler, 1996).

The objectives of the researcher will also influence the inputs. The frequency of the data should be selected according to the availability and desired horizon of the forecast. A longer horizon forecast should use more aggregated data whereas a shorter horizon should use more detailed data (Wu, Chau, & Li, 2009).

2) Data collection

Cost and availability of the data should be considered in the collection of the data for the variable chosen in the previous step. Time spent in collecting data cannot be used pre-processing, training and evaluating the network performance.

Moreover, all data should be checked for errors and missing observations, even though these problems can be tackled in a variety of ways. Little and Rubin (2014) recommend either dropping or assuming a value for the missing observation by averaging or interpolating with nearby observations. Honaker and King (2010) avert these options since they can add biases and inefficiencies and propose more advanced methods.

3) Data pre-processing

The objective of pre-processing data is to highlight important relationships, remove noise and support the network in learning the relevant patterns by analyzing and mutating the inputs and outputs of the model. Very infrequently the data is inputted to the model in an untreated form. The simplest transformation is to scale the data between the lower and upper bounds of the activation functions (Famili, Shen, Weber, & Simoudis, 1997; Kotsiantis, Kanellopoulos, & Pintelas, 2006).

Harvey and Shephard (1993) and Box, Jenkins, Reinsel and Ljung (2015) highlights two of the most used transformation techniques for forecasting in neural networks: first differencing is used to remove any linear trend from the data and the natural logarithm of a variable is used transform data that takes both small and large values as well as data characterized by a right-hand tail distribution.

Data pre-processing requires much trial and error. If using a small training set relatively to the number of parameters, a possible method to select appropriate input variables would be to test several combinations in smaller subsets with each combination differing by two or three variables (Wu, Chau, & Fan, 2010).

4) Training, testing and validation sets

Generally, time series are divided into three distinct sets: training, testing and validation. Training sets are used by the ANN to learn the patterns present in the data set. It should be the largest data set so that the ANN has the best possible representation of the reality present in the data. The testing set, which should range between 10% to 30% of the training set, is used to test the ability of the trained network to generalize. The network in which the testing set has the best performance should be selected. Finally, the validation set should be used to check the network with the most recent contiguous observations. The size of the sets should be chosen to have a balance between a sufficiently large training sample to represent the data and to have enough data for the remaining sets (Hepner, Logan, Ritter, & Bryant, 1990; Dawson & Wilby, 1998; Maier & Dandy, 2000).

The selection strategy of the testing set can be twofold: selecting random observations from the training set or selecting the observations immediately following the training set. On the one hand, by selecting random observations from the training set it is possible to avoid having a tampered testing set with a specific characteristic. Nonetheless, deterministic methods such as choosing every nth observation is not recommended, since the results may be biased. On the other hand, by using the set of observations immediately after the training set, the most recent data set available is used (Ghezelbash & Keynia, 2014).

5) Neural Network paradigms

A neural network can be constructed in a variety of ways. Two main characteristics define the organization of the neural network: Architecture and neurodynamics. The architecture defines the number of neurons in each layer and the type and number of interconnections. Neurodynamics define the characteristics of a given neuron, including the activation function and how the inputs are combined (Basheer & Hajmeer, 2000).

The selection of the number of hidden layers, hidden layer neurons and activation functions are analyzed in the following sub-chapters.

5.1) Number of hidden layers

The generalization function of the neural networks is provided by its number of hidden layers. Neural Networks with one hidden layer and a sufficiently large number of neurons are capable of estimating any continuous function. By increasing the number of layers, computation time also increases and overfitting[3] may occur. It is recommended that the ANN starts with one or at most two hidden layers. Empirical evidence suggests that more than four hidden layers will not improve the results (Mehrotra, Mohan, & Ranka, 1997).

5.2) Number of hidden neurons

In order to select the most suitable number of hidden neurons, experimentation must be used. Nawari, Liang and Nusairat (1999) suggest using a geometric pyramid rule, i.e., for example in a three-layer network with *m* inputs and *n* outputs, the hidden layer would have *SquareRoot*(*m* x *n*) neurons. Nonetheless, the required number of hidden neuros could still go down from half the suggested number and up to two times. Hua (1996) suggests using a rule of 75% of the number of inputs as the number of neurons. Trippi and Turban (1992) set an upper bound on the number of inputs and hidden neurons by suggesting there should be at least five times as many training observations as weights. Regardless of the suggested method, the network that works best on the testing set using the fewer number of neurons should be used (Mehrotra, Mohan, & Ranka, 1997).

5.3) Number of output neurons

[3] Overfitting – when a forecasting model has too few degrees of freedom; The model memorizes individual points instead of learning the general pattern present in the model; Overfitting is highly dependent on the number of weights (which is dependent on the number hidden layers) and on the size of the training set (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014).

ANNs with more than one output, more precisely if outputs are widely spaced, will produce worst results than networks with a single output. The training of the neural network works by minimizing the average error over all the output neurons. The solution is to have specialized neural networks by using a network for each forecast. Moreover, the specialization will require a smaller neural network with a simpler trial and error process to reach a tuned final model (Sheela & Deepa, 2013).

5.4) Activation functions

The output of a processing neuron is determined by the activation function. Typically, neural networks utilize the sigmoid function even though others such as the hyperbolic tangent, arc tan, ramping, step and linear have also been proposed. Linear functions are not appropriate for nonlinear mapping and classification (Duch & Jankowski, 1999; Karlik & Olgac, 2011).

A sigmoid function should be used if the intended learning pattern is an average behavior, whereas the hyperbolic tangent function should be used if the learning pattern involves deviations from the average. For binary variables, the step and ramping functions are recommended since the sigmoid approaches zero and one asymptotically (Nawari, Liang, & Nusairat, 1999).

As mentioned previously, the raw data must be scaled to fit the lower and upper bounds. In linear scaling, the minimum and maximum values should be scaled according to expression 8 (Kaastra & Boyd, 1996).

$$SV = AF_{MIN} + (AF_{MAX} - AF_{MIN}) \times \frac{(D - D_{MIN})}{(D_{MAX} - D_{MIN})} \tag{8}$$

where:

SV – Scaled value;

TF_{MIN} – Activation function minimum function;

TF_{MAX} – Activation function maximum function;

D – observation value;

D_{MIN} – Observations' minimum value;

D_{MAX} – Observations' maximum value.

6) Evaluation criteria

A variety of criteria may be used to evaluate the quality of the solutions. The sum of the squared errors is the most commonly used criteria. Percentage differences, asymmetric least squares, least fourth powers are other examples (Hedman, 2012).

7) Neural Network training

Training a neural network consists on iteratively presenting it with examples of known correct answers, until it is able to find suitable weights between neurons and an acceptable generalization of the model by determining the global minimum of the error function it is evaluated on. If the algorithm finds a local minimum, it can get "trapped" and not find a global minimum.

7.1) Number of training iterations

The training stage should be stopped if any of the two following scenarios occurs: if there is no improvement in the error function based on a sufficient number of randomly selected starting weights, i.e. if convergence occurs; or after a predetermined number of iterations and the network's ability to generalize is reached. Nonetheless, both the scenarios agree that the final objective is to find generalization on the validation set (Yin, Rosendahl, & Luo, 2003).

The main advantages of the convergence method are that one can have more confidence that the global minimum is reached, replication is more likely to occur than in the fixed number of sets method and the researcher does not have to suggest two parameters, particularly the number of iterations the training stage should have and how to determine the optimal tested network (Kaastra & Boyd, 1996).

7.2) Momentum and training rate

The objective of training is to minimize the total squared errors at each iteration. A backpropagation algorithm is trained by applying a gradient descend algorithm that contours the error surface by moving down the steepest slope (Attoh-Okine, 1999). The total squared errors can be determined using expression 9.

$$E = \frac{1}{2}\sum_{m}^{M} E_h = \frac{1}{2}\sum_{h}^{M}\sum_{i}^{N}(t_{hi} - O_{hi})^2 \tag{9}$$

where:

E – Total error of all patterns

E_h – Error pattern *h*;

h ranges over the number of input patterns;

i is assigned to the *i*th output;

t_{hi} – Desired output for the *i*th output when the *h*th pattern is presented;

O_{hi} – Actual output of the *i*th output neuron when *h* is presented.

The learning rule to modify the weight between neurons *i* and *j* is presented in expressions (10) to (12) (Kaastra & Boyd, 1996).

$$\delta_{hi} = (t_{hi} - O_{hi})O_{hi}(1 - O_{hi}) \tag{10}$$

$$\delta_{hi} = O_{hi}(1 - O_{hi})\sum_{k}^{N}\delta_{hk}w_{jk} \tag{11}$$

$$\Delta w_{ij}(n+1) = \varepsilon(\delta_{hi}O_{hj}) \tag{12}$$

where:

δ_{hi} – Error signal for neuron *i* for pattern *h;*

ε – Learning rate;

n – Presentation number.

The learning rate is a constant of proportionality and determines the size of the weight changes. The weight change of a neuron is proportional to the impact of the weight from that neuron on the error. Eqs. (9) and (10) represent the error signal for an output neuron and a hidden neuron respectively.

During the training stage, an error function which is changing greatly without any sign of continuous improvement can be a sign of a high learning rate, whereas if there is little to no improvement in the training stage, it is a sign of a low learning rate.

Backpropagation is a method to increase the learning rate of the network. By applying a momentum term in the backpropagation algorithm, the researcher is determining how past weights impact the current weight changes (Hecht-Nielsen, 1992). The modified learning rate that includes a momentum factor is presented in expression 13.

$$\Delta w_{ij}(n+1) = \varepsilon(\delta_{hi} O_{hj}) + \alpha\, \Delta w_{ij}(n) \quad (13)$$

Where α is the momentum term.

Using a momentum term has the advantage of suppressing side by side oscillations, since it allows to suppress high frequency variations since each new search direction is a sum of both the current and previous gradients. By having a two-period moving average, momentum values that are too great will prevent the high fluctuations of the algorithm. Common practice suggests that training should star with a high learning rate, such as 0.7 and decrease as training proceeds (Hinton, Srivastava, Krizhevsky, Sutskever, & Salakhutdinov, 2012).

8) Implementation

The implementation step requires a careful evaluation of the available data prior to its collection. A number of factors need to be considered, such as data availability, evaluation criteria and training times. Once implemented, a neural network performance will degrade over time unless reevaluations continue taking place (Kaastra & Boyd, 1996).

3.3.4.2 – 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 (Haykin, 1994; Mikolov, Karafiát, Burget, Černocký, & Khudanpur, 2010). These networks are the focus of this subsection, where the model architecture and the recommended loss function in literature are presented in detail.

1) Model Architecture

As a sub-class of ANNs, RNNs are composed of three main layers: the input, recurrent hidden and output layers. By adding a recurrent feature to the standard hidden layer, it is possible to introduce recurrent cycles (or feedback loops) over time which allows these networks to process sequential data over time more effectively (Sutskever, Martens, Dahl, & Hinton, 2013).

The network is trained by supplying a dataset of input-target pairs and minimizing the loss functions by optimizing the weights of the network. By minimizing the difference between output and target pairs, the total loss value of the network decreases (Sutskever, Martens, & Hinton, 2011).

The input layer is comprised by *N* input units, x_t, that include a sequence of vectors through time *t* as $\{\dots, x_{t-1}, x_t, x_{t+1}, \dots\}$, where $x_t = (x_1, x_2, \dots, x_N)$. Each input unit is connected to each hidden unit in the hidden layer through a weight matrix W_{IH}. Moreover, the hidden layer is comprised by *P* hidden units, $h_t = (h_1, h_2, \dots, h_P)$, connected among themselves through time with recurrent connections defined by a weight matrix, W_{HH}. The networks update this internal state h_t at each timestep, $t = (1, \dots, T)$, using the hidden layer's activation function, f_H, based on both the previous step, h_{t-1}, and the current input, x_t (see expression 14, where b_h is the bias vector of the hidden units).

$$h_t = f_H(W_{IH}x_t + W_{HH}h_{t-1} + b_h) \quad (14)$$

Finally, the output layer is updated by the hidden layer through a weight matrix W_{HO}. The output layer can be computed through expression 15, where f_o is the output layer activation function and b_o is the bias vector of the output layer.

$$y_t = f_O(W_{OH}h_t + b_O) \quad (15)$$

In each timestep, the output layer represents a prediction based on the output from the hidden layer. Therefore, the hidden state provides a representation of the past states of the network over the course of the timesteps, which allows the network to make accurate predictions at the output layer.
Figure 17 shows the RNNs architecture described in the previous paragraphs.

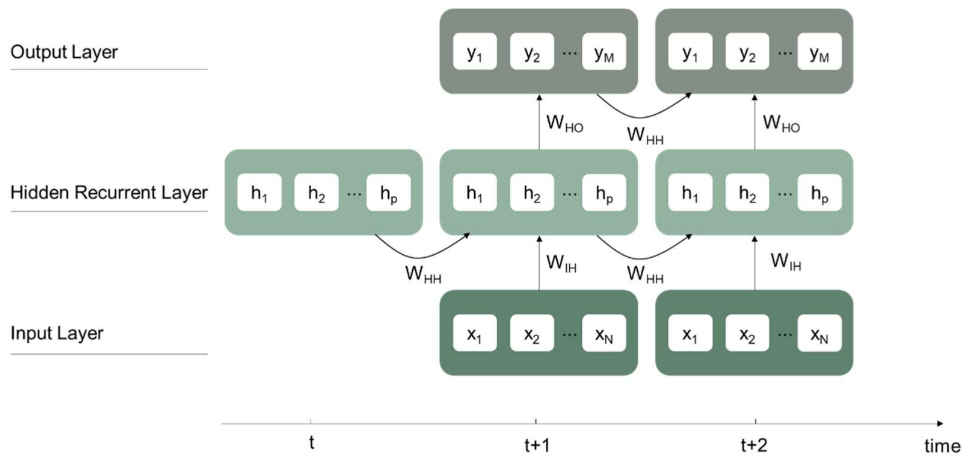

Figure 17. **Recurrent Neural Network**

2) *Loss Function*

The performance of the network is evaluated through its loss function, $\mathcal{L}$. The loss function compares the output, y_t, with the target supplied in the input-target pair, z_t, and it is calculated at every timestep (see expression 16).

$$\mathcal{L}(y, z) = \sum_{t=1}^{T} \mathcal{L}_t\,(y_t, z_t) \quad (16)$$

The total loss value is the summation of losses at each timestep. As referred in the previous sub-section 3.3.4.1, the error function is trained by minimizing the mean squared error, using a gradient descent algorithm contours the error surface by moving down the steepest slope.

