Application of predictive maintenance in an agricultural tire manufacturing plant

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To my parents and brother

Abstract

Continental AG has decided to expand their Rubber Division product portfolio by resuming production of agricultural tires. With that purpose, a serious investment was made in their Lousado plant, Continental Mabor, to create a new facility, with new technology, to host the new production line for these tires.

In order to minimize the associated maintenance costs for the new machines and to maximize their uptime and useful life, a proper maintenance plan must be developed. Prior to this work, only preventive (time-based) maintenance operations took place at this new facility, and no condition monitoring through sensors or frequent measurements was being performed. This work provides a predictive maintenance plan to be implemented in these new machines, with the aim of increasing the proportion of planned maintenance activities and their standardization, with the ultimate objective of reducing, in the long run, the number of failures and their severity.

The first step was to find what failures were happening and their causes. This analysis was conducted with the aid of existing breakdown reports and of the maintenance personnel. Then, the maintenance actions and measurements that could be performed to mitigate those failures and their causes were idealized, as well as the recommended tool to execute them, if it was the case. The frequency of execution of the actions was then estimated using reliability analysis tools such as the Weibull distribution (in case of a non-constant failure rate) or simple linear regression (in case of a constant failure rate), based on the failure data and frequency provided by the breakdown reports, which allowed the estimation of the MTBF for each machine subassembly considered. An automatic monthly plan generator was developed using VBA based on the estimated execution periodicities, providing a useful aid for the engineering maintenance coordination team.

The developed plan however, did not follow a pure condition-based maintenance approach, due to the lack of existing data on machine condition. Therefore, in order to complement the analysis and to demonstrate the approach's potentialities, data from a critical parameter for one selected machine's condition was gathered. To study the evolution of that parameter throughout time a condition-based model using a discrete time Markov chain was developed. Alternative condition-based policies with different preventive maintenance thresholds were simulated using the Monte Carlo simulation technique and compared with other policies, such as time-based and failure-based, based on their failure and maintenance costs. A sensitivity analysis to some of the underlying assumptions of the idealized model was performed to test the obtained optimal solution's robustness and viability. One other parameter from a different machine was studied, with the aim of identifying its good condition values and define alarm and stoppage criteria for each tire measure and machine combination.

The conducted work's results should reflect more in the long run than in the short run, as predictive maintenance plans need some time to mature and really embed in the organizational culture and people's way of thinking. Despite that, even in the short run the obtained results look encouraging: the maintenance maturity has increased in most of the machines, like expected, reaching beyond the desired target levels and looking balanced between each other; the MTBF's have increased in the majority of the plant's machines, meaning less frequent failures; and the MTTR's have generally decreased, meaning the failures witnessed are less severe. In addition, it is shown that effective condition-based policies implementation can result in significant cost savings through both downtime reduction and repairing costs lowering.

Future work suggestions comprise the adjustment of periodicities according to accumulated experience, a viability study about the presence of a dedicated predictive maintenance team, the review of time-based preventive maintenance checklists and the implementation of sensors that allow the knowledge of a machine's state at any moment.

Resumo

A Continental AG decidiu expandir o seu portfolio de produtos da sua *Rubber Division* ao retomar a produção de pneus agrícolas. Com esse propósito, um sério investimento foi feito na sua fábrica de Lousado, a Continental Mabor, para criar novas instalações, com nova tecnologia, para albergar a sua nova linha de produção para esses pneus.

De forma a minimizar os custos de manutenção associados às novas máquinas e para maximizar o seu tempo disponível e tempo de vida útil, um plano de manutenção apropriado deve ser desenvolvido. Antes deste trabalho, apenas operações de manutenção preventiva (baseadas no tempo) tinham lugar nesta nova fábrica, sem que algum tipo de monitorização da condição através de sensores ou medições frequentes fosse realizado. Este trabalho tenta providenciar um plano de manutenção preditiva para ser implementado nestas novas máquinas, com o objetivo de aumentar a proporção de ações de manutenção planeadas e a sua standardização, com o derradeiro propósito de reduzir, no longo prazo, o número de avarias e a sua severidade.

O primeiro passo foi identificar quais as avarias que estavam a acontecer e o que as estava a causar. Esta análise foi conduzida recorrendo aos relatórios de avarias existentes e ao pessoal responsável pela manutenção. Em seguida, as ações de manutenção e medição que podiam ser realizadas para mitigar a ocorrência de avarias e as suas causas foram idealizadas, bem como as ferramentas recomendadas para a sua execução, se fosse o caso. A frequência de execução dessas ações foi depois estimada usando ferramentas de análise de fiabilidade como a distribuição de Weibull (em caso de taxa de avarias não constante) ou regressão linear simples (no caso da taxa de avarias ser constante), baseado nos dados de avarias e sua frequência obtidos através dos relatórios de avarias, o que permitiu a estimativa do tempo médio entre avarias para cada subconjunto de máquina considerado. Um gerador automático dos planos mensais de manutenção foi também desenvolvido usando VBA, baseado nas periodicidades de execução estimadas, proporcionando uma ajuda útil à equipa de engenharia que coordena a manutenção.

O plano desenvolvido, no entanto, não seguiu uma abordagem puramente baseada na condição, devido à falta de dados sobre a condição das máquinas. Por isso, e de forma a complementar a análise e demonstrar as potencialidades dessa abordagem, dados relativos a um parâmetro crítico da condição de uma máquina selecionada foram recolhidos e um modelo baseado na condição desenvolvido usando cadeias de Markov de tempo discreto, para estudar a evolução desse parâmetro ao longo do tempo. Várias políticas baseadas na condição com diferentes limites para manutenção preventiva foram simuladas usando a técnica de Monte Carlo e comparadas com outras políticas, tais como baseadas no tempo e na falha, considerando os seus custos de falha e manutenção. Uma análise de sensibilidade a alguns dos pressupostos do modelo idealizado foi executada para testar a robustez e viabilidade da solução ótima obtida. Um outro parâmetro de outra máquina foi também estudado, desta vez com o objetivo de identificar os valores para os quais a condição desta era “boa” e definir critérios de alarme e paragem da máquina para cada combinação de medida de pneu e máquina.

É esperado que os resultados do presente trabalho se reflitam mais a longo prazo do que a curto prazo, uma vez que planos de manutenção preditiva como o idealizado requerem algum tempo para maturar e se embeberem na cultura da organização e na forma de pensar das pessoas. Apesar disso, mesmo no curto prazo os resultados obtidos parecem encorajadores: a maturidade da manutenção aumentou na maioria das máquinas, como esperado, ultrapassando os níveis-alvo e apresentando-se balanceada entre todas elas; os tempos médios entre avarias aumentaram em quase todas as máquinas da fábrica, significando uma menor frequência de avarias; os tempos médios de reparação, por seu lado, diminuíram em boa parte das máquinas, significando falhas menos severas. Além disso, demonstra-se que a implementação de políticas de manutenção baseadas na condição eficientes pode resultar em poupanças significativas, através quer da redução de tempos perdidos, quer da diminuição dos custos de reparação.

As perspetivas de trabalho futuro sugeridas compreendem o ajuste das periodicidades consoante a experiência acumulada, o estudo da viabilidade da existência de uma equipa dedicada à manutenção preditiva, a revisão das *checklists* usadas nas ações de manutenção preventiva (baseada no tempo), bem como a implementação de sensores que permitam o conhecimento do estado de uma máquina a qualquer momento.

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Acronyms

PLT – Passenger and Light Trucks tires

CST – Commercial Specialty Tires

RCM – Reliability Centered Maintenance

TPM – Total Productive Maintenance

LCC – Life Cycle Cost

FMECA - Failure Modes Effects and Criticality Analysis

FMEA – Failure Mode Effect Analysis

ICT – Information and Communication Technologies

MTTF – Mean Time To Failure

MTBF – Mean Time Between Failures

MM – Maintenance Maturity

MTTR – Mean Time To Repair

LSE – Least Squares Estimation

MLE – Maximum Likelihood Estimation

CBM – Condition-Based Maintenance

TBM – Time-Based Maintenance

FBM – Failure-Based Maintenance

CM – Corrective Maintenance

PM - Preventive Maintenance

VBA – Visual Basic for Applications

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1 Introduction

Nowadays, and in contrast to what had been an industry-wide general thought for several years, maintenance is no longer regarded as a cause for lost production time. Managers over the years have become more and more aware that effective maintenance plans can contribute to extend their equipment's useful life and prevent it from having critical and extensive breakdowns that can stop an entire production line for long periods. The recognition of maintenance as a potential profit generator (through cost savings), however, is a fairly recent development (Waeyenbergh and Pintelon 2002). Managers have realized they could obtain significant savings both in new equipment and spare parts purchase, and in productivity gains through an increased equipment availability.

Bearing this in mind, and considering also that the automotive industry is one of the most, competitive industries in the world, it is easy to associate that effective maintenance operations and policies give a crucial contribution to success and can create a decisive competitive advantage over the other players in the market.

According to Kroeze (2015), there are three crucial requirements for a tire manufacturer to be successful: rapid development, compressing their development processes to innovate faster and take new concepts to market faster, at lower cost; automated manufacturing, replacing the traditional labor-driven manufacturing, in order to achieve higher levels of operational efficiency and product consistency, while there is a growing need to maximize increasingly scarce human skills; and proactive service and maintenance operations, to ensure that downtime is no longer seen as a necessary evil, but as a phenomenon that can be increasingly engineered out. In the remainder of this chapter, a brief company presentation is introduced, followed by a succinct characterization of the tire market, with a special focus on the agricultural tire market, and a short description of the project.

1.1 Company presentation

This project took place at Continental Mabor, Indústria de Pneus, S.A. (Continental Mabor). This tire manufacturing plant belongs to the worldwide known German tire manufacturer Continental AG.

1.1.1 Continental AG

Continental AG was founded in Hannover, Germany, in 1871, and has been growing steadily ever since. With a workforce totaling more than 240,000 employees worldwide (Continental 2018b), Continental is present in many different markets, although all of them connected to mobility and the automotive industry, ranging from rubber products (tires) to chassis, interior designs, powertrains and safety devices.

This product diversity made it the second largest supplier for the automotive industry, exceeding €40 billion in revenue in 2016, only behind Bosch (Statista 2017). This position was achieved through the corporate strategy of acquisitions, the most notable one being the acquisition of Siemens VDO Automotive AG for €11.4 billion in 2007 (Reuters 2007). In 2008 however, due to difficulties in integrating VDO's business, Continental was targeted by a takeover bid from Schaeffler AG, a ball-bearing company whose size was about a third of Continental's, who still controls just under 50% of Continental AG (Mason 2008). Schaeffler and Continental combined overtook Bosch as the leading vehicle components supplier by 2009, in the meanwhile since then Bosch has regained top position in the market.

In 2016, 7% of Continental's worldwide sales were invested the company's research and development division, which demonstrates its constant pursuit for improvement and how the company wishes to stay as innovative as possible.

Continental AG is divided in two main business groups: the Automotive Group and the Rubber Group. The Automotive Group, on the one hand, has three divisions: Chassis & Safety, Interior and Powertrain. The Rubber Group, on the other hand, has two divisions: Tire Division/Corporate Purchasing (where Continental Mabor inserts itself) and the ContiTech Division. The Automotive Group is the largest business group, accounting for roughly 60% of total sales, even if the largest division in terms of sales is the Tire Division (Figure 1), representing 26% of total sales (Continental 2017).

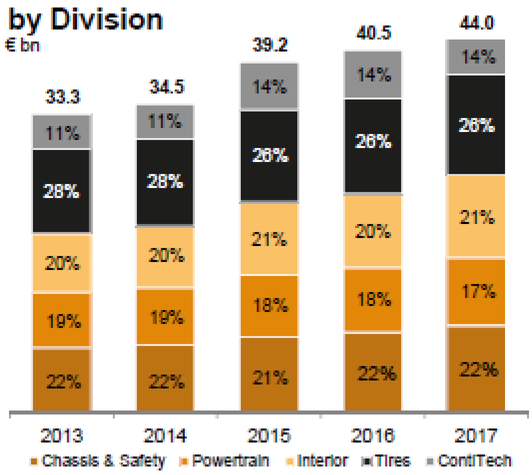

Figure 1 - Continental consolidated sales evolution by division. Source: Continental (2017)

In terms of markets, by observing Figure 2, it can be seen that the main customers are located in Europe, North America and Asia. This is not surprising given that the majority of car manufacturers and their plants are located in these continents. However, increasing globalization happening nowadays may, in the future, redistribute these sales figures in a more levelled way across the globe.

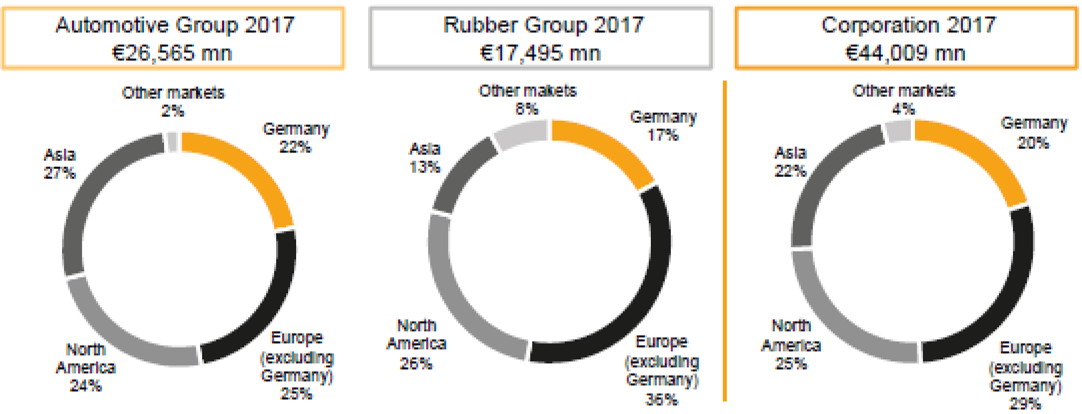

Figure 2 - Sales by market in 2017. Source: Continental (2017)

Continental AG's mission is propelled by four megatrends: promote safety, intelligent mobility through information, protect the environment and promote affordable mobility, enabling freedom and access to all.

1.1.2 Continental Mabor

Continental Mabor was born in December 1989. Its name comes from the union of two renowned companies in the rubber manufacturing sector: Mabor, at a national level, and Continental AG, a world-wide corporation.

In July 1990 the great restructuring program that transformed the former facilities of Mabor into one of the manufacturing units of Continental began. Starting from an average daily throughput of 5,000 tires per day in 1990, a throughput of 21,000 tires per day was achieved in 1996, meaning that production had quadrupled. Nowadays, Continental Mabor has an average production capacity of 57,000 tires per day, presenting itself as one of the plants in the whole group with better productivity indexes (Continental 2018a). It employs over 2,000 people and is the fourth biggest exporting company of Portugal (Cardoso 2018), exporting 98% of their €878 million business volume.

Because of the high quality and productivity reputation Continental Mabor has gained over the years, the facilities have expanded in 2017 to host the production of the new agricultural tire line of Continental AG.

1.2 The tire manufacturing sector

Specifically speaking about the tire market, there are two main revenue generators: the new vehicles market and the replacement market. Continental claim that about a third of all vehicles in Europe are commercialized with Continental tires (Continental 2018a), which demonstrates the confidence car manufacturers have in Continental's tires' quality and performance. As of 2017, Continental was the fourth largest tire manufacturer, only behind Bridgestone, Michelin and Goodyear, totaling $12.6 billion in revenue (Statista 2018).

The tire market has been experiencing a shrink in the last years, especially due to the recent increase of the natural rubber price (Mordor Intelligence 2017), forcing manufacturers to increase their final products' price.

The agricultural tires market, more specifically, is characterized by increasingly sophisticated tire designing. Moreover, with the powerful farm vehicles, the productivity and need for tires with improved traction on a wide range of surfaces are increasing. The company with the highest market share in the global agricultural tires market is Michelin (Mordor Intelligence 2017).

The replacement tire segment is expected to constitute a major market share, due to the inherent efficiency that makes it universally applicable in varied agricultural purposes. Furthermore, one of the biggest challenges the agricultural tire manufacturers face is the exposure to frequent raw material price fluctuations, primarily of steel and rubber. With a raw material intensive industry, the profit margins of the manufacturers are correlated with the raw materials prices, among which natural rubber constitutes around 40 to 45% of the total costs (Mordor Intelligence 2017). This currently is working as an advantage for tire manufacturers, as the prices for natural rubber have been in a decreasing trend since 2011, and stabilized since the beginning of 2018.

Notwithstanding, the Asia Pacific agricultural tire market is growing, due to the agricultural machinery demand, especially in India, since it possesses a large irrigated land area. Whereas owing to the high food demand, Europe and North America hold a combined market share of 60%, which has influenced the agricultural tires market (Mordor Intelligence 2017).

1.3 Brief project description

In 2017, Continental AG decided to resume production of tires for agriculture vehicles, something they had dropped quite a long time ago. To do so, Continental Mabor in Lousado was chosen to host the new production plant, due to their excellence in quality and productivity. $53.78 million were invested on agricultural tires production, increasing Continental AG's portfolio by the next three years and cover about 100 different tire types (Mordor Intelligence 2017).

There were installed several new machines that compose the new production line for the manufacturing of agricultural tires. These machines, although fairly new, still experience several breakdowns due to many needed adjustments and because of the limited knowledge about them and their performance.

This project merged from the need to implement a predictive maintenance plan which was nonexistent at this unit. It took place at Engineering Departments no. 7 and 8, that compose the new CST facility at Continental Mabor. The objectives to be achieved consist in the development of an initial framework over which the engineering departments can work on, and the establishment of the predictive maintenance plan, composed by a set of routine maintenance operations and measurements in the machines, the tools that should be used to perform those operations and the periodicity with which those operations should be executed.

1.4 Document structure

This thesis is divided in four main sections. In Section 2 of this document, a literature review presenting previous works made on the field of maintenance, as well as an introduction to the various types of maintenance according to several authors is presented. In Section 3 the problem and the methodologies used to tackle it are introduced in detail, as well as the initial situation. In Section 4 the proposed solution and plan is discussed and presented, as well as all the relevant steps towards it. A condition-based model used to study the degradation evolution of a parameter is also proposed. In Section 5 the obtained results from the plan implementation and from the condition-based model developed are presented and discussed, and a sensibility analysis on some of the model's assumptions is performed. Finally, in Section 6 conclusions about the project are drawn, as well as suggestions for future work both from the research and the company's perspective.

2 Literature review on maintenance practices

Maintenance can be defined as “the process of preserving a condition or situation or the state of being preserved”, or as “the process of keeping something in good condition” ("Oxford Dictionaries" 2018).

Its importance lies in the fact that it allows the extension of an equipment’s useful life, as well as its availability and, consequently, throughput. Thus, the choice of the maintenance policy can play an active role in the performance of a plant and its equipment.

2.1 Evolution of the maintenance concept

The approach to maintenance has changed dramatically since the implementation of the concept. Up to the decade of 1940, maintenance was considered only as a necessary evil (Waeyenbergh and Pintelon 2002) that provided an unavoidable cost, and the only maintenance that took place was Corrective Maintenance (CM). Whenever an equipment failure occurred, the system was returned to operation. Authors differ about who was responsible for those tasks: Waeyenbergh and Pintelon (2002) claim it was a production task, while Murthy *et al.* (2002) argue that there already existed a specialized maintenance workforce. Maintenance was neither incorporated into the design of the system, nor was the impact of maintenance on system and business performance duly recognized (Murthy *et al.* 2002).

According to Murthy *et al.* (2002), the evolution of operations research, its applications during World War II and subsequent use in industry led to the widespread use of Preventive Maintenance (PM). Since the 1950s, operations research models for maintenance have appeared at an ever-increasing pace. The impact of maintenance actions on the business performance was still not addressed, and Waeyenbergh and Pintelon (2002) describe that at this stage, maintenance was seen as only a technical matter.