3.4 – Literature Review Synthesis

As the literature key concepts are detailed across the chapter, this section has the objective of synthesizing and systemizing the previously introduced papers related to non-production warehouse inventory policies.

In order to analyze the different papers, a classification according to the different concepts and stages of an inventory management policy development is applied. The methodology as well as the tested operational dimensions are also referred. Lastly, an indication of whether the article had a real application is mentioned.

In terms of the applied operational dimensions, they are classified according to the characteristics reviewed along the paper. Only the relevant papers that add value to the thesis were considered in Appendix II. Papers that simply present concept definitions are not regarded.

3.5 – Chapter Considerations

In this chapter, a literature review is performed concerning warehouses, inventory management and forecasting methods with a focus on their applications and relationships regarding the problem under study. These three concepts are of the most importance and must be fully understood in order to achieve the desired efficiency in the future stock management policy.

Warehouses represent the intermediary stock in a company's supply chain. They provide value by stabilizing variability along the supply chain and by providing the means for a high service level. Five focus areas suggested by Gu, Goetschalckx and McGinnis (2010) are explored regarding the design of a warehouse, namely, the structure, sizing, layout, equipment and operational strategy that should be implemented. The daily operations of a warehouse as well as the performance measures that should be utilized to evaluate them were also explored and have an important role in the overall performance of warehouses.

Due to the increasing importance of companies having a low inventory level but at the same time having a high service rate, inventory management policies were presented, with a special focus on spare parts inventory management due to its high demand uncertainty and typically high cost of SKUs.

Due to the high demand uncertainty of spare parts, forecasting methods are also a main point of the chapter, with special regard to their classification. Artificial Neural Networks, which are a machine learning algorithm can be used as a forecasting method. The design suggested by Kaastra and Boyd (1996) comprises eight steps in total and it is of the most importance to implement a successful forecasting technique for intermittent demand items. Recurrent Neural Networks are a sub-class of Artificial Neural Networks that present a higher performance when processing sequential data over time.

The development of the present literature review serves as a theoretical basis for the development of the practical case study presented in the future chapter.

4. Data collection and solution approach

The case study and analyzed available research on the topic under the scope are presented on the previous two chapters. In chapter 2 the main specifications of the problem faced by Schaeffler Portugal are outlined, and in chapter 3 available literature on the problem is presented. The goal of the present chapter is to introduce the methodology followed to reconfigure the stock management policy of Schaeffler Portugal's non-production warehouse, as well as to analyze and segment the available data provided for the case study development.

Since the main objective of the present thesis is to review the stock management models applied to the products of the non-production warehouse of Schaeffler Portugal, the current chapter is organized according to the following structure: Section 4.1 briefly introduces the DMAIC methodology used to develop the problem under the scope, reviewing the objectives of each individual step of the procedure. Section 4.2 introduces the boundaries of the problem and formalizes the problem under study for the warehouse management team; In section 4.3 the critical data of the project is collected and pre-analyzed; Section 4.4 presents the analysis stage, where the critical data collected in the previous section is evaluated; Finally, in section 4.5 chapter considerations are outlined from the data analysis performed during the chapter.

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. The methodology includes six steps to achieve the main objective of the dissertation, which are summarized in figure 18. The approach is based on the framework proposed by Dale, Bamford and Van der Wiele (2016) and it is briefly described next.

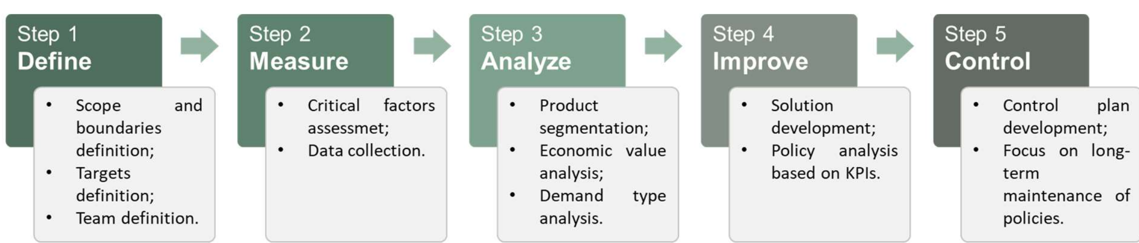

Figure 18. **DMAIC framework and objectives definition**

The first step aims at clearly defining the scope and boundaries of the problem at hand. Moreover, the selection of appropriate performance metrics and the targets definition allow to characterize the problem unambiguously. The project champion and team members are also set during the first step.

During the second step of the framework, the critical factors of the process are measured in order to be analyzed. This includes not only selecting the outputs to be improved but also developing a data collection plan to compile data on the performance measures relevant for the system under the scope of the analysis.

The third step of the methodology produces a segmentation of the products managed by the non-production warehouse. An economic value and a demand segmentation are performed to the data previously collected. This segmentation is recommended due to the intermittent nature of the products managed by the warehouse. The third step is critical to reach a solution in the following chapter and to provide a solid background for the case study resolution, identifying possible root causes for underperforming metrics described in the first step.

The fourth step presents the development of solutions for the problems being tackled by the dissertation. Policies are developed according to each product segment previously identified, to better suit its requirements. Process and policy changes are analyzed based on the expected KPI improvements that result from the implementation of the solutions, including the (s, Q*) review policy as well as ANNs forecasts.

Finally, the fifth step focuses on how to maintain the long-term gains from the identified solutions. This involves ensuring the changes are fully integrated into processes as well as communicating the findings with the warehouse personnel. A control plan is developed to summarize the strategic actions that should be considered to continuously improve the stock management policies over the long-term horizon.

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 project charter containing the detailed scope is produced considering the four phases of the defining stage: i) team definition; ii) problem definition; iii) targets definition; and iv) project charter formalization. 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 (see figure 19).

Each member of the team should have relevant training concerning the application of a DMAIC cycle held by the MOVE trainer (specialized in continuous improvement methodologies), as well as a clear understanding of the desired outcomes of the project.

The project sponsor decides the investment allocation and validates the project plan. The project leader establishes the project organization, planning, implementation rhythm, reports issues and concerns, supports decision making and communicates the ongoing status to the sponsor. The coach is a MOVE trainer whose contribution is to help the team with the application of the DMAIC cycle namely with any implementation issues that may arise. The project manager reports the project status to the project leader, implements and coordinates the project and the project team. The warehouse workers assist the project manager with the required data to implement the activities.

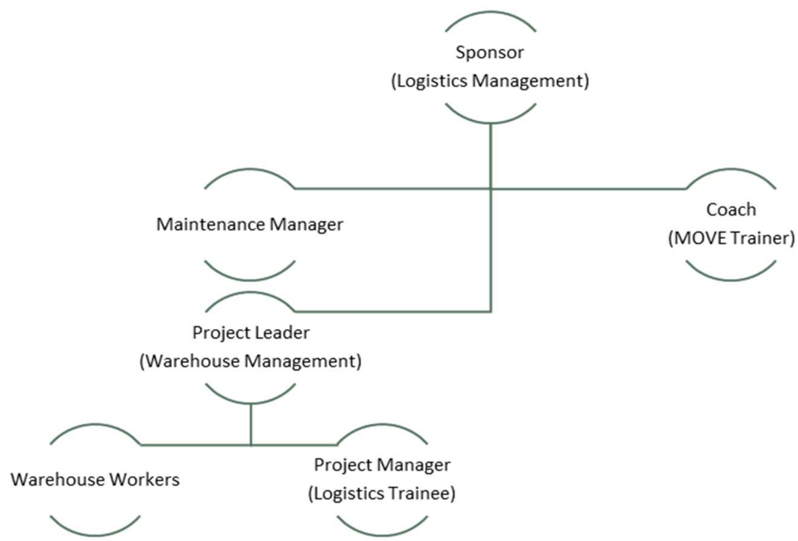

Figure 19. **Project team chart**

ii) Problem definition

To clearly define the problem, the "5W&1H" methodology (*What-Who-When-Where-Why-How*) is applied. This is a strategic tool used to establish a tactical plan where the responsibility for the tasks is assigned to the team members. The methodology is structured in order to promptly assess the required elements for the implementation of the project. The elements can be described as:

- What – Describes the tasks;
- Who – Assigns a responsible to the tasks;
- When – Calendarizes the tasks;
- Where – Assigns a location to the tasks;
- Why – Assigns a justification to the tasks;
- How – How should each task be executed;

After a brainstorming with the project team to develop the "5W&1H" methodology application, the scope of the project became clearly defined and is presented in table 7.

Table 7. **5W&1H methodology chart**

Element	Is	Is not
What	Critical Products of the non-production warehouse;	Other Products from the non-production warehouse;
Who	Warehouse management; Maintenance supervisor;	-
When	From February 2019 to October 2019;	-
Where	Non-production warehouse of Schaeffler Portugal;	Raw materials, components and finished products warehouses of Schaeffler Portugal;
Why	Intermittent demand of products; High inventory costs; Improvement of ordering process;	-
How	Stock demand patterns analysis, Manufacturing Resource Planning (MRP) type proposals and forecasting through the application of an artificial neural network algorithm;	-

After the clear definition of the problem, a plan including every step of the project is developed by the project manager and communicated to the project team with the respective tasks until the conclusion of the project. The project timeline with every essential task, separated by each stage of the DMAIC cycle, is presented in appendix III.

iii) Targets definition

Once the problem definition is completed and the scope of the project is fully characterized and understood by the team, a target is placed by the Project Sponsor regarding certain KPIs.

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.

iv) Project Charter

To formalize the project formulation, a project charter is presented in appendix IV, where the project scope, tasks and objectives are defined. The goal is to have a layout where information is summarized and clearly identified.

4.3 – Measuring Stage

The measuring stage is one of the most important stages in the DMAIC methodology. In this stage, all the necessary data for the project is collected to be analyzed during the following stage. After the data collection, a pre-analysis is performed to screen the products that should be analyzed differently either due to insufficient data or due to specific characteristics of the products.

4.3.1 – Data collection

Once the problem is characterized, data is collected and categorized in order to be further analyzed and serve as a basis to identify improvements in the warehouse stock management policy. Therefore, the following categories of data are gathered:

- Amount of stock in the non-production warehouse and respective price in April 2019;
- Demand record of products between January 2018 and April 2019;

The files are collected using the ERP platform SAP, where all the movements of the products are kept in a record. Each product file has its reference in the system, a product name, the quantity in stock, the unit and aggregated prices, among other parameters. Table 8 is an example of a system record of a product currently in stock at the warehouse.

Table 8. **System record of a product - example**

Reference	Description	Quantity (units)	Unit price	Total price
063132985-0000	Multi panel 6AV6 643-1AX6	6	289,79 €	1738,74 €

The demand record file holding the product's demand between January 2018 and April 2019 shows the product reference, the description of the product, the demand date, the associated production order and the machine where the product was applied (if applicable), among other parameters. Table 9 exemplifies a product demand record collected from the system.

Table 9. **System demand record - example**

Reference	Description	Production order	Demand date	Quantity (units)	Machine
063132985-0000	Multi panel 6AV6 643-1AX6	15794856	06-05-2018	1	AJK

In April 2019, a total of 2 646 different SKUs was registered in the company's SAP 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, in the case of immediate need. 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. Additionally, these products are subject to natural wear and have the risk of becoming unusable.

4.3.2 – Data screening

The screening process allows to identify different groups of products and to categorize them in order to be analyzed in the present dissertation. In an early phase, 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 (approximately 44%) had no recorded demand during that period. These products are further explored in section 4.4.2 and are classified as "Group of products without demand between 2018 and 2019".

Moreover, the products with demand between 2018 and 2019 are subject to a deeper analysis in section 4.4.1 and are named as "Group of products with demand between 2018 and 2019". Alongside the complete list of products, the warehouse manager selected a list of 50 critical parts that independently of the demand recorded in the past and economic value, should be analyzed for a policy review.

Table 10 summarizes the different groups of products that were identified previously.

Table 10. **Existing product groups**

Group description	Number of products (units)	Total price
Group of products in stock in April 2019	2 646	465 000 €
Group of products with demand between 2018 and 2019	1 479	293 000 €
Group of products without demand between 2018 and 2019	1 167	172 000 €
Group of critical products selected by the warehouse manager	50	75 500 €

4.4 – Analyzing Stage

During the analyzing stage, the gathered data is evaluated to develop a solution to the case study. In this stage, any causes that might compromise the performance of the system are also identified.

4.4.1 – Group of products with demand between 2018 and 2019

In this section, an analysis on the group of products with a recorded demand between 2018 and 2019 is performed. In total, 1 479 products belong to this category and require a deep analysis since they have a high importance to the smooth operations of the company. The products of the group are segmented according to their economic value and recorded demand during January 2018 and April 2019. These two dimensions allow to understand the importance the products have in the company's stock and to define a more efficient management policy.

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. Products are sorted according to the total stock price they represent in the warehouse. The price being considered is the purchase price of the item, excluding the value added tax.

Firstly, information regarding each individual item currently in stock in the warehouse is collected. Next, a table is sorted in a decreasing order of product price. Lastly, the accumulated value of each reference is calculated by adding the value of the previous items to it (see expression 17).

$$Accumulated\ Product\ Price\ (n) = Product\ Price\ (n) + Accumulated\ Product\ Price\ (n-1) \quad (17)$$

Finally, the percentage weight of the accumulated price of each product is calculated using expression 18.

$$\%\ of\ the\ accumulated\ product\ price\ (n) = \frac{Accumulated\ Product\ Price\ (n)}{Total\ Accumulated\ Price} \times 100 \quad (18)$$

Table 11 represents some values obtained from the ABC analysis table.