In the 1970s, maintenance was not anymore seen as an isolated function, and there were some integration efforts with other functions in the company, as maintenance was now seen as a profit contributor (Waeyenbergh and Pintelon 2002). Some new approaches emerged, such as Reliability Centered Maintenance (RCM), where the connection between reliability and maintenance was recognized. According to Moubray (1991), under the RCM model maintenance is carried out at the component level and the maintenance effort for a component is a function of its reliability. At the same time, the Japanese evolved the Total Productive Maintenance (TPM) in the context of manufacturing, where maintenance is viewed in terms of its impact on the manufacturing through its effect on equipment availability, production rate and output quality (Murthy *et al.* 2002).

Both RCM and TPM are upgrades from the latest operations research models for PM previously described in the way that they view maintenance in the broader business context and consider the link between component failures and their impact on business performance. However, they still have the downside of assuming a nominal operating condition and not considering the load of the equipment. Short-term strategies such as these models need good predictive models to assess the condition of different elements of the network and their residual lives, which requires a good understanding of the degradation mechanism and building models based on this and field data. However, long-term strategies need to take into account issues such as the socio-political and demographic trends and the capital needed, and these models fail to do so (Murthy *et al.* 2002).

The latest trends in maintenance go exactly in this direction. They emphasize the need to cross the factory boundaries and to look for globalization and greater integration with the other functions, especially with production (Waeyenbergh and Pintelon 2002). It is about pursuing optimality in maintenance operations, making the best use possible of the information and communication technologies (ICT) and sensorial data to achieve such goal.

2.2 Developing the maintenance concept

Three important factors can be pointed out as critical success factors of a maintenance concept (Pintelon *et al.* 1997): (1) the production personnel and maintenance workers' knowledge and competence to prevent disruptions at an early stage; (2) management skills regarding planning and control of maintenance tasks as well as Human Resources Management: studies have shown company-wide maintenance knowledge and participation of manufacturing personnel in the planning of maintenance are of major importance (Jonsson 1999); (3) flexibility to exploit opportunities and trends, such as the expanding maintenance services market and the ICT.

Bearing these in mind, Waeyenbergh and Pintelon (2002) propose a general framework for developing a maintenance concept, based on multiple standard concepts widely used in industry, such as RCM or TPM. This framework is divided in five modules of steps.

The first one aims to capture the real objectives of the maintenance plan to be developed, which can be divided into smaller ones, like availability, quality, safety, flexibility or cost.

The second module is where the technical analysis takes part. The Most Important Systems (MIS) are identified according to a set of criteria, like ease of detection, the impact on safety, loss of production or repair cost. These factors can be weighted according to each production line's characteristics and help to prioritize the maintenance actions. The criticality analysis can be done using a table, where failures are evaluated according to possible severity factors, its frequency of occurrence and the repairing costs required, both in material and manpower.

The third module is one of the most important, as is when the actual maintenance policy is chosen and optimized. These maintenance policies can be to keep the component running until it fails (Failure-Based Maintenance), to monitor its functioning using some measurable parameters (Condition-Based Maintenance), or to carry maintenance action after a specific amount of time, assuming that failures are predictable (Time-Based Maintenance). Then, the maintenance policy chosen for each component must be optimized and fine-tuned, to retrieve maximum benefits from it.

Finally, the fourth and fifth modules are related to performance measurement and continuous improvement, acting on the first three modules and make the necessary adjustments to them.

Maintenance policies ultimately divide themselves into two broad categories (see Figure 3): preventive (before failure) and corrective (after failure). In the preventive maintenance category there are mainly two subdivisions, which will be discussed next.

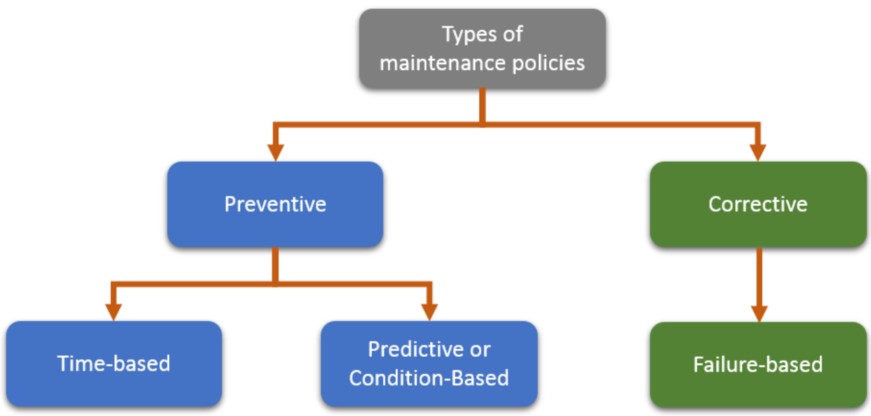

Figure 3 - Types of maintenance policies

2.3 Corrective maintenance

Reactive or corrective maintenance (CM) is the practice of fixing equipment when it breaks down or when performance deteriorates to a point that it is no longer acceptable. This is the traditional approach to maintenance, because it is the most natural — we tend to fix things when they break. That's also why it is the most commonly maintenance policy used (Hemmerdinger 2015). This type of maintenance is also often referred to as unplanned maintenance, even if sometimes incorrectly, as one may plan to only perform corrective maintenance.

In the short term, it seems to cost less, as the cost of maintenance equals only what it takes to repair a broken unit. If nothing breaks, then very little is spent on maintenance. However, these savings are an illusion (Hemmerdinger 2015).

The disadvantages of reactive maintenance are mostly not visible to management, which is why so many facilities continue to use this approach. It results in increased costs due to unplanned downtime, additional costs involved with repair or replacement of equipment, as well as an inefficient use of staff resources, who are always in "firefighting mode" (Hemmerdinger 2015).

Theoretically, this approach might work well when all equipment is new, since a high degree of uptime and sound performance are reasonable expectations early in the equipment's lifecycle (Hemmerdinger 2015). However, as so is happening at Continental Mabor, new equipment needs monitoring and adjusting, and possibly early-intervention maintenance. Failure to provide such maintenance will eventually lead to a premature failure of the equipment and the lifetime cost of the equipment will skyrocket, as replacement parts will always be needed regularly, and its lifetime will be severely reduced (Hemmerdinger 2015).

Also, if it is expected for the equipment to work non-stop for a long period of time, it is well thought to implement a maintenance plan that considers the fact that the equipment's condition will deteriorate in the future right from the beginning, or at least in parallel with a CM team to respond to any unexpected breakdown.

2.4 Preventive maintenance

Preventive maintenance activities (PM) refer to all maintenance actions that are programmed before the breakdown takes place. This does not necessarily mean that these activities only occur when the equipment is up; in fact, some activities may be performed when the equipment is down, for example because of an inability of the CM team to solve the problem or because the breakdown happened too close to a preventive maintenance activity, and so equipment maintenance is postponed until the time of that planned activity.

In the literature, preventive maintenance is often divided in two types: time-based and predictive maintenance, also referred to as condition-based maintenance (CBM).

2.4.1 Time-based maintenance

Time-based maintenance (TBM) relates to regular maintenance operations to maintain equipment in a good state, preventing unplanned downtime and increased costs due to unpredicted equipment failure. It consists in carrying out the operations in machines and equipment before the failure or the breakdown takes place, at previously established fixed time intervals (time-based monitoring or maintenance). The objective of time-based PM is to prevent failures before they happen and therefore to minimize the probability of failure (Ruiz *et al.* 2007), being part of the planned maintenance category. It is normally conducted using a pre-defined checklist, that states all the actions and components that must be verified.

Its biggest difference when compared to CM is that it is performed when the equipment is still up (Caballé *et al.* 2015) and the fact that they take place in pre-scheduled periods, regardless of the actual condition of the equipment.

This maintenance policy has the clear advantages of reducing an equipment’s downtime and the risk of unexpected failures, while increasing its long-run life and reliability. Consequently, it enables to reduce not only the costs associated with direct machine repair and components replacement, but also the costs related to the lack of production during downtime.

However, it still has the disadvantage of not considering the current state of the equipment. For example, if an equipment’s PM operation is scheduled to take place in 3 weeks’ time, even if it remains in a good state after the 3 weeks, it must stop because a PM action has been scheduled. This aspect may not be considered by many as critical, but minding the equipment´s condition into consideration can reduce unnecessary maintenance actions and eliminate the risks associated with preventive maintenance actions (Alaswad and Xiang 2017).

2.4.2 Predictive or condition-based maintenance

Like TBM, a predictive maintenance policy is based on the tenet that a proactive approach is better than a reactive one. However, instead of repairing based on a predetermined schedule, the predictive approach does repairs based on the actual condition of the equipment (Hemmerdinger 2015). Predictive maintenance is introduced as an advanced maintenance technique. It is popularly reported in the literature and its decision-making process relies on the diagnostic/prognostic of the system condition over time (Nguyen *et al.* 2015).

A CBM policy has the advantage of being able to overcome the disadvantages of the “classic” TBM approach. Allows to cut the unnecessary maintenance operations given by too conservative TBM policies and mitigate the risks associated with optimistic ones, by simply monitoring, constantly or periodically, the equipment’s state. On the other hand, it also has the disadvantage of requiring the gathering of large quantities of information through sensors and other measuring devices in the equipment, whose installation and purchase may prove to be costly. However, the obtained availability and productivity gains often overrule the investment made, as an appropriate condition monitoring and maintenance management technologies can greatly increase the efficiency and profitability of industrial production (Zhen *et al.* 2010).

In predictive maintenance, the system state is monitored through perfect inspections. When a fault is detected upon inspection, a CM operation replaces the failed system by a new identical one. However, both the fault and the CM operation can be very expensive because of, e.g., lower efficiency, production losses, security hazards or unplanned intervention. In this context a CBM policy can be profitable to avoid failure occurrence at the lowest cost and to improve the availability and safety of the maintained system (Grall *et al.* 2002b).

Many industries, from automotive to chemical, already use sensorial data to monitor their equipment’s performance and state, and with very good results, as this proactive intervention technique has enabled to reduce downtime close to zero (Kroeze 2015). However, in the tire manufacturing industry, there is still little effort being done on transporting those practices to their manufacturing plants.

The annual cost of maintenance has been reported to go up to 15% for manufacturing companies, 20%–30% for chemical industries (Nguyen *et al.* 2008), and 40% for iron and steel industries (Chu *et al.* 1998). Thus, developing new maintenance technologies and arranging proper maintenance scheduling has become more and more important to enhance production and economic efficiency. Despite this economic factor, the maintenance of equipment always has a major impact on system reliability, availability and security (Zhen *et al.* 2010).

A CBM program should consist of three key steps (Lee *et al.* 2004):

1. Data acquisition (information collecting), to obtain data relevant to system health.
2. Data processing (information handling), to handle and analyze the data or signals collected in step 1 for better understanding and interpretation of the data.
3. Maintenance decision-making (decision-making), to recommend efficient maintenance policies.

2.5 Maintenance performance indicators

The performance and competitiveness of manufacturing companies is dependent on the reliability, availability and productivity of the production facilities. To ensure the plant achieves the desired performance, maintenance managers need a good track of performance on their maintenance processes. Maintenance performance indicators should not be defined separately from other company indicators, but should be the result of a careful analysis of the interaction of the maintenance function with other organizational functions, most evidently with the production function, aligning the maintenance objectives with the manufacturing and corporate objectives. Notwithstanding, the defined indicators should have a certain level of standardization, allowing its company-wide comparison (especially in the case of large multinational corporations).

A few of the most commonly used maintenance performance measurements are: total operation time, total unavailability duration, expected total cost, expected cost per time unit and availability (Zhen *et al.* 2010); maintenance maturity (MM), mean time between failures (MTBF) and mean time to repair (MTTR). Total operation time and total unavailability duration are absolute measures to evaluate equipment performance, but analyzing availability (a relative measure giving the percentage of time the equipment is up compared to its total working time) is often more relevant, especially when comparing machines with different working times. Total cost and total cost per time unit have the aim to quantify and keep track of maintenance expenditures. The latter three were the ones used to assess the proposed plan's performance and therefore will be further explored in Section 3.

2.6 Reliability analysis

Reliability analysis inserts itself in the second of three steps previously introduced: data processing. Reliability analysis is the called term for data analysis which allows, by fitting the failure events to a known distribution, their statistical study and functioning characterization (Jardine *et al.* 2006).

The two most used distributions to fit event data when performing reliability analysis present in literature are the exponential distribution and the Weibull distribution (Das 2008).

The exponential distribution has the advantage to be very easy to understand, implement, and can provide good approximations to machine failure distributions (Diallo *et al.* 2001); (Savsar 2000); (Yazhou *et al.* 1995). However, it has the disadvantage of not being capable to fit to every data series, namely when the failure rate has an increasing or decreasing tendency. For this kind of data, Weibull distribution is used. In reliability work, Weibull distribution has the advantage of being a versatile distribution which is expected to fit many different failure patterns (Ireson *et al.* 1996) by adjusting its distribution parameter values.

Researches have been studying the application of failure distributions to machine reliability analysis (Das 2008). Yazhou *et al.* (1995) studied the probability distribution of machining center failures in 24 cutter-changeable CNC machine tools. To identify the failure distribution, the failure data were fitted to a probability plot taking a linear regressive approach and on a Weibull paper, and then evaluated for goodness-of-fit by correlation analysis. Dai *et al.* (2003) applied type I censored data for machining centers to fit on Weibull distribution, checked by goodness-of-fit test. The Weibull parameters were found by the Maximum Likelihood Method (MLE) method.

Since the exponential distribution can be considered as a special case of the Weibull distribution, (shape $\beta = 1$ and scale $\theta = 1/\lambda$) (Das 2008), Weibull distribution can be used to fit to any kind of machine failure distribution and is next introduced with more detail.

Weibull distribution

The Weibull distribution, named after its inventor, Waloddi Weibull, is widely used in reliability engineering and in other applications due to its versatility and relative simplicity. Its application to define the maintenance periodicities was used in this work. The general expression of the Weibull probability distribution function is given by the three-parameter Weibull distribution expression (2.1):

$$f(T) = \frac{\beta}{\theta}\left(\frac{T-\gamma}{\theta}\right)^{\beta-1} e^{-\left(\frac{T-\gamma}{\theta}\right)^{\beta}} \tag{2.1}$$

where β is the shape parameter, θ is the scale parameter and γ is the location parameter.

Frequently, the location parameter is not used, and the value for this parameter is set to zero. Depending on the values of the parameters, the Weibull distribution can be used to model a variety of life behaviors. An important aspect of the Weibull distribution is how the values of β and θ affect the shape of the *pdf* curve, the reliability and the failure rate.

The value of the Weibull shape parameter, β, has a distinct effect is the failure rate. Weibull distributions with $\beta < 1$ have a failure rate that decreases with time, also known as infantile or early-life failures. Weibull distributions with β close to or equal to 1 have a fairly constant failure rate, indicative of useful life or random failures. Weibull distributions with $\beta > 1$ have a failure rate that increases with time, also known as wear-out failures. These comprise the three sections of the classic "bathtub curve" (Figure 4). On the other hand, a change in the scale parameter, θ, has the same effect on the distribution as a change of the abscissa scale. Increasing the value of θ while holding β constant has the effect of stretching out the *pdf* to the right and decreasing the "peak" of the *pdf* curve (ReliaSoft Corporation 2002).

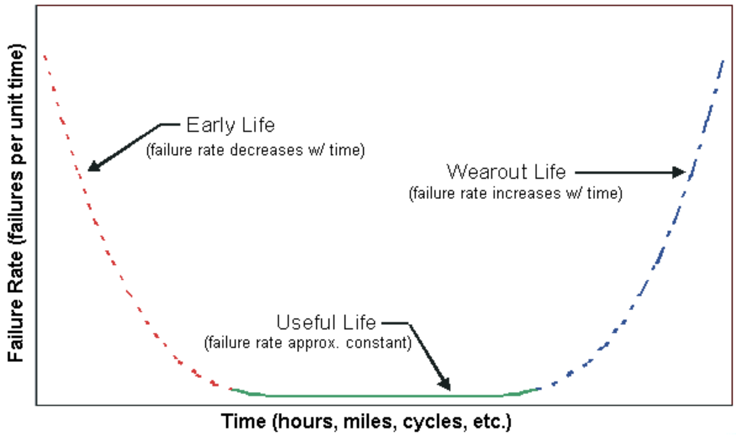

Figure 4 - The bathtub curve. Source: ReliaSoft Corporation (2002)

For these parameters to be useful in any kind of analysis, they must be estimated from the gathered data. Two methods are the most used: Least Squares Estimation (LSE) and Maximum Likelihood Estimation (MLE). The method used in this thesis was the MLE (see Appendix A).

Considering that the machine failure event data can be fitted to a Weibull distribution, machine reliability for machine j can be written as:

$$R_j(t) = exp\left[-\left(\frac{t}{\theta_j}\right)^{\beta_j}\right] \tag{2.2}$$

where t = planned time period for the part under consideration and θ_j and β_j are the scale and shape parameters for machine j, respectively (Das 2008).

The Mean Time to Failure (MTTF) can be considered equal to Mean Time Between Failures (MTBF) for a repairable system when complete samples (failures) are analyzed for the estimation of MTTF (Abernethy 1996). There are a few limitations on using the MTTF as a metric, as it is not time-dependent. However, for enterprises it is a much more easily interpretable and tangible metric than the reliability probability, and enables to satisfy one of this thesis' purposes, which is to determine the maintenance actions' periodicities. If it is considered that failure data corresponds to the equipment's early life and, therefore, to the first part of the bathtub curve (Figure 4), and that from that moment on the equipment will enter the useful life part of the bathtub curve, one may assume that the MTTF will remain constant, from that moment on. Assuming this as true, the MTTF can be estimated through the Weibull failure model (2.3), using data from the early life stage of the equipment.

$$MTTF = \theta\Gamma\left(1 + \frac{1}{\beta}\right) \tag{2.3}$$

where Γ is the gamma function (Das 2008).

Weibull analysis applications and variants

In literature one can found different ways to obtain the time to failure of components. Some authors look to adapt a model based on a statistical distribution like Weibull, while others seek to develop their own algorithms and models that can better suit the process data in question.

In order to investigate maintenance performance of a process system, Weibull analysis is used as a statistical tool to predict the availability and reliability of process equipment (Zulkafli and Mat Dan 2016), being the most widespread and commonly used method in the field of failure prediction. This model provides adequate results even if there is relatively low number of samples and allows to model the decreasing, constant and increasing part of the bathtub curve (Irinyi and Cselko 2017), shown in Figure 4.

Irinyi and Cselko (2017) also propose the CROW-AMSAA method to overcome Weibull distribution's main disadvantage, that is the fact that it can only model one single failure mode. Zulkafli and Mat Dan (2016), on the other hand, analyze data from a gasification process and use pure Weibull analysis, estimating the shape and scale parameters to obtain the MTTF and, consequently, the failure rate of each component to schedule maintenance operations.

Other authors use modified Weibull distribution models to predict the failure rate. Yujie *et al.* (2017) propose an improved Weibull-based Generalized Renewal Process, where the failure rate is predicted by estimating the Weibull parameters θ and β from failure data utilizing an estimation algorithm.

2.7 Data analysis combining event data and condition monitoring data

Data analysis for event data only is known as reliability analysis, which fits the event data to a time between events probability distribution and uses the fitted distribution for further analysis. In CBM, however, additional information, condition monitoring data, is available, thus a combined event data and condition monitoring analysis is beneficial and can be accomplished by building a mathematical model (Jardine *et al.* 2006).