Table 11. **ABC analysis - Economic Value Analysis**

Reference	Quantity (units)	Total price	Accumulated product price	% accumulated product price
058630058	100	20 600,00 €	20 600,00 €	6,55 %
216423198	46	10 168,56 €	30 768,56 €	9,79 %
(…)	(…)	(…)	(…)	(…)
115389741	1	0,01 €	292 614,81 €	100 %

Through the data obtained from the complete version of table 11, it is possible to build the ABC curve presented in figure 20. Each green point of the curve corresponds to a value of the percentage weight of the accumulated price of each product and to the respective number of products present in the warehouse (for example, 20% of the products correspond to 77% of the total accumulated products price present in the non-production warehouse).

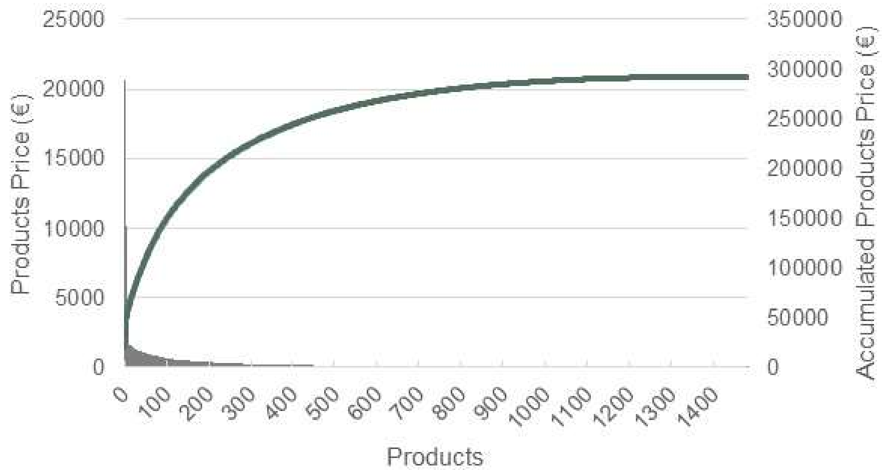

Figure 20. **ABC curve - Economic Value Analysis**

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 12.

Table 12. **ABC analysis segmentation**

Class	Number of products (units)	% of products	Accumulated % of products	% of product price	Accumulated % of product price
A	296	20	20	77	77
B	444	30	50	18	95
C	739	50	100	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. Class B products are not as important as items from class A, nonetheless they should also be monitored since potentially, with a variation in stock, they be included in category A. Finally, class C items have a higher risk of cost in terms of occupied space and the warehouse manager should consider whether it is needed to have these items in stock at all.

Demand Type Analysis

In addition to economic value, the products demand type is an extremely useful characterization technique. It allows to understand the consumption rate of materials and to efficiently manage the warehouse stocks. In the same way an economic analysis allows to identify the economic weight of each product, a demand type analysis allows to frame products in stock management models.

As mentioned previously in section 3.2.3.2, demand can be characterized according to two variables: average time between demand and demand variability. Both variables are obtained through the products demand records. Data is grouped in monthly periods to identify demand patterns that would be smoother in case daily demand patterns were considered (see figure 21).

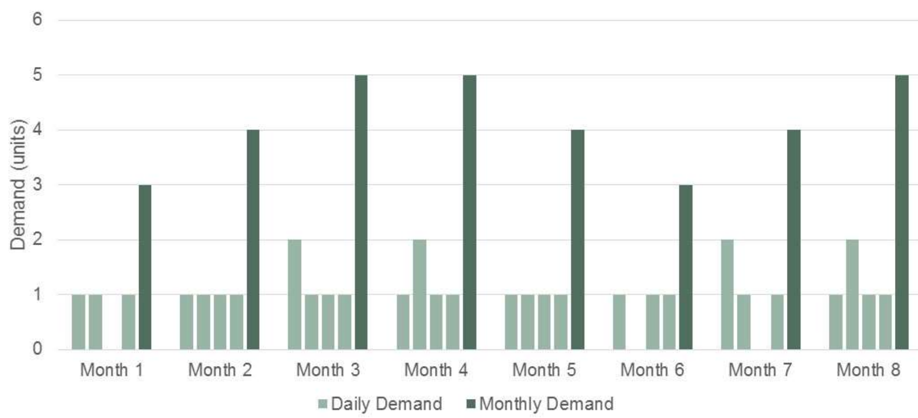

Figure 21. **Monthly demand aggregation**

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 an average demand interval neither variability in the demand. In total, 351 items are under these conditions.

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. Firstly, the average demand value and respective standard deviation are calculated for each item so that the demand variability coefficient is determined (notice that the variability coefficient is an dimensionless variable). Secondly, the average time between demand is computed. The computations are made using days (and subsequently converted to months) in order to increase the precision of the categorization. Figure 22 represents the items segmentation of the multi demand items.

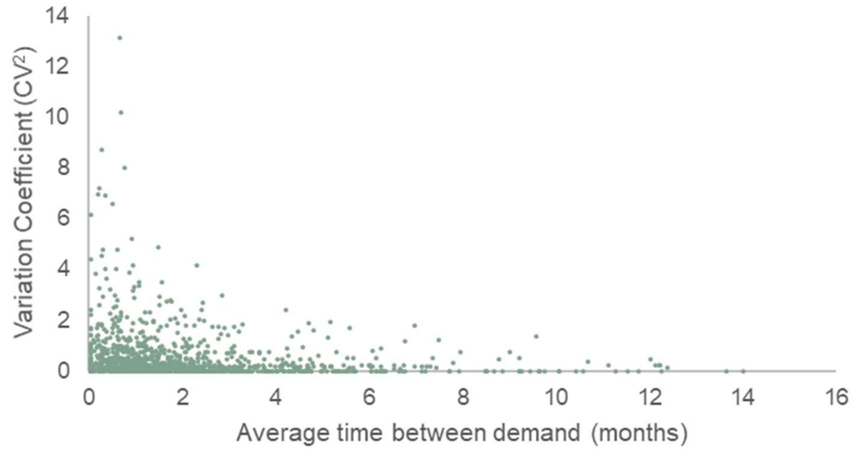

Figure 22. **Average time between demand and demand variability**

Analyzing the plot, one can observe that there is a higher concentration of items when the average time between demand is lower than three months and the demand variability is lower than one.

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 23 represents the 727 items segmented across the four regions – erratic, lumpy, smooth and intermittent.

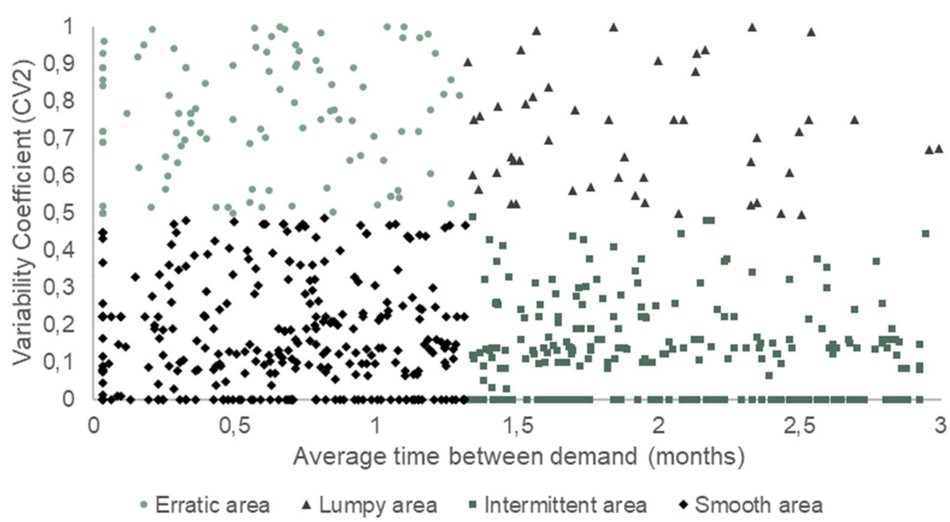

Figure 23. **Items segmented in four regions**

Examining the plot, it is possible to observe that there is a high number of items in the smooth and intermittent regions, which is evidenced in table 13. This table introduces the considered number SKUs categorized according to the demand type, the respective percentage, the weight each item has in the current stock value (April 2019), the demand and the respective average value of demand.

Table 13. **Summary table of SKU categorization**

Demand type	Number of products (units)	% of products	% of value in stock	Number of orders	Average value of demand (€)
Single	351	24	22	351	184,40
Smooth	305	21	35	5 278	19,52
Intermittent	484	32	33	2 115	45,93
Erratic	204	14	5	8 166	1,78
Lumpy	135	9	5	666	19,78
Total	1 479	100	100	16 576	17,65

Table 13 shows that the largest category of products is the one with an intermittent nature (32%) and represents almost a third of the SKUs present in the warehouse. This indicates that even though a large portion of the demanded products have a low variation in the demanded quantity, the time interval between demands is high. The total value associated to these SKUs, although not disclosed, is also significant, representing a third of the total value present in the warehouse (33%). The nature of this category of SKUs is located in between the smooth and the single categories, being associated to items that might be used to maintain different equipment yet are more specific than smooth demand items.

The single demand items are the second group in the hierarchy of number of products in the warehouse, representing 24% of products. These SKUs are typically associated with the occasional maintenance of equipment, where they represent replacement parts for specific equipment. The items in this category typically have a very high cost, which can explain this category having the highest average value of demand among all the categories (184,40€).

Items in the smooth demand category represent more than a fifth of the total products in the warehouse (21%). These SKUs have a higher inventory turnover than items in the remaining categories and are less specific, hence the low demand variability. These items are typically associated with common maintenance activities and are likely to be used across different equipment.

SKUs in the erratic and lumpy demand categories represent 14% and 9% of the total number of products present in the warehouse respectively. The low average price of the items in the erratic category should be highlighted (1,78€) as well as its number of orders (the highest among all the categories).

Lastly, to conclude the analysis of the group of products with demand between 2018 and 2019, table 20 is presented. This table combines the results obtained from both the economic value and demand type analysis, categorizing the demand with respect to the demand type as well as to each economic value class (A, B or C). The table presents the number of products in each economic value class, segmented by each of the five demand type classes. Moreover, the percentage value for each demand type class segmented by the respective economic value class is also presented. Finally, table 20 presents the percentage of products present in each demand type class, for each A, B and C classes.

Table 14. **Economic Value and demand type analysis**

Demand type	Economic Value					
	A		B		C	
	Number of products (% value in the demand type)	% of products	Number of products (% value in the demand type)	% of products	Number of products (% value in the demand type)	% of products
Single	77 73,6	26,0	105 21,3	23,6	169 5,1	22,9
Smooth	60 84,3	20,3	117 13,1	26,4	128 2,6	17,3
Intermittent	126 75,7	42,6	155 19,2	34,9	203 5,1	27,4
Erratic	17 49,0	5,7	43 33,0	9,7	144 18,0	19,5
Lumpy	16 67,7	5,4	24 21,7	5,4	95 10,1	12,9

From the analysis of table 20, it is possible to conclude that the intermittent demand category presents the highest number of products across the three classes. Single demand items present the second highest number of items in classes A and C whereas smooth demand items present the second highest number of items in class B. Smooth demand items also present the third highest number of items in both classes A and C whereas single demand items present the third highest number of items in class B. Finally, erratic demand items occupy the fourth position in terms of highest number of items across the three classes and lumpy demand items occupy the fifth.

4.4.2 – Group of products without demand between 2018 and 2019

The goal of the present section is to analyze the group of items without demand between the 2018 and 2019 period that might be in an obsolescence situation. Moreover, an analysis on the possible gains in terms of shelf space is recommended in the end of the section.

These items are identified by cross-referencing the list of existing stock in the warehouse in April 2019 with the list of the demanded items during the period of January 2018 to April 2019. In total, 1 167 different items are found 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 only be considered in case they are not classified as critical items. 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.

To analyze the possible gains in terms of space by excluding the referred items, one could take a representative random sample of products and analyze the occupied shelf space. Once the space would be identified, a generalization could be made for the remaining items without demand in the warehouse in order to determine the total amount of space that could be saved by excluding the items.

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 (chapter 5). All items with a recorded demand that are selected belong to class A of the ABC analysis (section 4.4.1). Although the warehouse manager has been advised against selecting items with no proven record of demand, 13 items were selected, since they belong to a core equipment of the plant, presenting a high downtime risk for the entire plant in case of failure.

Similar to table 13 presented in section 4.4.1, table 15 classifies the critical items according to demand type and identifies products that have no recorded demand during the analyzed period. An economic value analysis is not performed since several critical items are only available for repairs (which in turn have different costs depending on the required repair). Moreover, due to the critically of the items, the analysis considers both items that are in stock and out of stock.

Table 15. **Item classification - Critical products**

Demand type	Number of products (units)	% of products	Number of orders
No recorded demand	13	28,9	0
Single	6	13,3	6
Smooth	14	31,2	274
Intermittent	9	20,0	33
Erratic	2	4,4	30
Lumpy	1	2,2	5
Total	45	100,0	348

Once the group of critical products selected by the warehouse manager have been segmented regarding the demand type, the stock management policy proposal should be prepared in regard for each category of products.

4.5 – Chapter Considerations

Chapter 4 presents the methodology followed to reconfigure the stock management policy of Schaeffler Portugal's non-production warehouse along with the data segregation necessary for the case study development, both in terms of economic value of products and available demand history. The DMAIC methodology is introduced to outline the framework in which the present thesis is produced. Each component of the DMAIC structure is briefly introduced as well as the expected outcome of each of the five components that are a part of the methodology.

During the Defining Stage, a formalization of the problem is presented, along with the project timeline, in order to fully characterize the team responsible for the process, as well as the targets defined for the project. Following the recall of the problem, the Measuring Stage is presented, where the data collection takes place, namely regarding the demand record of products between January 2018 and April 2019 as well as the amount of stock present in the warehouse and respective price in April 2019. From the data collection, a product segmentation takes place and serves as the basis for the following stage.