Time-dependent proportional hazards model

A time-dependent proportional hazards model (PHM) is a popular model in survival analysis and suitable for this kind of analysis, as it relates the failure probability to both time and condition variables. The hazard function for this model is of the form presented in (2.4), where $h_0(t)$ is a baseline hazard function, $x_1(t), \dots, x_p(t)$ are covariates which are functions of time, and $\gamma_1, \dots, \gamma_p$ are coefficients.

$$h(t) = h_0(t) \exp\left(\gamma_1 x_1(t) + \cdots + \gamma_p x_p(t)\right) \tag{2.4}$$

A commonly used baseline hazard function is the hazard function of the Weibull distribution. MLE is usually used to build a PHM from event data and condition monitoring data (Jardine *et al.* 2006). Among the authors that provide works on this method, are Jardine *et al.* (1987) and Vlok *et al.* (2004).

Markov chains and Hidden Markov model

In probability theory, a Markov process, named after Russian mathematician Andrey Markov, is a stochastic process that satisfies the Markov property, i.e., if one can make predictions about the future based solely on the current process state being, therefore, a memoryless process (Serfozo 2009). A Markov chain is a type of Markov process that has either discrete state space or discrete index set (often representing time), but it is also common to define a Markov chain as having discrete time in either countable or continuous state space (Asmussen 2008). A discrete time Markov chain is typically characterized by its probability transition matrix, which contain the transition probabilities from one state to another.

Markov chains have many applications as statistical models to describe real-world processes, being the most frequently used example the modeling of queuing lines. As will be later explained, it also enables to model the degradation of an equipment throughout its life, being one of the most used approaches in the condition-based maintenance field.

Hidden Markov model (HMM) is another appropriate model for analyzing event and condition monitoring data together. An HMM consists of two stochastic processes: a Markov chain with finite number of states describing an underlying mechanism and an observation process depending on the hidden state. Event data and condition monitoring data are then used to train the HMM, i.e., to estimate model parameters. Since full likelihood function is not available for an HMM, a statistical approach known as EM algorithm is usually used for parameter estimation (Jardine *et al.* 2006). Examples of works with HMM were developed by Bunks *et al.* (2000) and Dong and He (2004).

2.8 Predictive maintenance techniques

There are two main types of predictive maintenance techniques: diagnostics and prognostics (Okoh *et al.* 2017). Diagnostics is the process of checking faults and the health state of sub-systems and units in an operational environment with the aid of sensors. During maintenance, inspection is required to identify components and provide information on the current performance status (Banjevic 2009). Prognostics is predicting the duration after which a component can no longer perform its intended or expected functionality to improve system safety. The International Standard Organization (ISO 13381-1:2004) define Prognostics as “the estimated-time-to-failure and the risk of existence or subsequent appearance of one or more failure modes” (Medjaher *et al.* 2012).

2.8.1 Diagnostic-based predictive maintenance

Machine fault diagnostics is a procedure of mapping the information obtained in the measurement space to machine faults in the fault space. This mapping process is also called pattern recognition (Jardine *et al.* 2006), which is usually a process resultant from data acquisition signals, gathered by sensors installed in the machines. Diagnostic approaches are normally supported by statistical or artificial intelligence approaches. Hu *et al.* (2015), for example, studied the application of Weibull distribution in cable partial discharge pattern recognition.

A common method of fault diagnostics through a statistical approach is to detect whether a specific fault is present or not based on the available condition monitoring information without intrusive inspection of the machine. This fault detection problem can be described as a hypothesis test problem with null hypothesis H0: Fault A is present, against alternative hypothesis H1: Fault A is not present. In a concrete fault diagnostic problem relying on sensorial data, hypotheses H0 and H1 would be interpreted into an expression using specific models or distributions (Jardine *et al.* 2006).

2.8.2 Prognostic-based predictive maintenance

The most obvious and widely used prognostics is to predict how much time is left before a failure occurs (or, one or more faults) given the current machine condition and past operation profile. The time left before observing a failure is usually called remaining useful life (RUL) (Jardine *et al.* 2006). The other method relies on obtaining a failure probability based on current condition and past operation profile, but it is mostly used when a failure can be catastrophic (e.g. nuclear power plant), and the literature on the topic is still quite scarce.

RUL estimation

Every condition-based policy is characterized by a threshold degradation level (value) which, when reached, triggers the execution of a PM action. The RUL consists in estimating the time to reach that defined threshold degradation level that should not be crossed (Varnier and Zerhouni 2012), given the current machine age and condition and its past operation profile (Jardine *et al.* 2006). For a correct interpretation of RUL, a proper definition of failure is required. There are two ways in describing the failure mechanism: assume that failure depends only on condition variables which reflect the actual failure level (failure occurs when the fault reaches a predetermined level), or building a model using available historical data to define failure (Jardine *et al.* 2006).

Banjevic and Jardine (2006) discussed RUL estimation for a Markov failure time process which includes a joint model of proportional hazards model (PHM) and Markov property for the covariate evolution as a special case. HMM, a stochastic process model discussed earlier, is also a powerful tool for RUL estimation (Chinnam and Baruah 2003). Daming and Makis (2004) introduced a partially observable continuous-discrete stochastic process model to describe the hidden evolution process of the machine state associated with the observation process. RUL estimation, as one of the prediction tasks, was given based on the model. Wang *et al.* (2000) proposed a stochastic process, called gamma process, with hazard rate as its mean for prediction of residual life.

Prognostics incorporating maintenance policies

RUL estimation plays an important role in prognosis-based CBM. Notwithstanding, prognosis is a wider field than RUL estimation, as it further aims to provide decision support for maintenance actions. The main idea of prognosis incorporating maintenance policies is to optimize the maintenance policies according to certain criteria such as risk, cost, reliability and availability. Literature in this field is dominated by cost-based CBM optimization (Jardine *et al.* 2006).

When it comes to the condition monitoring interval, there are two types: continuous and periodic. In continuous monitoring, one continuously monitors (usually by mounted sensors) a machine and triggers a warning alarm whenever an inconsistency is detected. Two limitations of continuous monitoring are its higher cost and the fact that to continuously monitor raw signals with noise may produce inaccurate diagnostic information. Periodic monitoring is, therefore, used due to being more cost effective and providing less reactive diagnosis (Jardine *et al.* 2006). Of course, the risk of using periodic monitoring is the possibility of missing some failure events which occur between successive inspections (Goldman 1999).

Several works use a stochastic model (gamma process) to describe the deterioration process. A very important contribution in this field was given by Grall *et al.* (2002b), who propose a continuous monitoring predictive maintenance structure for a gradually deteriorating single-unit system, that enables optimal inspection and replacement decision to balance the failure and unavailability costs on an infinite horizon. To do so, two maintenance decision variables are considered: the preventive replacement or fault threshold (M) and the inspection intervals (T_i) based on the system state (X_t) allowing for irregular inspection intervals (Figure 5). The choice of these variables is of most relevance as they are directly correlated with the economic performance of the maintenance policy.

The system is assumed to fail when the system state is greater than a fixed L, degradation characteristic of the considered system. Moreover, the deterioration process between two maintenance operations is assumed to be stochastic, time-homogeneous and to evolve by means of positive, increasing jump processes with independent stationary increments; inspections are assumed to be perfect and maintenance actions instantaneous.

The proposed maintenance decision frame is as follows (see Figure 5), and is the most frequently found across CBM literature:

a. If $X_{T_i^-} \geq L$ (system failed), a corrective maintenance action takes place, and the system state is set to "as good as new" ($X_{T_i^+} = 0$) - regeneration;
b. If $M \leq X_{T_i^-} \leq L$ (system still functioning, but too deteriorated), a preventive maintenance action occurs, and the system state is also restored to "as good as new";
c. If $X_{T_i^-} < M$ the the system is left unchanged until the next inspection.

Castanier *et al.* (2003) and Dieulle *et al.* (2003) have similar approaches. The first ones study a condition-based maintenance policy for a repairable system subject to a continuous state gradual deterioration monitored by sequential non-periodic inspections. Taking advantage of the semi-regenerative (or Markov renewal) properties of the maintained system state, the maintenance policy is evaluated in terms of the long-run system availability and expected maintenance cost. The latter ones assumed a one-level replacement policy in a continuously deteriorating system, modeled by a gamma process, which is inspected at random times sequentially chosen by help of a maintenance scheduling function.

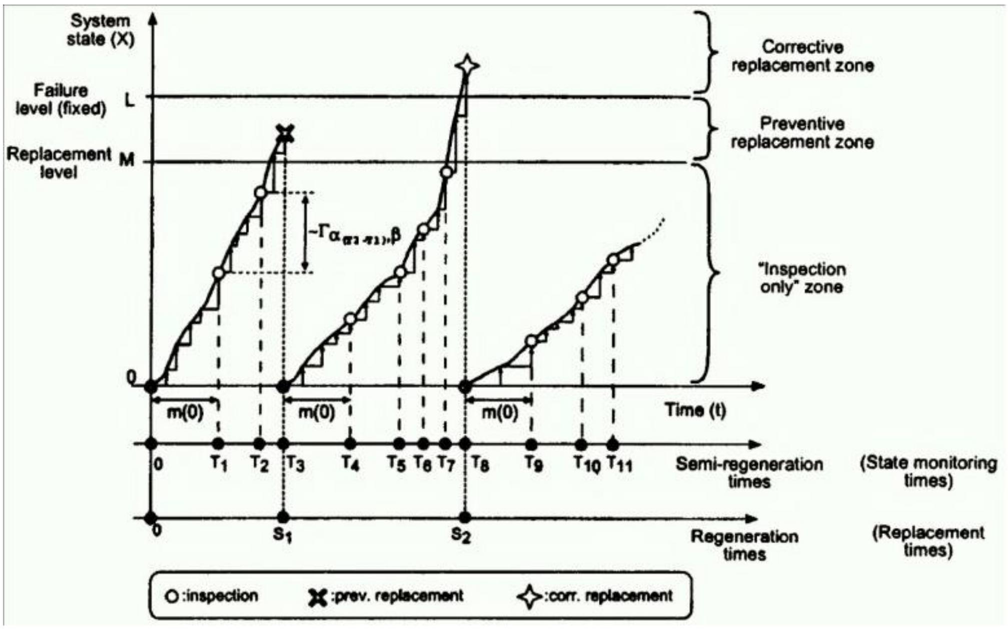

Figure 5 - Schematic evolution of the system state. Source: Grall *et al.* (2002b)

One different approach is to discretely model the deterioration process, i.e., deterioration levels are split into a set of pre-set number of discrete states. Grall *et al.* (2002a) propose an analytical model for a stochastically and continuously deteriorating single-unit system using a Markovian process to model the degradation process. The system condition is divided into a discrete number of thresholds (N), that comprise the number of states ($S_1, \dots, S_N$) in the Markov chain. Inspections may take place at some possible $t_k = k\Delta t$ times, which are possible but not mandatory inspection times, being Δt an arbitrarily chosen time or imposed by the maintenance policy. The system state upon inspection is what determines at which t_k time should the next inspection take place (Figure 6). This model also aimed to test the influence of the number of thresholds N in the total maintenance cost.