The analysis of the data collected previously takes place in the Analysis Stage of the chapter, where products are evaluated according to the available records of demand. Products that present a robust set of demand records are analyzed economically according to an ABC analysis, as well as segmented according to two dimensions – average time between demand and demand variability – into four categories: erratic, lumpy, intermittent and smooth demand products. Items that do not present any demand record are considered obsolete and a deeper analysis is recommended before excluding them from the warehouse. Lastly, a group of critical products is selected by the warehouse manager to represent the sample of products analyzed in the following stage. All the products represented in the sample are present in class A of the ABC analysis.

5. Case Study Resolution

The present chapter describes the application of the stock management policies to the product segments identified in the previous chapter. Thereby, section 5.1 introduces the proposed solutions to manage the product segments, detailing the stock management parameters for each approach. Moreover, it describes the impact the current policies have in products characterized by a low demand variability. Forecasting is performed using ANNs to analyze the reliability of this tool to determine the stock management parameters of high demand variability items. In section 5.2, a control plan for the proposed implementation is introduced in order to present strategic actions to ensure the continuous improvement of the warehouse operations. Finally, section 5.3 the main chapter considerations are presented.

5.1 – Improving Stage

During the improving stage, solutions are recommended and analyzed for the case study. The expected variation in the KPIs from the implementation of the proposed solutions are also evaluated in this stage with the sample critical products as well as a plan to implement the methodology in the larger dataset composed of all the products in the warehouse.

5.1.1 – Warehouse stock management

The main objective of the present dissertation is to review the stock management models applied to the products of the non-production warehouse of Schaeffler Portugal. A review of the current policies is applied to the critical products of the warehouse.

Items are firstly framed in the existing stock management models of SAP. Next, the stock management parameters are determined. Later, the present situation is compared with the proposed scenario and finally the obtained data is analyzed.

The analysis performed in section 4.4 allows to segment each SKU according to its demand type and economic value (the latter is not performed for the critical products due to the variability of repair costs). As mentioned previously, items can be distributed across six different demand patterns. Erratic and smooth demand patterns are characterized by a shorter interval between demands, whereas lumpy and intermittent are characterized by longer intervals between demands. Erratic and lumpy demand patterns are defined by a high demand variability, whereas items with a smooth and intermittent demand patterns have a low demand variability. Finally, there are items with a single demand over the analyzed period and items with no demand over the same period.

5.1.1.1 – MRP Type Proposal

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, MRP ZT and MRP ND. MRP ZV is characterized by a manual reorder of items to external suppliers once a reorder point is reached. MRP ZT orders materials according to a planned schedule of orders. Finally, MRP ND is applied whenever there is no automatic or manual item requirement generation whenever an item reaches a low stock level.

Nonetheless, SAP offers other types of stock management models that are currently not being applied by the management team such as MRP ZS. The method uses a prognostic MRP algorithm and can set the reorder point automatically based on consumption and a defined forecast scenario. The company tried implementing it previously, nonetheless the implementation failed due to a lack of precise demand data and the added complexity of maintaining the method.

Single demand items are typically associated with sporadic maintenance of equipment. The economic value associated to these items is high and the permanence of these items in the warehouse should be properly reasoned. Moreover, the inactivity of some of the mentioned equipment may compromise the proper operation of the equipment. Therefore, items characterized by this kind of demand should utilize MRP ZT as the stock management model. With proper maintenance schedules, items can be ordered in due course to be utilized. Nonetheless the criticality of each item should be under consideration so that the normal functioning of the plant is not affected by the lack of these items.

Items with smooth and intermittent demand patterns can be managed through MRP ZV. As the items do not present a high variability in the demand patterns, they can efficiently be managed according to a classic demand scheduling system.

Finally, items with a higher variability, such as items with an erratic and lumpy demand patterns can be managed according to an MRP ZS from the moment there is a robust demand history available.

It should be mentioned that 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.

5.1.1.2 – Parameters determination

The goal of the current section is to determine the parameters that guide the stock management models of the proposed methodologies – MRP ZV, from SAP – and forecasting using ANNs. Firstly, the parameters that define the MRP ZV are determined. Secondly, an artificial neural network is developed in order to forecast demand for the erratic and lumpy demand items and evaluate whether this machine learning method might be considered a good fit for these items in the future. MRP ZT does not require the determination of any parameters.

MRP ZV parameters determination

The MRP ZV stock management model follows the (s, Q*) review policy (see section 3.2.1). The minimum stock (s) needs to be established (level of stock which triggers a new order). The purchase order is requested with a certain quantity (Q*) when the available stock reaches the minimum stock. The safety stock (Q_{safety}) is the quantity that should be available at all times to prevent stock out due to an unpredicted demand.

The smooth and intermittent demand items within the critical products group are being considered for the current analysis due to the low variability nature of the items. In the first step of the analysis the demand along 2018 and 2019 is grouped monthly for each item. The average demand (μ_D) as well as the respective standard deviation (σ_D) are then determined. Next, the average replenishment time (μ_L) and the respective standard deviation (σ_L) are obtained. Table 16 summarizes these values. Expressions 4 and 5 are then applied to collect the average demand during the supply period (μ_{DL}) and the respective standard deviation (σ_{DL}) for each item (also in Table 16).

Table 16. **Average demand and standard deviation during the supply period**

Reference	μ_D (units/month)	σ_D (units/month)	μ_L (months)	σ_L (months)	μ_{DL} (units)	σ_{DL} (units)
217628680	0,27	0,00	1,57	0,00	0,42	0,00
073757713	1,20	0,37	0,17	0,00	0,20	0,15
216416574	0,80	0,64	0,25	0,02	0,20	0,32
(…)	(…)	(…)	(…)	(…)	(…)	(…)
083925503	0,87	0,26	0,84	0,41	0,73	0,43

In the next step, the information required to calculate the safety stock quantity (Q_{safety}), minimum stock (s) and order quantity (Q*) is gathered. A service level of 95% is being considered for these items. Assuming the available historic demand of products behaves according to a normal distribution, the considered safety factor (k) is1,64. The service level is defined by the non-production warehouse manager and it might be adapted according to the criticality of each product.

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. Table 17 shows the 9 considered scenarios, demonstrating the effects that both the cost of processing an order and the cost of maintaining the product in the warehouse annually have in the optimal order quantity for item 058630058.

Table 17. **Optimal order quantity sensitivity analysis**

Scenario	C_a=€0,50 I=3%	C_a=€0,50 I=5%	C_a=€0,50 I=7%	C_a=€1 I=3%	C_a=€1 I=5%	C_a=€1 I=7%	C_a=€2 I=3%	C_a=€2 I=5%	C_a=€2 I=7%
Q* (units)	4	3	3	2	2	2	2	2	2

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. Moreover, in March 2019 the company had 100 units in stock of the referred item. When questioned regarding the high value of stock, the warehouse manager justified it with a price discount when ordering a higher number of products. Nonetheless, after analyzing the demand data and since there is no minimum lot size for the item, the price discount does not justify the current high stock present in the warehouse and it should be kept under a better observation.

Performing a similar analysis to the remaining items characterized by low variability demand, figure 24 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% improvement in the overall stock of the warehouse.

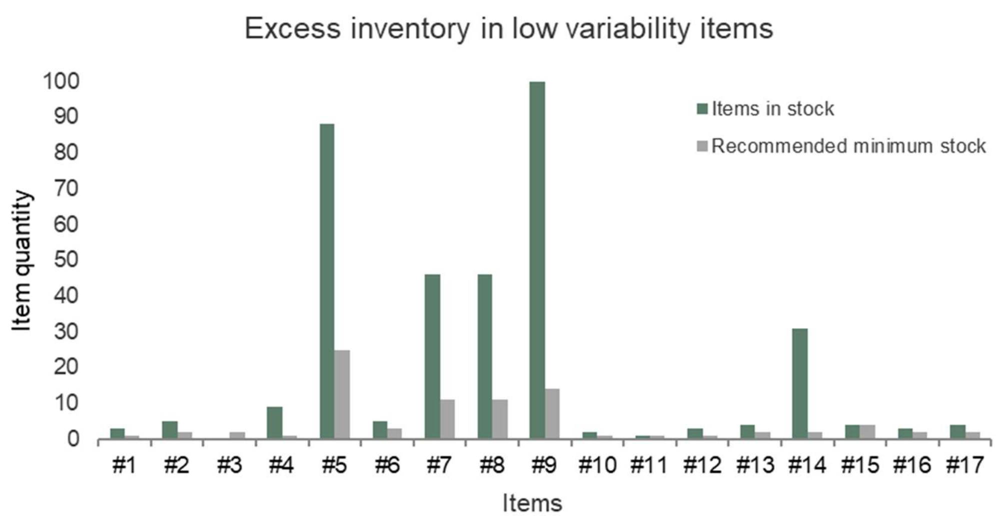

Figure 24. **Excess inventory in low variability items**

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 3.3.4.1). Items within the critical products group are considered for the current analysis, more specifically, items characterized by erratic and lumpy demand patterns due to their high variability nature. 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 erratic and lumpy demand items (item 063988470 and 222781246). For simplification purposes, item 058645900 is referred as item A, item 063988470 as item B and item 222781246 as item C.

Regarding the architecture of forecasting demand using RNNs, it involves using three distinct datasets – training, validation and testing sets. As RNNs are supplied with a dataset represented by input-target pairs, the input data, represented by *N* observations, corresponds to training set, and the target data, which is represented by *M* observations corresponds to the validation set, in which the *N* dataset is immediately followed by the *M* dataset (see figure 25).

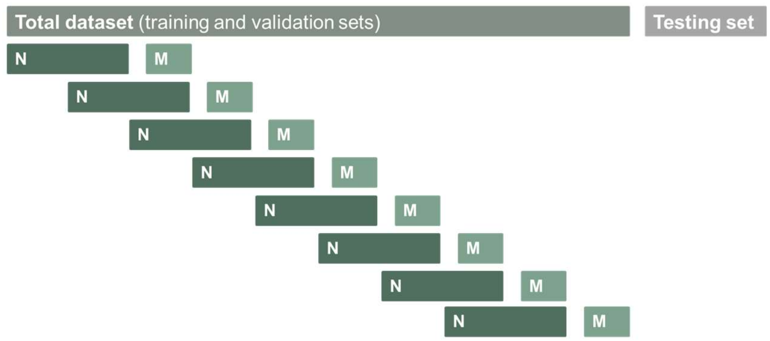

Figure 25. **Architecture of RNNs**

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.

The model is developed using the software Spyder, a Python 3.7 based environment, distributed through Anaconda 1.9.7. Spyder "is a powerful scientific environment written in Python, for Python, and designed by and for scientists, engineers and data analysts. It offers a unique combination of the advanced editing, analysis, debugging, and profiling functionality of a comprehensive development tool with the data exploration, interactive execution and deep inspection" (The Spyder Website Contributors, 2018).

All the tests are performed on an Intel® Core™ i5-4200M CPU @ 2.50GHz processor with the Windows 10 operating system.

Variables selection and data collection

Selecting the appropriate input variables for the problem at hand is a critical step to produce reliable predictions. The analysis considers the available demand records as the only source of data for inputs. ANNs are able to identify complex nonlinear relationships from the past historical demand data, therefore, the considered input is the available demand from January 2018 to March 2019.

If available, other sources of data that drive demand patterns could also be used, such as the spare parts demand records due to the plant's maintenance schedule or even the utilization rate of machines to predict the failure of the specified spare part. Even though the latter might be available, the expected added accuracy of the results by using such data is not expected to offset the added time and cost of collecting and processing it.

As mentioned previously in section 4.4.1, demand data is aggregated in monthly periods to identify demand patterns that would be smoother in case daily or weekly demand patterns were considered.

The data has been retrieved from the company's SAP system in April 2019 and it does not contain missing observations.

Data pre-processing

Data pre-processing supports the network by transforming input data into a representation that is more suitable for the downstream estimators to learn relevant patterns, removing noise and highlighting important relationships.

As mentioned in section 3.3.4.1, in general, learning algorithms benefit from standardization of the data set. Therefore, the model input (available demand from January 2018 to March 2019) has been scaled between zero and one, so that the demand's maximum value for a given period is scaled to unit size and its minimum value for another given period is scaled to zero. This scaling technique allows very small standard deviations of features and to preserve zero entries in sparse data increasing model's robustness. Table 18 samples the transformation of the inputs from item A have suffered with pre-processing, from January to October 2018.

Table 18. **Pre-processing - scaling between zero and unity**

Month/Year	Jan/18	Feb/18	Mar/18	Apr/18	May/18	Jun/18	Jul/18	Aug/18	Sep/18	Oct/18
Demand (Original)	10,0	4,0	12,0	7,0	5,0	6,0	12,0	7,0	9,0	21,0
Demand (Scaled)	0,3529	0,0	0,4705	0,1764	0,0588	0,1176	0,4705	0,1764	0,2941	1,0

Training and testing sets

The size of the training and testing sets can have a substantial effect in the accuracy of the output of the network. According to Gholami, Chau, Fadaee, Torkaman and Ghaffari (2015), the testing set size should range between 10% and 30% of the total dataset size so that the training set is large enough to have the ability to generalize. Table 19 shows the size of each dataset (train and test) depending on the percentage of the testing set range. Moreover, a sensitivity analysis is performed in order to properly estimate the size of the sub-sets for the item under study (figure 26). The performance measure for the analysis is the model's loss function, in this case the mean squared error. This function calculates the difference between predicted and actual values, squares the result, and finally calculates the mean value. At every timestep, the model tries to minimize it.