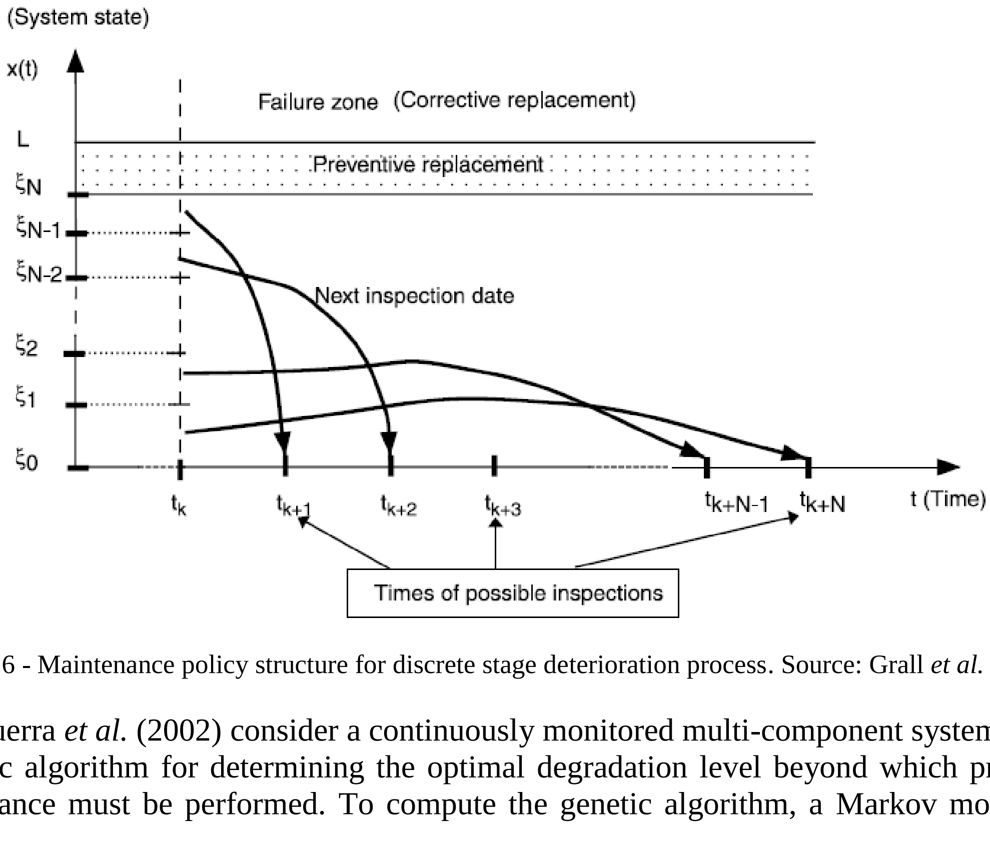

Figure 6 - Maintenance policy structure for discrete stage deterioration process. Source: Grall *et al.* (2002a)

Marseguerra *et al.* (2002) consider a continuously monitored multi-component system and use a genetic algorithm for determining the optimal degradation level beyond which preventive maintenance must be performed. To compute the genetic algorithm, a Markov model for a repairable single-component degrading system is used, such that the increase in degradation, or decrease if a maintenance action is performed, is such to lead, with different probabilities, the component from the current degradation level to any other. The proposed Markov model comprises also the possibility of random shock failures (random failures that may occur independently from the degradation level). The evolution of the degrading system is then estimated using Monte Carlo simulation. The modeling approach followed in this thesis is closely related to this work and combined with the approach of Grall *et al.* (2002a) and with the decision frame provided by Grall *et al.* (2002b).

An identical approach to the one provided by Grall *et al.* (2002a) is given by Amari and McLaughlin (2004), who consider a discrete stage deterioration process, modeled using Markov chains, subjected to periodic inspection. They present algorithms to find the optimal maintenance parameters to maximize system availability. Hontelez *et al.* (1996) formulate the decision process as a discrete Markov decision problem based on a continuous deterioration process to find the optimum maintenance policy with respect to cost.

Some authors even provide models that not only prescribe the inspection times and the critical thresholds, but also interact with the production scheduling. These problems are usually called “joint maintenance and production scheduling problem". Varnier and Zerhouni (2012) propose a mixed integer linear programming model that intends to optimize the makespan (total schedule duration) of a flow-shop in which the machines are subject to predictive maintenance operations. Xiao *et al.* (2016) developed a joint optimization model to minimize the total cost including production cost, preventive maintenance cost, minimal repair cost for unexpected failures and tardiness cost. This way, the total cost depends on both the production process and the machine maintenance plan associated with reliability. Pan *et al.* (2012) provide a single-machine based scheduling model incorporating production scheduling and predictive maintenance, introducing the machine’s effective age and remaining maintenance life to describe machine degradation.

3 Problem description

Continental Mabor is one of the best manufacturing facilities across the whole Continental group, achieving excellence performance indexes in parameters such as productivity, quality and safety. These levels were achieved not only using the best engineering practices at the service of the productive process, but also due to the recognized skills and constant willingness to learn of its employees. Combining these factors with the implementation of effective maintenance policies, it is possible to retrieve as much as possible from the installed capacity and resources.

Bearing this in mind, by opening the new agricultural tire manufacturing unit (CST) at Lousado, Continental hopes to obtain, in the long run, close performance measures to the ones verified at the Passenger and Light Trucks tire (PLT) manufacturing unit. To achieve that, maintenance policies have a decisive role. This thesis came along as an attempt to complement the already existing maintenance practices, and to provide the establishment of a basis for future improvements.

In this section, the project context and the initial situation verified at the CST plant will be discussed, as well as the methodologies used to tackle the problem. The productive process of the CST manufacturing unit will also be introduced, as well as the predictive maintenance actions that already take place in the PLT facilities.

3.1 Project context description

Since machine breakdown reduces production efficiency, maintenance in manufacturing systems is used to keep machines in good condition to decrease failures, making maintenance planning become more and more important in manufacturing processes (Pan *et al.* 2012).

The new machines installed are the first ones to be introduced in the entire Continental Group, being in study the installation of similar ones in other factories worldwide. Being a pioneer facility, the importance of a well thought maintenance plan is obvious, benefiting not only this facility, but also others in the group that will possibly employ this technology in the future, by providing if not the actual plan and policy (since every facility has its own characteristics, like employees' skills and level of care for maintenance), a reasonably good starting point.

These machines were tailor-made and developed in strict collaboration with the supplier, and so they are still subject to corrections in their parameters and programming logic. Moreover, production flow is small and there are many stoppages, increasing their propensity to failure.

A CBM program, if properly established and effectively implemented, can significantly reduce maintenance costs by reducing the number of unnecessary scheduled preventive maintenance operations (Lee *et al.* 2004). However, the intent of this predictive plan is not to reduce the number of scheduled preventive maintenance operations, but for it to act as a complement with the goal of reducing the number and time length of machine breakdowns.

3.2 Brief description of the productive process

In order to comprehend the maintenance plan, it is required to briefly introduce the productive process for an agricultural tire (Figure 7), for a better understanding of the type of tasks these machines are subject to.

The first step is the mixing process, where natural and synthetic rubber are mixed together with other materials, resulting in rubber compounds with different characteristics, according to the type of tire to be manufactured. This process, however, does not exist in the CST facility, as all the rubber compounds used come from the PLT mixers.

The second step of production, and the first one to take place at the CST plant, is the preparation process. At this step, the tire components are manufactured, involving several different machines, each one producing or preparing distinct tire components. Still, some of the components come from outside the facility, namely: the innerliner (interior layer of the tire that assures the tire holds high pressure on the inside), the body plies (other rubber and textile layers that give the tire structure strength) and the textile or metallic belts (that give the tire strength and dent resistance while allowing it to remain flexible). In the CST plant the following stages take place: the extrusion process, where the tire sidewalls (that give strength and resistance against the environment) are produced, performed by the *Extruder*; the cutting process, where the belt and the body plies are cut with a specific angle according to the tire type to be produced, performed by the *Combicutter*; the *Bead Winder*, a machine that constructs the bead (a set of steel wires wrapped in a rubber compound with a specific diameter that will be in direct contact with the rims); and finally the *APEX*, responsible for the application of a slim extruded rubber layer that mates against the bead (the apex).

Next, occurs the tire building process. For this step, three types of machines are used. First, the tire carcass is built in the *Carcass Building Machine*. The tire carcass consists of several material layers that are, sequentially, wrapped up around a drum: innerliner, one or more body plies and the tire sidewalls. The carcass is then expelled from the drum and goes to the *Green Tire Building Machine*. There, the belts are applied against the body plies. Finally, the *Strip Winder* applies the tread, a thick extruded profile that surrounds the tire carcass. This is the compound that will contact the surface, and thus includes additives to impart wear resistance.

Afterwards, the innerliner is sprayed with an "ink" in the *Spraying Machine*. This stage does not add value to the final product but is essential to guarantee the product quality at the end of the curing process, as it helps the demolding of the tire and extends the presses' bladders' useful lives.

The curing process is where the tire gains its final shape. The sprayed tire is put in a *Curing Press*, where it is subject to high temperature and pressure. These conditions confer the tire higher resistance and contribute to the acquirement of its final shape.