Table 19. **Splitting the dataset into training and testing sets**

Train/Test Split	67 / 33 (%)	73 / 27 (%)	80 / 20 (%)	87 / 13 (%)
Size of the train dataset	10	11	12	13
Size of the test dataset	5	4	3	2

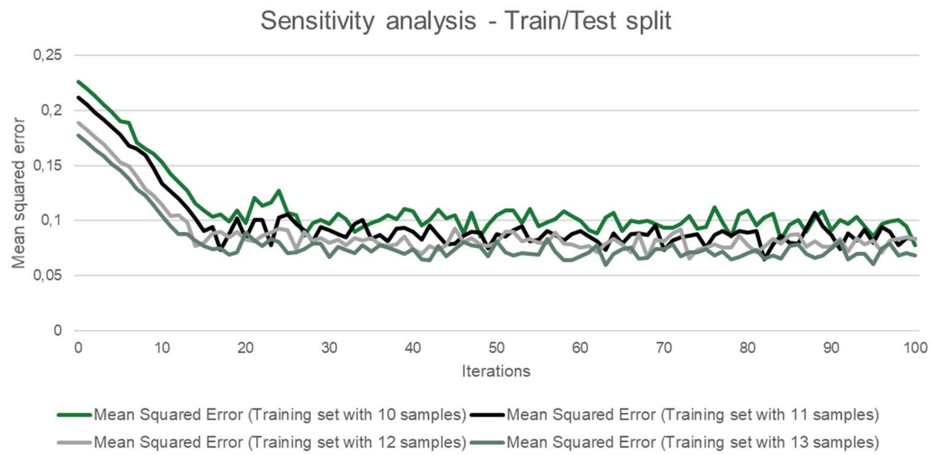

Figure 266. **Train/Test split sensitivity analysis**

Figure 26 shows that:

- Independently of the Train/Test size ratio, the mean squared error stabilizes after 15 iterations;
- The mean squared error decreases consistently as the Train/Test size ratio increases;
- From the total dataset of 15 months Train/Test size ratio with the lowest mean squared error is "Train size = 13; Test size = 2", corresponding to an 87/13 (%) ratio. The mean squared error values range between 0,18 and 0,07 until the 15th iteration and between 0,08 and 0,06 after the 15th iteration.

The ratio "Train size = 13; Test size = 2" is consistent with the testing size being located within the 10% and 30% of the total dataset size. Therefore, it is utilized in the following phases of development of the neural network.

Number of hidden layers and neurons

The hidden layers of a neural network provide its ability to generalize. Mehrotra, Mohan and Ranka (1997) describe this process as a trial and error process and recommend starting it with one hidden layer, increasing the number of layers if necessary. Kaastra and Boyd (1996) refer that a network with simply one hidden layer and a large enough number of neurons theoretically should have the ability to estimate any continuous function. Moreover, the authors indicate ANNs with at maximum two hidden layers are widely used and prove to have satisfactory results.

The number of neurons in each hidden layer is just as important as the number of hidden layers and both variables should be analyzed together when designing a neural network. The same number of neurons are considered for each layer. In order to reach the best scenario possible, 20 scenarios were tested to evaluate the which would provide the most promising results. Table 20 indicates the considered scenarios regarding to the number of hidden layers and neurons. Appendix V-A to Appendix V-E show how the neural network performs based on the previously chosen KPI (mean squared error). The samples are grouped based on the number of hidden layers (Appendix V-A to appendix V-D) as well as on the best performing number of neurons for the different layers (Appendix V-E).

Table 20. **Number of hidden layers and neurons - sensitivity analysis**

Number of hidden layers	1	2	3	4
Number of neurons	10	10	10	10
	20	20	20	20
	30	30	30	30
	40	40	40	40
	50	50	50	50

The different sets of parameters (Appendix V) provides the following conclusions:

- Across the sets with a different number of hidden layers, as the number of neurons increases, the mean squared error stabilizes with a lower number of iterations;
- As the number of hidden layers increases, the difference in the mean squared error in the first iteration decreases;
- Generally, across the sets with a different number of hidden layers, the variability in the mean squared error decreases as the number of neurons increases;
- The set with one hidden layer and 50 neurons outperforms the sets with 2, 3 and 4 hidden layers, independently of the number of neurons, in terms of the average mean squared error as well as of the variability of the same KPI.

The set with the highest performance is thus the one with one hidden layer and 50 neurons. This set has the lowest average mean squared error as well as the lowest variability of the same KPI. The conclusion is in line with the reviewed literature which states that it is recommended that the ANN starts with one or at most two hidden layers since these parameters provide reasonable results with a lower computational effort (section 3.3.4.1).

Number of output neurons

As mentioned by Sheela and Deepa (2013), ANNs with one output generally produce better results than networks with several outputs, since training the network involves testing different sets of weights so that the average error overall output neurons is minimized. The current case study involves the demand prediction for the following month of activity. Therefore, it involves the prediction of one single output parameter.

Activation functions

Sigmoid functions are commonly used in time series forecasting as the activation function since they are nonlinear and continuously differentiable, which are desirable properties for network learning. Other activation functions could be used but often present lower performing results when used for time series forecasting. Consequently, the sigmoid function is used as activation function when compiling the model.

Evaluation criteria

A loss function is required so that the backpropagation property of a network can successfully update its internal parameters to minimize the loss function. As mentioned previously, the chosen loss function or evaluation criteria is the mean squared error. The outputs provided by the network are evaluated based of the loss function, which in turn represents how satisfactory the results are based on historical data. The mean squared error is the recommended evaluation criteria for neural networks.

Number of iterations

The main goal of choosing the number of iterations of a neural network is to find a sufficient number of iterations that provide generalization on the validation set. Therefore, a fixed number of iterations is used so that across all the analysis performed, the resulting patterns could be compared independently from the resulting loss function values. Figures A-E (appendix IV) show that the loss function decreases until 80 iterations for all the considered scenarios. Hence, it is possible to conclude that with the considered number of iterations, the network has developed enough generalization on the validation set.

Training rate adjustment

Neural networks are trained using a gradient descent algorithm, which follows the outline of the error surface by moving down through the steepest slope to minimize the error function. The training rate directly impacts the optimizer by adjusting the weights in the opposite direction of the gradient.

On the one hand, if the considered training rate is low, the neural network will produce more reliable results as long as it does not find any local optimal value. This approach also takes more time to optimize since the steps towards the minimum value are smaller. On the other hand, if the neural network uses a high training rate, it may not converge or it may even diverge.

Figure 27 is a representation of how the neural network is impacted by different values of training rates. It is possible to conclude that for the same number of iterations, the loss improves steadily and slowly using a training rate of 0,00001 until 0,01. The considered KPI is the result of the average mean squared error of last 10 iterations of the network for the considered training rate. Moreover, for a training rate of 0,01 to 0,1, the mean squared error has the steepest decrease, where it is possible to find the absolute minimum of the function. From a training rate of 0,2 and higher, the performance measure increases until it reaches a convergence point, indicating that the optimizer skips the minimum of the function.

Figure 277. **Training rate sensitivity analysis**

Solution implementation and parameter tuning aggregation

After analyzing how parameter tuning directly affects the outcomes of the network, it is possible to configure an ANN to fit the constraints of the considered product. Therefore, based on the previously considered steps, table 21 summarizes the solution's parameters that provided the best performing neural network. Appendixes VI to VII VIII report the parameter tuning for items B and C.

Table 21. **Tuned parameters for item A**

Resulting tuned parameters (item A)					
Parameters	**Variables and collection**	**Pre-processing**	**Train/Test Split (%)**	**Number of hidden layers**	**Number of neurons**
Value	Demand records from January 2018 to March 2019	Unit Scaling	87 / 13	1	50
Parameters	**Number of output neurons**	**Activation function**	**Evaluation Criteria**	**Number of iterations**	**Training rate**
Value	1	Sigmoid	MSE	80	0,09

Empirical results

In this section the results of each ANN under the test set are presented. 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. Figures 24-26 show both the real and predicted demands resulting from the neural networks.

The predicted demand for item A has the same value of the real demand (4 units) in February 2019 (figure 28). 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 27 for all the considered products.

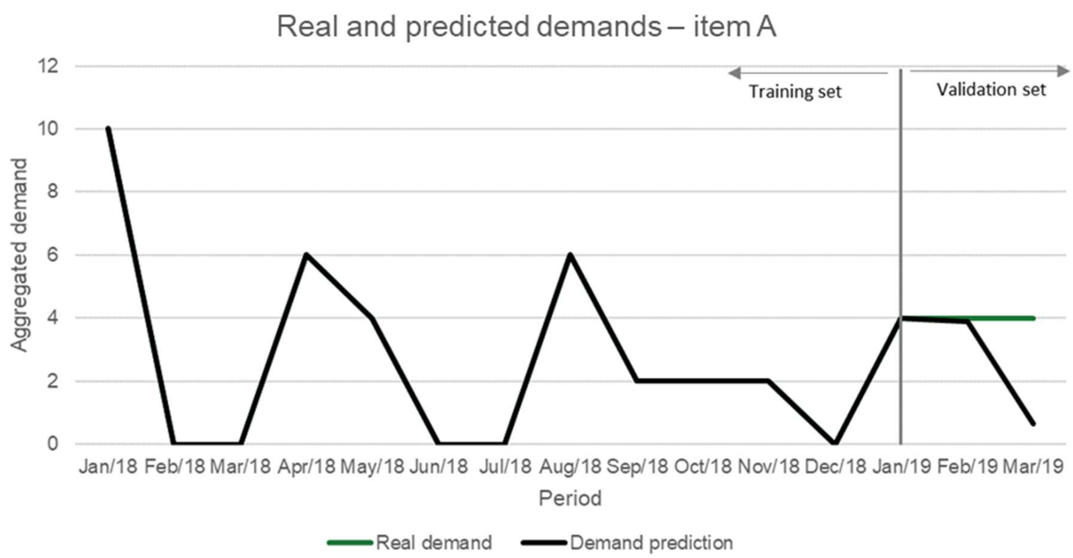

Figure 28. **Real and predicted demands - item A**

Figure 29 represents the real and predicted demands for item B. In this case, the algorithm performed reasonably well, 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.

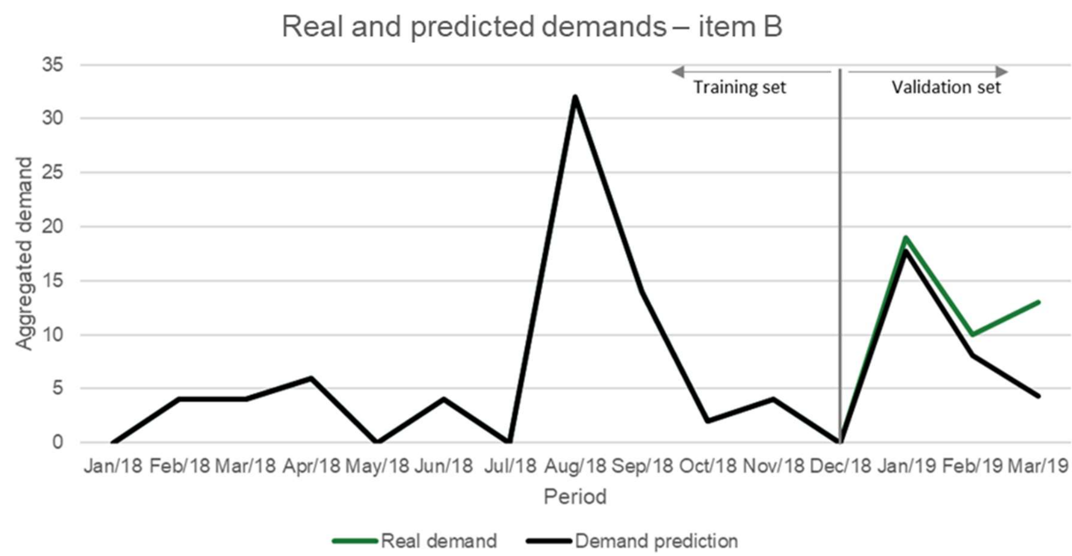

Figure 29. **Real and predicted demands - item B**

Finally, figure 30 plots both the real and predicted demands of item C. Although the algorithm has performed fairly well in predicting the rising and declining demand trends for January and February 2019 respectively, 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.

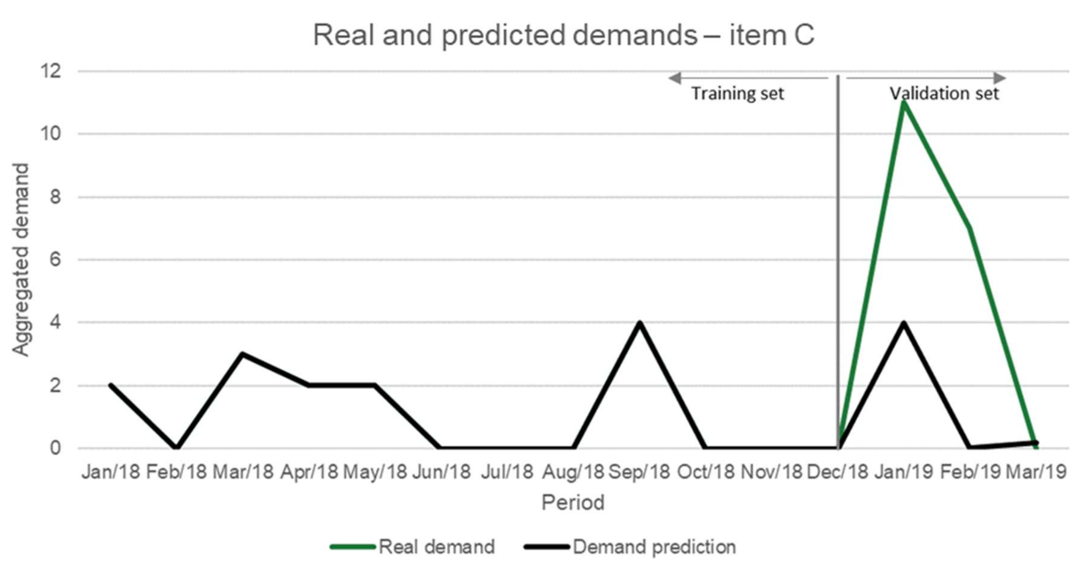

Figure 30. **Real and predicted demands - item C**

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.

Setting the ordering point to one month and assuming that the level of stock available at the plant in January 2019 is the real stock level at that point in time, table 24 allows to evaluate how the stock level would be affected if the neural network's predictions were considered. The value presented for the predicted demand is rounded to the highest integer value.