Finally, the last step is the final inspection, where the tire is subject to visual inspection and a radial eccentricity check. If any defect is found or the tire does not meet specifications, a final rework station is used to correct those defects, whenever possible.

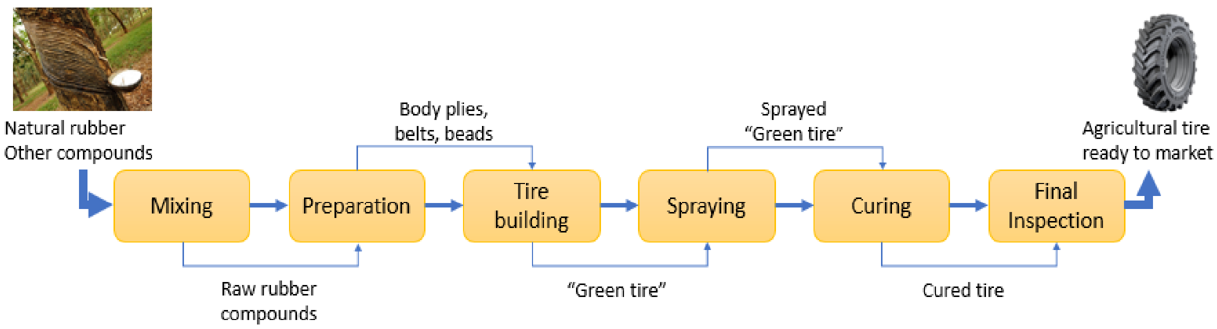

Figure 7 - Production process of an agricultural tire flowchart

3.3 Maintenance concept at Continental Mabor

At Continental Mabor, maintenance is regarded as an indispensable operation to keep productivity and quality levels at the highest possible. In fact, in the engineering departments, the two main divisions are projects and maintenance. Besides the dedicated maintenance teams, there are also many engineers whose job is to assure maintenance is performed correctly.

Initially, maintenance actions at the CST facility were only twofold: corrective and preventive (time-based) maintenance. CM is performed by teams of mechanical and electrical technicians, who respond directly when a breakdown occurs. These teams are the ones responsible for the direct repair of the machines, returning them into a good state and allowing production to resume, and for the replacement and repair of wearied parts that no longer perform at the required levels. Unlike CM, PM is performed by teams that aren't dedicated to the CST facility. Depending on the machine, the PM team of the analogous department in PLT is asked to come to the CST facilities to perform the required maintenance operations.

Therefore, the PM operations need to be jointly scheduled with the PLT departments, to avoid overlaps. All PM operations in the CST facility were to be scheduled on Thursday mornings, matching the weekly shift when production is stopped. Not all machines are subject to PM tasks in the CST plant in the same day, and there are even occasions when there are no PM operations scheduled for the entire facility. However, even in these situations, production always stops.

PM operations are performed by the PM team according to a set of tasks (checklist) that were developed by the engineers responsible for maintenance in the PLT. Because of this, and due to the fact that those engineers do not know all the specificities of the CST machines (in some production steps the machines operate in a very different way from the ones at PLT), not all the tasks listed in the checklist are applicable.

3.3.1 Predictive maintenance at Continental Mabor

In the CST facilities, predictive maintenance actions are yet to be implemented. This is explained by the fact that machines are new and because production is not in full flow.

In the PLT manufacturing unit, however, some predictive maintenance initiatives already take place. These initiatives are still in the early phases of development, as there is no serious sensorial data being collected. Predictive maintenance actions are mainly based in routines carried out by a dedicated team, that receives daily a plan given by production about which machines and which maintenance actions to perform in a given day. The majority of these actions are still not based in the monitoring of components, but instead based on the experience of multiple past hours of production and failure records. However, there is a minority that already considers the equipment's performance like, for example, the measurement of engines' energy consumption.

Besides the practices described above, a framework for more effectively dealing with unexpected breakdown patterns was recently implemented. This approach is called Concurrent Engineering and was adapted and applied to maintenance. It consists in the gathering of multidisciplinary and independent teams to focus and tackle a specific problem (in this case, a breakdown pattern) that has been identified. Each team is assigned a leader and, during the project's extension, all members, regardless of their department of origin, respond to that leader.

In the context of Continental Mabor, this methodology consists in gathering members from the corrective maintenance shifts (who are very knowledgeable about machine breakdowns' diagnosis), the preventive maintenance teams (members that have a deep knowledge about the parts and the montage), and the projects team (who are responsible to buy the machines and are mostly engineers). This multidisciplinary approach allowed to reduce the ratio between unplanned and planned maintenance time to a quarter in only a few years of its application.

3.4 Initial situation

In this subsection, initial breakdown data and maintenance performance indicators will be introduced, to provide a basis for the study. The responsibility for the maintenance of the machines in the production line is divided between the engineering departments: Engineering

Department 7 (ED7) is responsible for the *Extruder*, *Combicutter*, *Bead Winder*, *APEX*, *Carcass Building Machines*, *Green Tire Building Machines* and *Strip Winder*, i.e. the Preparing and Building processes; Engineering Department 8 (ED8) is responsible for the *Spraying Machine*, *Curing Presses* and *Final Inspection*. The machines in the final inspection stage will not be addressed due to the almost inexistence of breakdowns that justify a predictive maintenance plan. This analysis will tackle the two engineering departments separately, since each department has its own maintenance team to execute the maintenance tasks.

3.4.1 Preparation and Tire Building

Firstly, the total monthly downtime due to breakdowns (not considering preventive maintenance actions or tooling change procedures) was analyzed. It was gathered data since the start of production, in April 2017, until February 2018. In Figure 8 the total downtime per month from April 2017 to February 2018 in ED7 is presented. The months from September 2018 to February 2018 are the ones that show higher downtime (over 50 hours each month), excluding December, in which the plant was closed for 28 days.

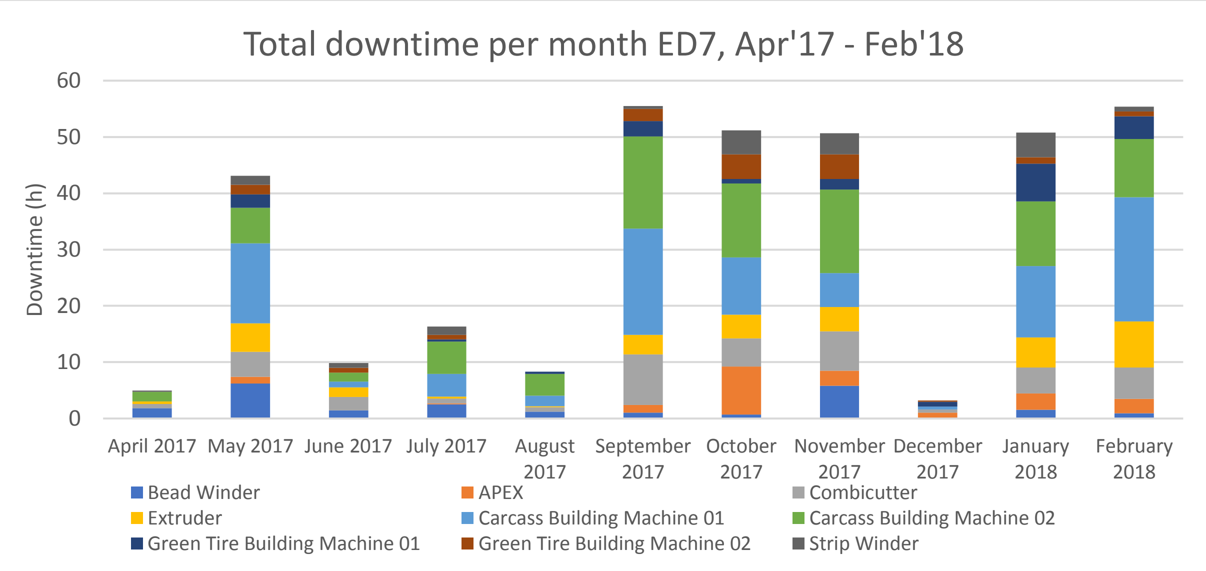

Figure 8 - Total downtime per month in ED7, from April 2017 to February 2018

One must remind that these 50 hours per month are for all the machines combined. However, if we consider that all preventive maintenance and tooling change actions are excluded, this means that those machines were stopped for more than half the available time (Table 1), and that they are new, this value can be considered as high. Note that the working time percentages refer to the period from January 2018 to April 2018, but they are assumed to being able to be extrapolated backwards until September 2017, based on the plot displayed on Figure 8.

Table 1 - Percentage of working time for each machine at ED7 from January 2018 to April 2018

Machine	Working Time (%)
Extruder	7%
Bead Winder	22%
APEX	19%
Combicutter	35%
Carcass Building Machines	53%
Green Tire Building Machines	53%
Strip Winder	53%

Secondly, for a better understanding of the distribution of the downtimes, it was given a deeper look into the period from September 2017 to February 2018. Figure 9 shows the distribution of downtime through the different machines for this period. It can be verified, more clearly, that the machines that have higher downtime are the *Carcass Building Machines*. This makes sense because not only these are the ones with higher load (Table 1), but they are also the most complex and difficult to program, requiring almost permanent adjustments.