Table 22. **Stock level considering ANN's predictions**

	Real demand			Predicted demand			Real stock level			Stock level based on predictions		
Item	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**	**A**	**B**	**C**
January 2019	-	19	11	-	18	4	-	26	19	-	27	26
February 2019	4	10	7	4	9	0	92	16	12	92	18	26
March 2019	4	13	0	1	5	0	88	3	12	91	13	26
Average of the period	4	14	6	2,5	10,(6)	1,(3)	90	15	14,(3)	91,5	19,(3)	26

Table 24 shows that the average predicted demand is lower than the real demand for the considered periods for the three items. As a consequence, 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. 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.

Using the same approach of section 5.1.1.2. - MRP ZV parameters determination - the minimum stock (s), order quantity (Q*) and safety stock (Q_{safety}) are determined for items A, B and C. The same service level of 95% is considered for the items. Table 25 summarizes the obtained average demand and standard deviations during the supply period or the considered products.

Table 23. **Average demand and standard deviation during the supply period**

Reference	μ_D (units/month)	σ_D (units/month)	μ_L (months)	σ_L (months)	μ_{DL} (units)	σ_{DL} (units)
A	2,77	2,99	0,83	0,20	2,30	2,78
B	5,83	8,73	0,78	0,32	4,55	7,93
C	1,08	1,38	0,22	0,37	0,24	0,76

Considering the same costs of maintaining a product in the warehouse and of processing an order as in section 5.1.1.2. – MRP ZV parameters determination – a sensitivity analysis is performed to demonstrate the effects the variables have in the optimal order quantity for items A, B and C.

Table 24. **Optimal order quantity sensitivity analysis**

Scenario Q* (units)	C_a=€0,50 I=3%	C_a=€0,50 I=5%	C_a=€0,50 I=7%	C_a=€1 I=3%	C_a=€1 I=5%	C_a=€1 I=7%	C_a=€2 I=3%	C_a=€2 I=5%	C_a=€2 I=7%
A	7	6	5	2	2	2	3	3	3
B	1	1	1	1	1	1	1	1	1
C	6	4	4	1	1	1	1	1	1

In the worst-case scenario (C_a = €0,50; I = 3%) the recommended order quantity is 7 units for item A, 1 unit for item B and 6 units for item C. The minimum stock currently defined for the items is respectively, 12, 20 and 6 units. According to the calculations for a service level of 95%, these values should be equal to, respectively, 7, 18 and 2 units.

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. Table 26 presents the results of both methodologies, under a test scenario where only the safety stock would be available at the company in the beginning of considered period, and the demand for the remaining periods is the real demand. 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 19.

$$Stock\ out\ cost/product/month = \frac{79\ 800\ 000}{12 \times 48} = 138\ 542\ € \qquad (19)$$

Table 27 supports the conclusion that the methodology with the lowest cost for the given test is the MRP ZV model. 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 19. The inventory holding cost for each product is determined using the values retrieved from table 26 and added to the stock out cost, giving the total cost per product. 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 (where a missing part immediately symbolizes stopping a production line), 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.

Table 25. **The effect of ANNs and MRP ZV on Total cost/method**

	Real demand			Test scenario stock level with replenishment based on ANNs			Test scenario stock level with replenishment based on the MRP ZV model		
Item	**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	692 710,00	0	0	692 710,00
Inventory holding cost (€)	-	-	-	4,50	14,00	1,00	8,50	16,50	4,50
Total Cost / product (€)	-	-	-	4,50	554 182,00	692 711,00	8,50	16,50	692 714,50
Total Cost / method (€)		-			**1 246 897,50**			**692 739,00**	

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.

To assure the control of the warehouse operations, a control plan is introduced, in order to present strategic actions to ensure the continuous improvement of the warehouse operations. Table 28 represents the control plan.

Table 26. **Control plan for the project**

KPI	How	Who	Frequency	Revision	Action Plan
% of items without demand	Control the number of items without demand present in the warehouse	Warehouse manager	Every six months	Yearly	List of products to consider for exclusion from the warehouse
Total stock value (€)	Decrease the total amount of stock present in the warehouse by reviewing the MRP ZV policy	Warehouse manager	Monthly	Every six months	Reduce the total amount of stock present in the warehouse
% of items present in SAP	Increase the uniqueness of the items present in the SAP system	Warehouse manager and Logistics manager	Every six months	Yearly	Increase the effectiveness and efficiency of stock control
% of items present in Schaeffler Group's European Spare parts warehouse	Increase the percentage of products that have an intermittent demand in the Group's centralized spare parts system	Warehouse manager and Logistics manager	Every six months	Yearly	Decrease the total amount of items present in the Group's plants, by centralizing the available items

5.3 – Chapter Considerations

Chapter 5 discusses and validates the results obtained following the proposed methodology of the dissertation, presented in the previous chapter. A stock management policy is proposed for each group of products based on the segregation made in the Analyzing Stage: (s, Q*) review and forecasting based on ANNs is also considered.

During the Implementing Stage of the chapter, products with a smooth and intermittent demand are analyzed according to a (s, Q*) review policy. Following the analysis of these products, it is observable that the products' stock displays major deviations regarding the suggested and current level of stock.

Moreover, products with an erratic and lumpy demand pattern are analyzed using an ANN. As the dissertations aims at solving a problem inserted in a real-world context, restrictions on data availability presented an inherent issue that translated into high uncertainty results from the network. Therefore, the latter proved to be unreliable, and an (s, Q*) policy is presented for the items under the scope of the analysis. Nonetheless, the application of ANNs in future reviews of the warehouse stock management policy is recommended as long as a robust set of data is available.

Finally, a control plan is presented in order to advise the management team on strategic actions to the continuous improvement of the warehouse operations, namely regarding the frequency of the reviews to the warehouse stock management policy.

6. Final remarks and future work

Warehousing is a fundamental activity within the supply chain management. This activity is responsible for managing intermediary stocks along the supply chain providing the means for a high service level by stabilizing variability along the chain caused by elements such as seasonality of demand. Automotive suppliers, such as Schaeffler Portugal, aim to reduce costs, enhance productivity and quality as well as increase operations flexibility. In this context, the present dissertation is developed in collaboration with Schaeffler Portugal in order to evaluate the current policy being adopted by the non-production warehouse of the company 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.

In the present dissertation, a characterization and analysis of the problem and its context are firstly presented in chapter 1, providing relevant information regarding key figures in the industry and its importance in the economic activity. From the characterization, it is possible to establish that the policies followed by warehouse management have an impact in the overall costs of manufacturing companies and should be rationalized accordingly.

Within this context, the Schaeffler Group and Schaeffler Portugal's operations are studied to further detail. The operations of the non-production warehouse of the company are the main focus of the present dissertation, namely regarding the definition of suitable re-order quantities for the critical products as well as defining suitable safety stocks for same products.

In order to support the development of a stock management policy, a literature review regarding warehouse and inventory management, as well as forecasting methods is conducted. From this review, it is possible to conclude that spare parts inventory management policies present more challenges when compared to regular inventory management policies, mainly due to the high demand uncertainty of these products. Artificial Neural Networks is a tool that has proven to have relevant positive impact in predicting the behavior of the demand of these products.

Supported by the literature review, a stock management policy is presented through the DMAIC methodology. This methodology is firstly 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 chapter.

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 to 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. A control plan is finally presented to advise the warehouse management team on future review policies in order to continuously improve the warehouse operations.

For future development of the subject studied along the dissertation, five improvement and analysis opportunities are identified that should considered.

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 parameter that depends on multiples factors. If explored correctly, the factors could provide meaningful insights which can lead to understand how spare parts demand is impacted by the different factors within an industrial environment.
Thirdly, to provide better cost estimates on all the scenarios real stock out and holding costs of the materials managed by the warehouse should be explored.
Fourthly, the impacts of developing a policy for the group of products without any demand record as well as the group of products with a single demand record could be analyzed since they represent a high volume of products in the studied warehouse.
Fifthly, on a final remark, the available data from Schaeffler Portugal non-production warehouse is still currently limited. It is strongly advised to make a greater effort in collecting real operational data, so that the defined policies can represent the reality as closely as possible.

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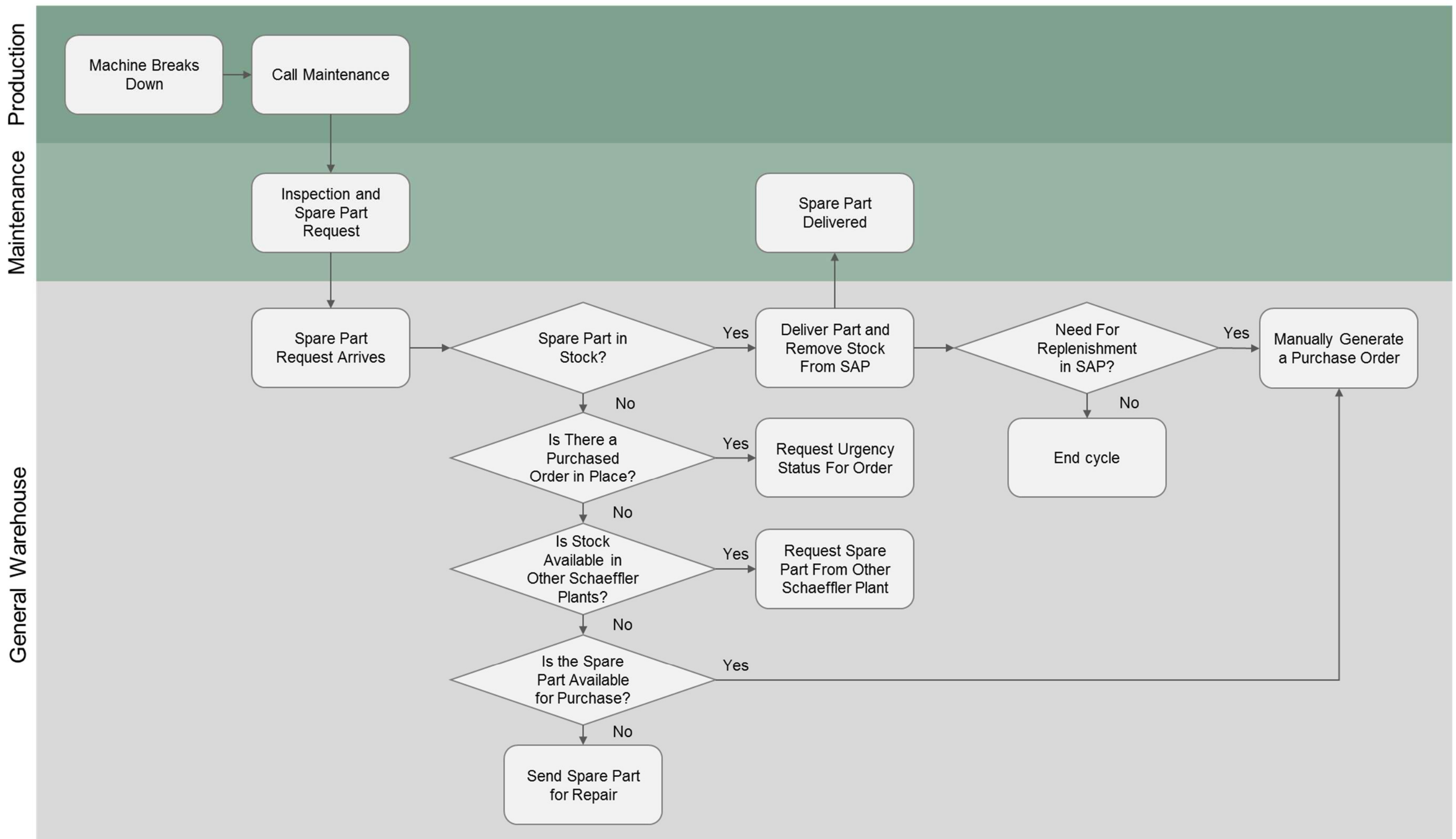
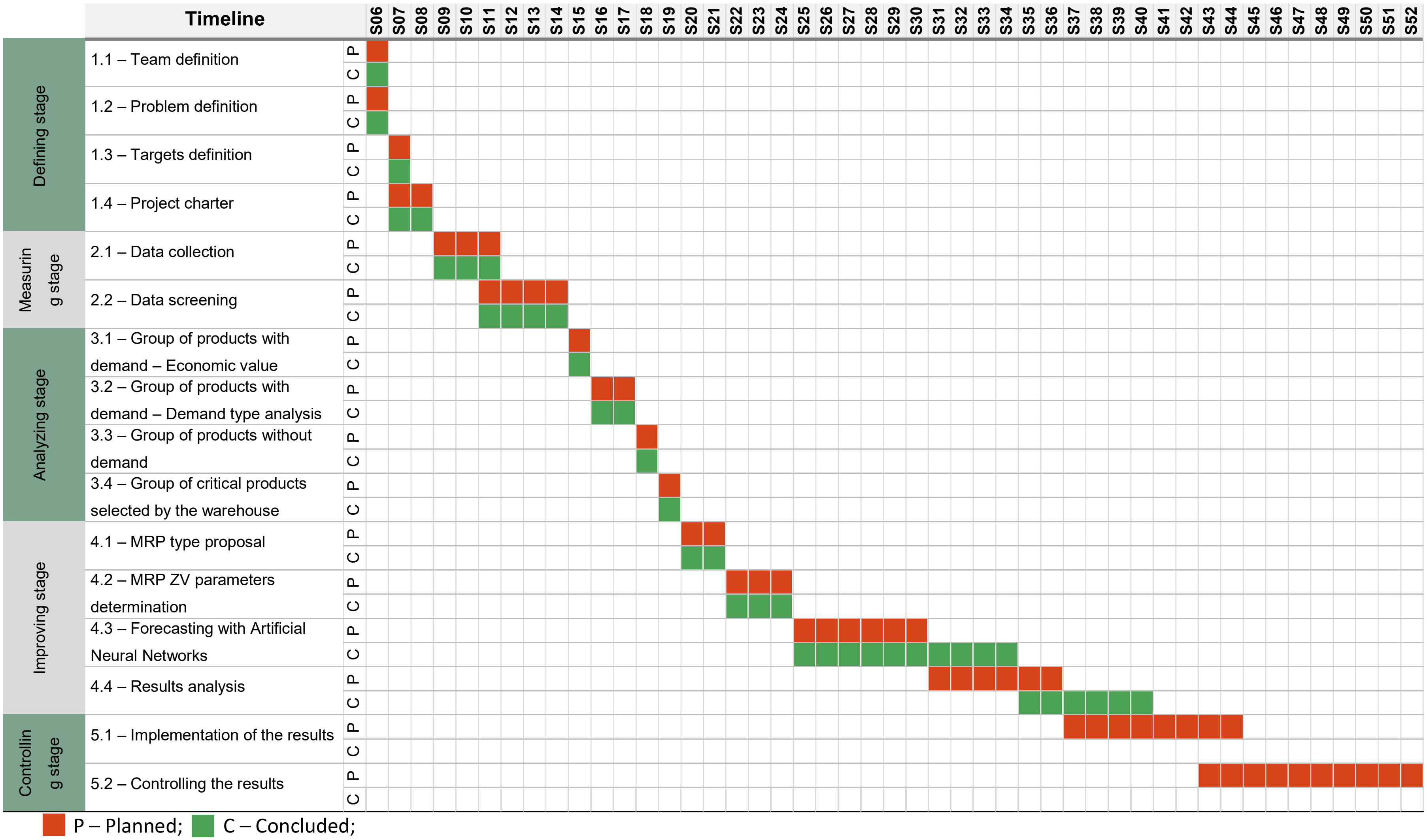
Appendix I – Problem Tree



Appendix II – Literature Review Synthesis

Paper	Warehouse Management	Inventory Management	Forecasting Methods	Methodology	Dimensions	Real-World Application
(Gu, Goetschalckx, & McGinnis, 2010)	●			Systematic framework;	Design, operations and performance measures;	
(Baker & Canessa, 2009)	●			Systematic framework;	Design and operations;	
(Roodbergen & Vis, 2006)	●			Analytic model with scenario analysis;	Layout;	
(Van Den Berg, 1999)	●			Literature survey;	Planning and control of operations;	
(II, 2000)	●			Policies evaluation;	Operations (picking policies);	
(Silver, Pyke, & Peterson, 1998)		●		Descriptive models;	Inventory management policies;	
(Wahba, Galal, & El-Kilany, 2012)		●	●	Systematic framework; Multi-criteria analysis for classification;	Inventory management; Intermittent demand; Demand forecasting;	
(Lengu, Syntetos, & Babai, 2014)		●		Empirical Investigation;	Spare parts inventory management (demand classification);	●
(Syntetos, Boylan, & Croston, 2005)		●	●	Statistical model;	Demand classification;	●
(Kaastra & Boyd, 1996)			●	Design guide;	Neural network design;	

Appendix III – Project Timeline



Appendix IV – Project Charter

SCHAEFFLER

Project Charter

Project-ID	XXXX	Project title	Reconfiguration of the non-production warehouse stock management policy

Business Case/As-is Situation, Problems, Task	
Business Case/As-is Situation:	Undefined re-ordering points of all the products in the non-production warehouse; Manual acceptance of all the orders by the non-production warehouse manager; Undefined optimum re-order quantity; Undefined safety stock; Undefined arrival time for the products in the non-production warehouse; Undefined keeping costs of materials in the non-production warehouse; Undefined out-of-stock costs.
Problems:	Undefined ordering policy of all the non-production warehouse products; High / Low stocks of critical materials.
Task:	Identify the critical items in the non-production warehouse; Define an ordering policy for each of the critical products of the non-production warehouse; Define an implementation plan for automatically generated orders in SAP for the high rotativity, low variability items.

Project Scope	
Within the project scope:	Critical Products of the non-production warehouse; Warehouse management; Intermittent demand of products; High inventory costs; Improvement of ordering process; Stock demand patterns analysis, MRP type proposals and forecasting through the application of an artificial neural network algorithm;
Outside the project scope:	Other Products from the non-production warehouse; Raw materials, components and finished products warehouses of Schaeffler Portugal;

Benefit, Targets, Measurement Parameters	
Benefit:	Increase the effectiveness of parts ordering; Increase the organizational workflow of the warehouse.
Targets:	5% stock value reduction for the non-production warehouse.
Measurement Parameters:	Total stock value in the non-production warehouse.

Team

Logistics management;
Maintenance management;
MOVE Trainer;
Warehouse management;
Project Manager;
Warehouse Workers.

Project Budget

Invest. needed: ☐ Yes ☑ No

Amount of invest.:

Prim. [T€]	Sekun.[T€]
Total Σ:	0 T€
Proj.budget	Select here

Approval (Signatures, Date)

Project Sponsor	Project Manager (Name - PersNo)

Appendix IV – Artificial neural network – Number of hidden layers and neurons sensitivity analysis for item A

Figure A - ANNs with 1 hidden layer

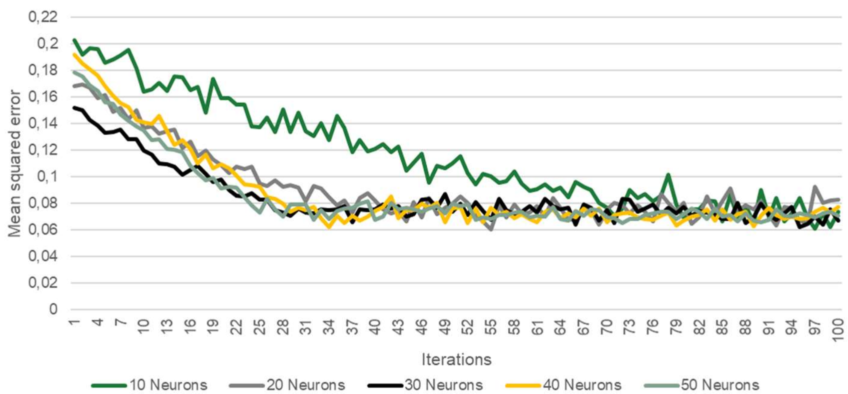


Figure B - ANNs with 2 hidden layers

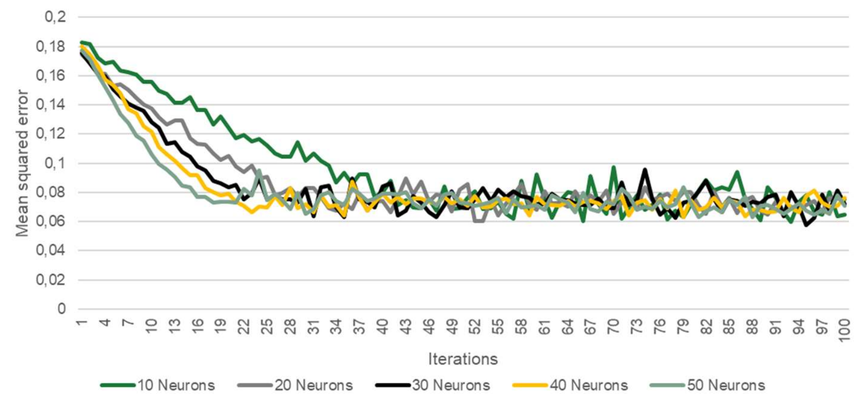


Figure C - ANNs with 3 hidden layers

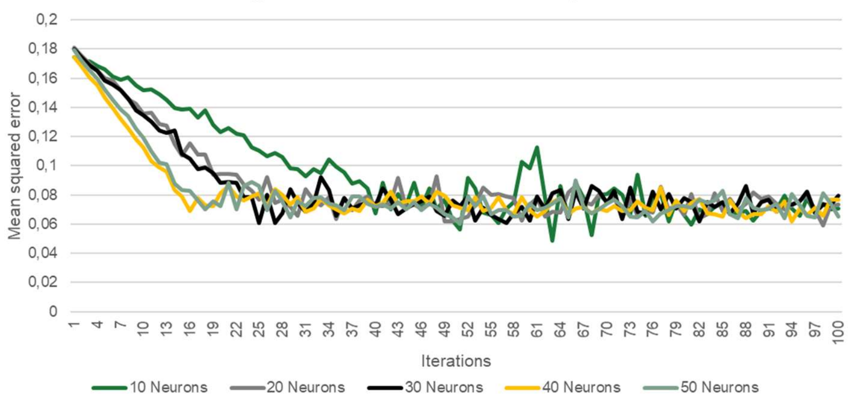
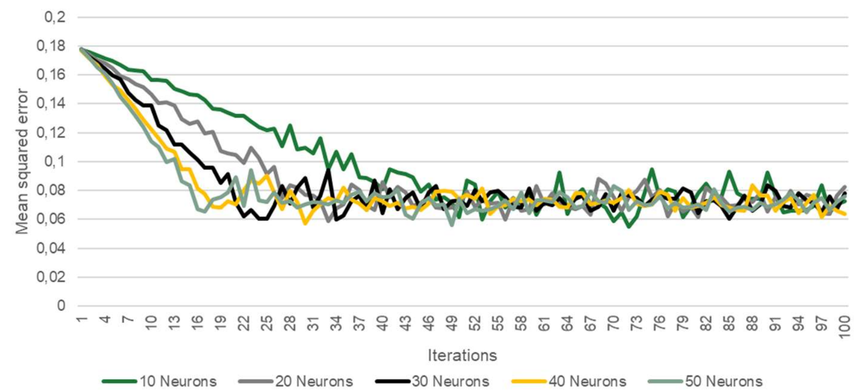
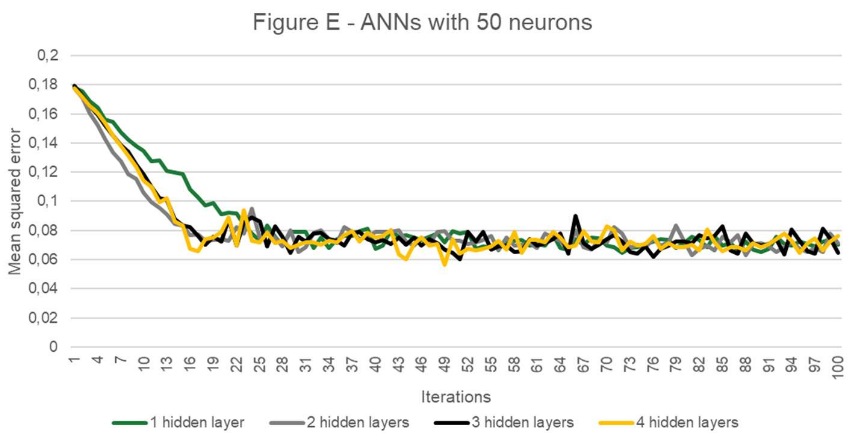


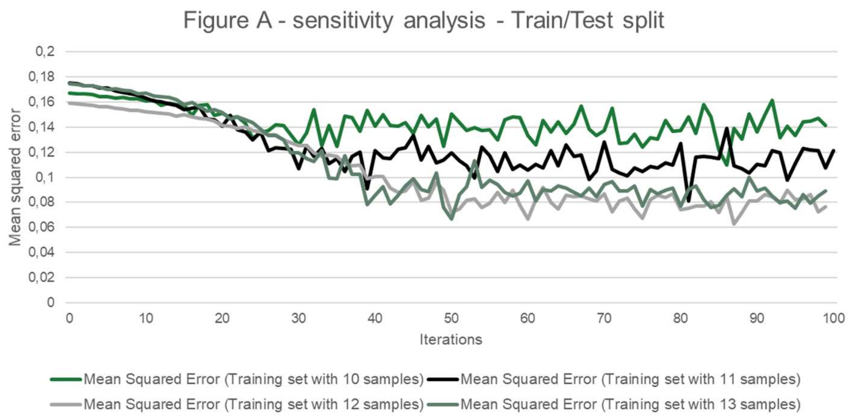
Figure D - ANNs with 4 hidden layers

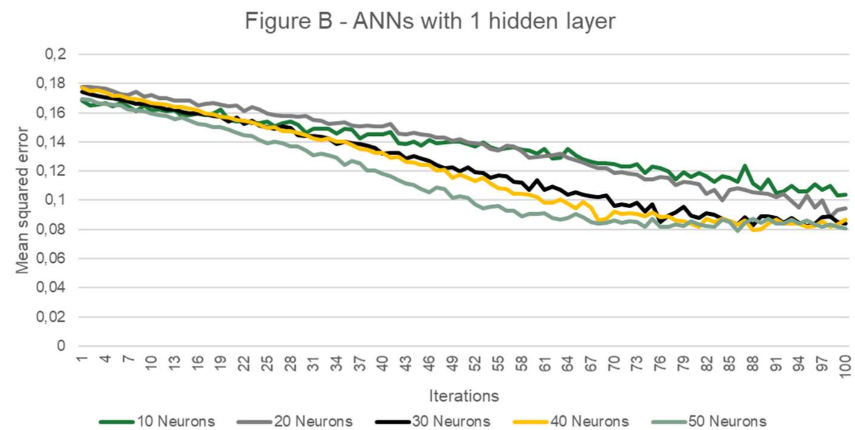


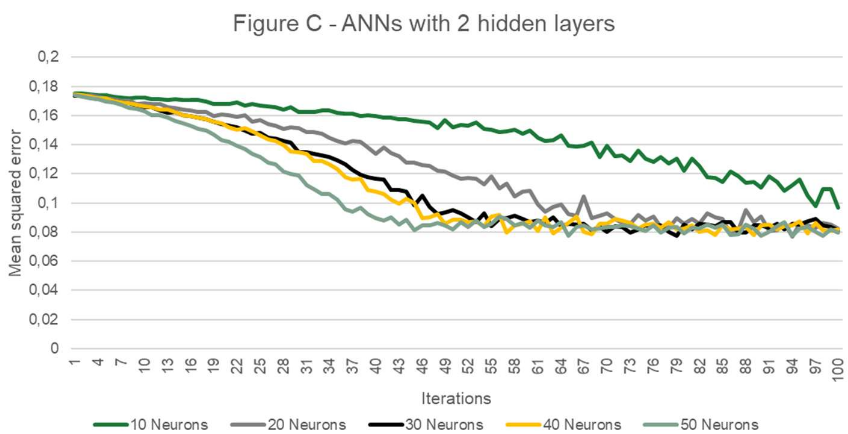
Appendix IV (continued) – Artificial neural network – Number of hidden layers and neurons sensitivity analysis for item A

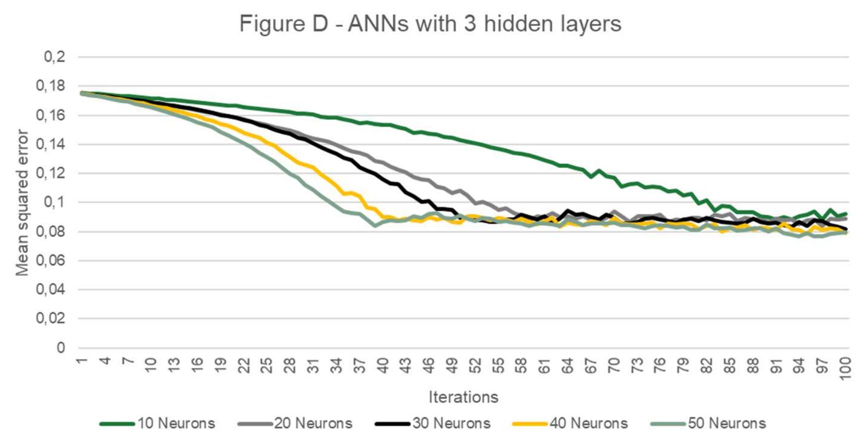


Appendix VI – Artificial neural network – Train/Test split, Number of hidden layers and neurons and training rate sensitivity analysis for item B









Appendix VI (continued) – Artificial neural network – Train/Test split, Number of hidden layers and neurons and training rate sensitivity analysis for item B

Figure E - ANNs with 4 hidden layers

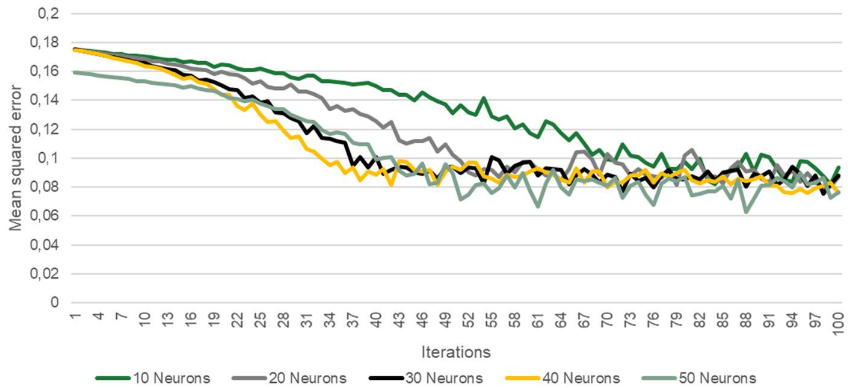


Figure F - ANNs with 50 neurons

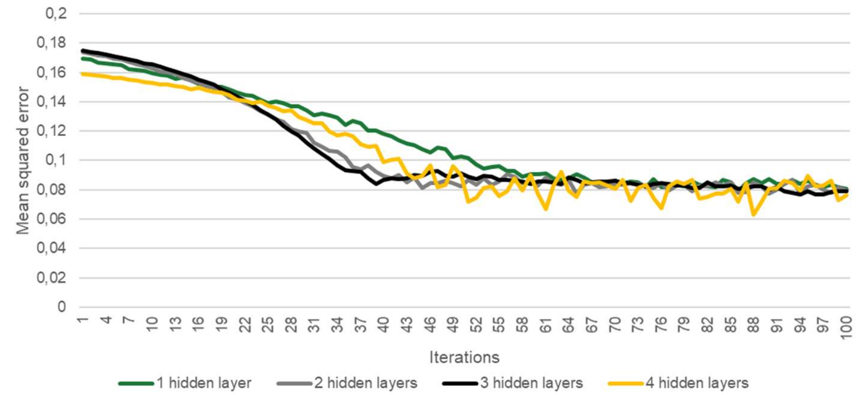
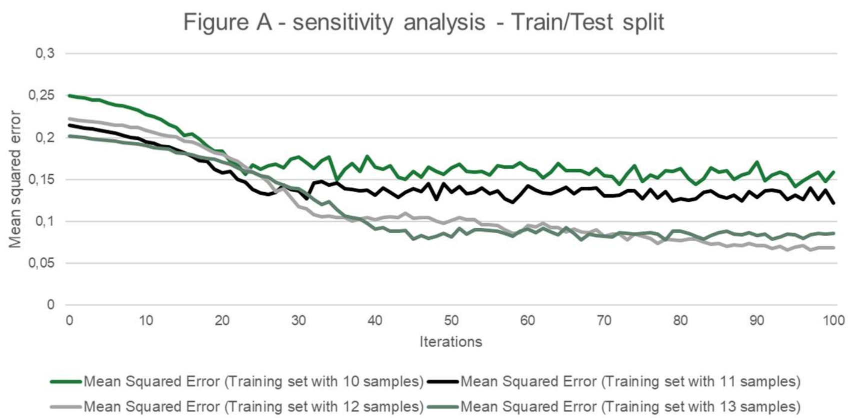
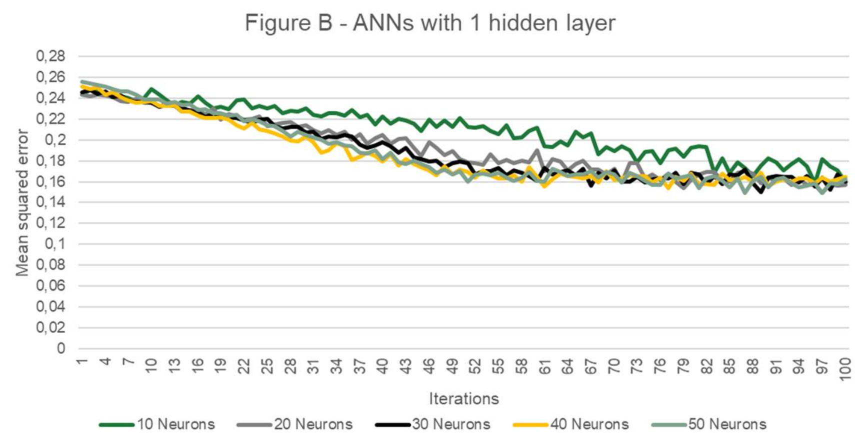
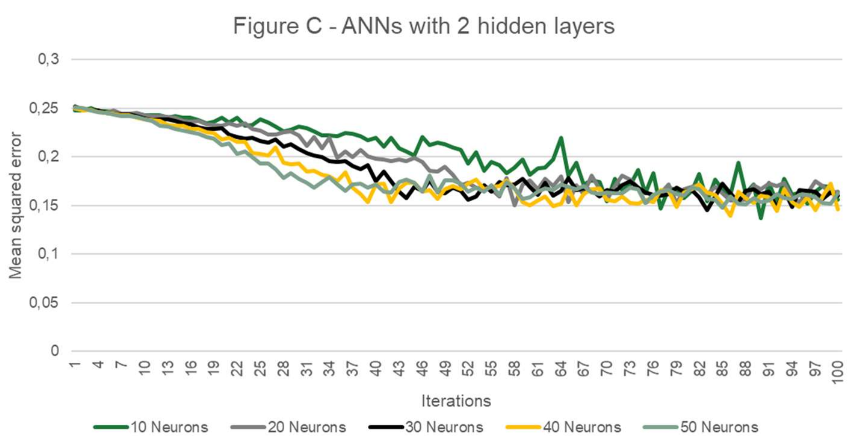


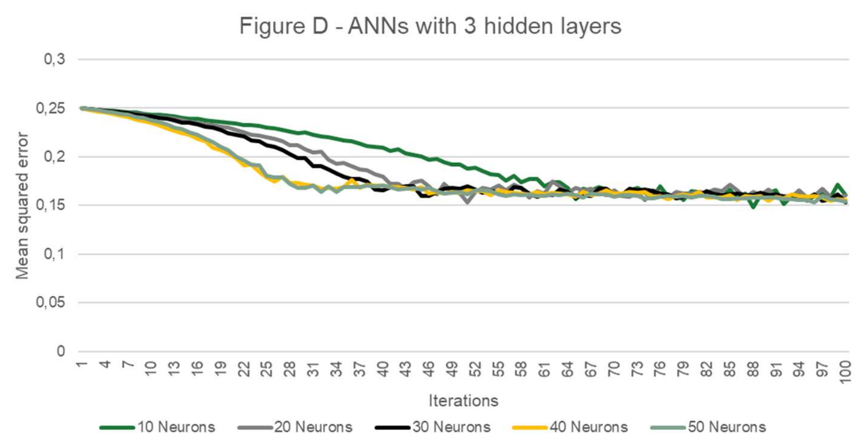
Figure G - Optimal training rate estimation

Appendix VII – Artificial neural network – Train/Test split, Number of hidden layers and neurons and training rate sensitivity analysis for item C

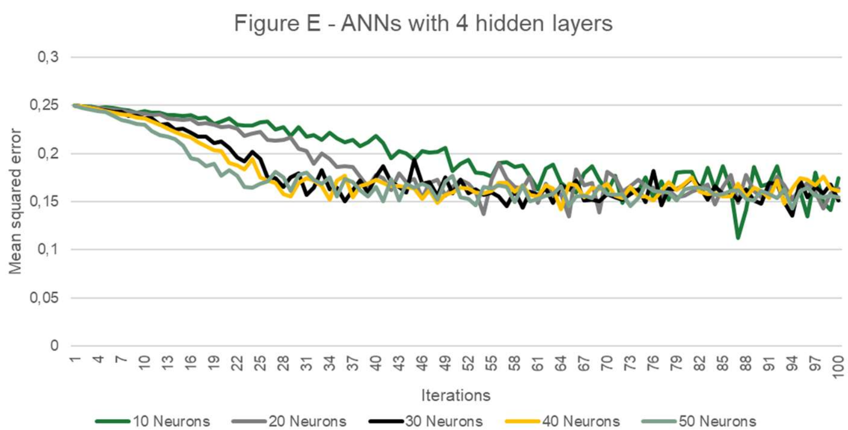


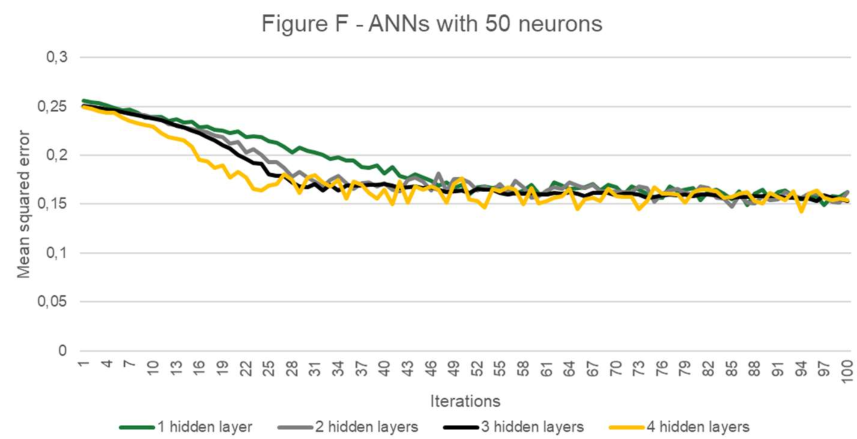


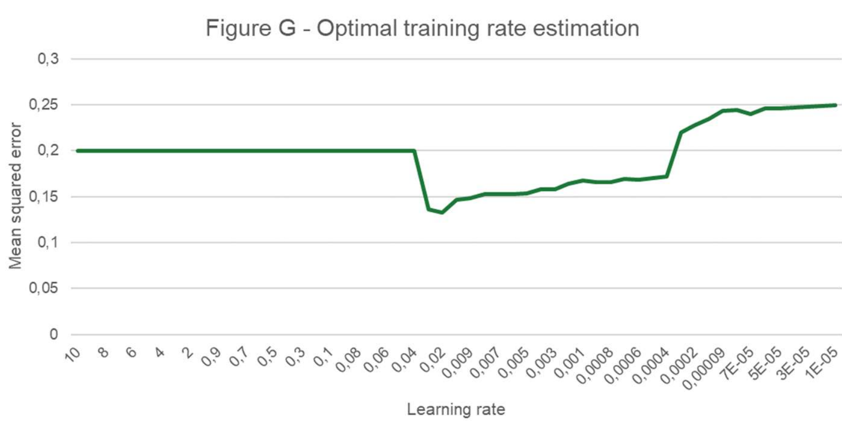




Appendix VII (continued) – Artificial neural network – Train/Test split, Number of hidden layers and neurons and training rate sensitivity analysis for item C







Appendix VIII (continued) – Artificial neural network – Resulting tuned parameters for items B and C

Tuned parameters for item B

Resulting tuned parameters (item B)					
Parameters	**Variables and collection**	**Pre-processing**	**Train/Test Split (%)**	**Number of hidden layers**	**Number of neurons**
Value	Demand records from January 2018 to March 2019	Unit Scaling	80 / 20	3	50
Parameters	**Number of output neurons**	**Activation function**	**Evaluation Criteria**	**Number of iterations**	**Training rate**
Value	1	Sigmoid	MSE	70	0,07

Tuned parameters for item C

Resulting tuned parameters (item C)					
Parameters	**Variables and collection**	**Pre-processing**	**Train/Test Split (%)**	**Number of hidden layers**	**Number of neurons**
Value	Demand records from January 2018 to March 2019	Unit Scaling	80 / 20	3	40
Parameters	**Number of output neurons**	**Activation function**	**Evaluation Criteria**	**Number of iterations**	**Training rate**
Value	1	Sigmoid	MSE	50	0,02