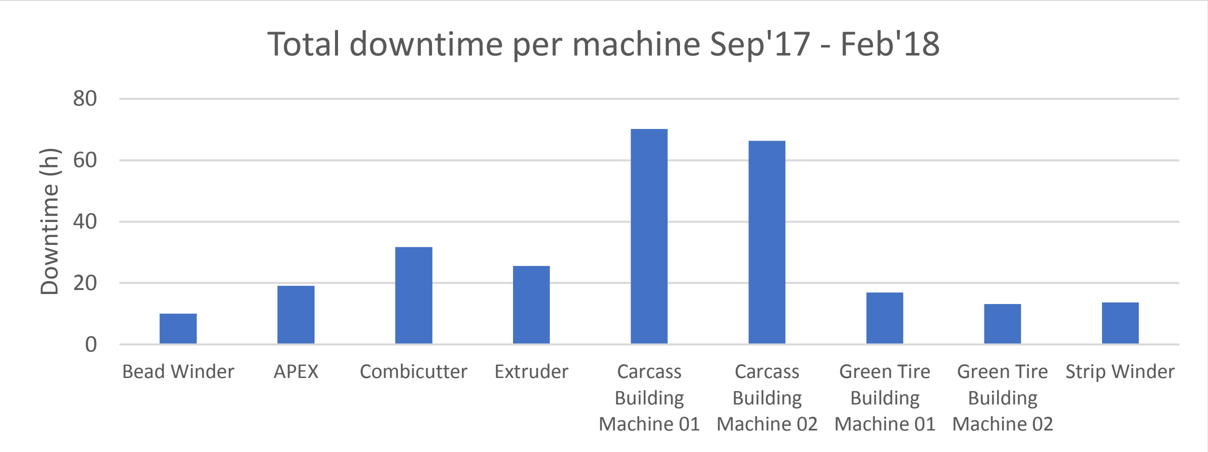

Figure 9 - Total downtime for each machine in ED7, from September 2017 to February 2018.

Finally, it is important to understand the relationship between the working time and the total downtime for each machine, to better assess their performance level (if they fail almost every time they work or if their failures are more spread out through their working time). For this a plot was constructed (Figure 10), for the previously considered range [Sep'17 – Feb'18], emphasizing the ratio between downtime and working time percentage. The differences observed are meaningful to conclude that the *Extruder* is clearly the machine with the worst performance overall, being the neediest machine for maintenance in relation to its working time.

This analysis allows to draw the conclusion that the machines from ED7 that would benefit the most from a predictive maintenance plan implementation are, for the aforementioned reasons, the *Carcass Building Machines* and the *Extruder*. On one hand, the *Carcass Building Machines* would benefit because they exhibit higher downtime; on the other hand, the *Extruder* would benefit as it is the machine with worst ratio between downtime and working time.

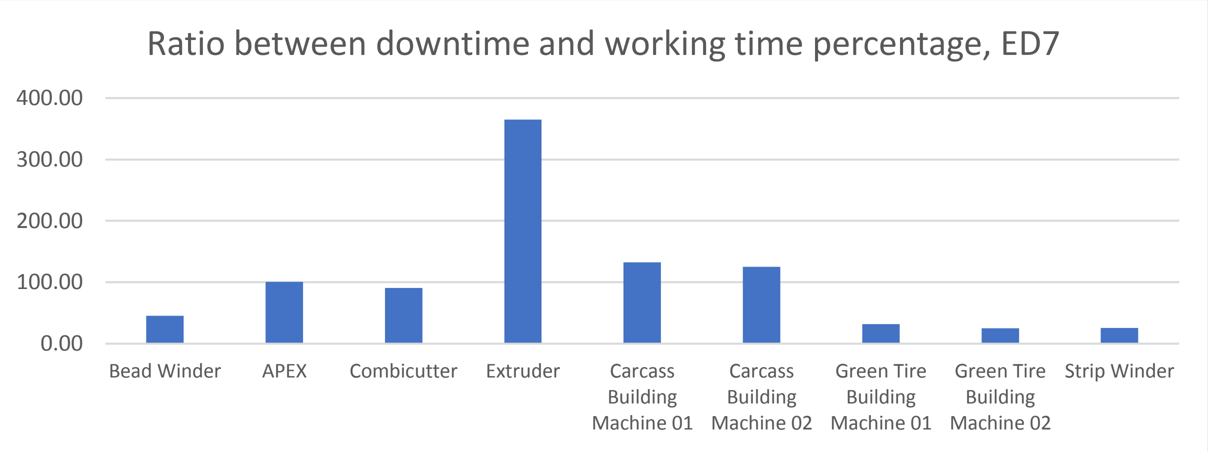

Figure 10 - Ratio between downtime and working time percentage for each machine in ED7

3.4.2 Spraying and Curing

The same rational sequence used for the preparing and tire building machines was followed to analyze the initial breakdown data for the spraying and curing machines. Here, preventive maintenance actions and tooling changes were also excluded. Nevertheless, there is a notable difference from the curing presses to the spraying machine and the other machines of ED7: not all curing presses work at the same time, as the installed capacity highly exceeds the actual needs. For example, one curing press may work for a whole month, almost non-stop, while the one right next to it may be stopped during that whole period.

For that reason, the plot in Figure 11, which represents the total downtime per month, from July 2017 to January 2018, some of the presses may have no downtime in a certain month and present a huge downtime in the following one. The exception here is the *Spraying Machine*, which is expected to be constantly working.

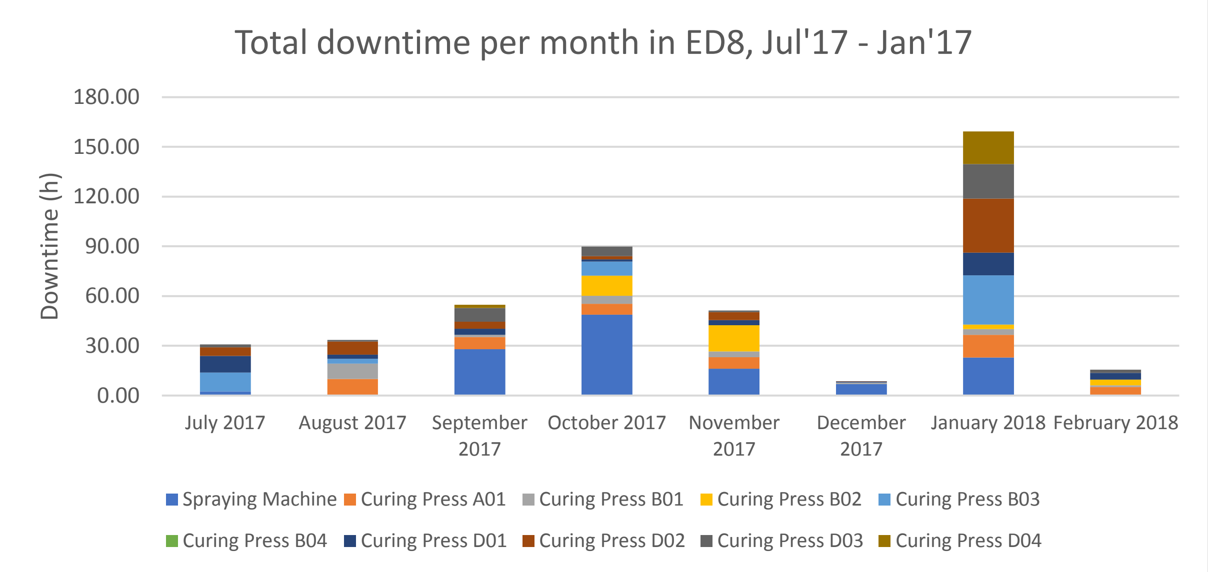

Figure 11 - Total downtime per month in ED8 machines, from July 2017 to January 2018

For that reason, the *Spraying Machine* is the only one worth analyzing its current working time percentage (which is of 9%) as the *Curing Presses'* work behaves like a binary variable, at the current point: a press either works at its full capacity for a relatively long period of time (1 or 2 months), or it does not work at all. The *Spraying Machine* is, therefore, the only one that works continuously, and its percentage of working time was obtained based on future improvements that will soon be implemented, that will increase the machine's throughput capacity.

The fact that the *Spraying Machine* is, unlike the *Curing Presses*, permanently working, also reflects in each machine's total downtime. In fact, it can be observed in Figure 12 that its downtime is significantly higher than the one verified in the *Curing Presses*. It also shows, if it is assumed that the downtime and the working time are directly correlated, that the work in the period in question is distributed through all the presses, meaning that all of them worked and stopped during this period, except for B04, which has not worked in this period.

An analysis of the relationship between downtime and working time is not as pertinent as it was for the preparing and building processes, since it was already concluded that the *Spraying Machine* would benefit from a more frequent maintenance plan implementation. Besides that, the *Curing Presses* are all very similar to each other, despite having three different classes, according to their size (A, B and D), so one can assume that their maintenance needs are also similar within each other, and only dependent of their state: working or idle.

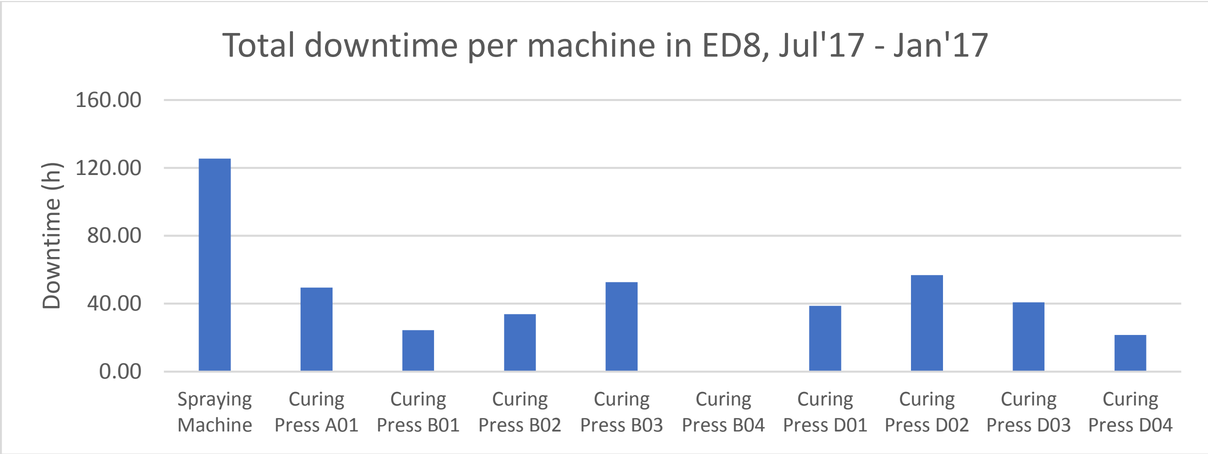

Figure 12- Total downtime per machine in ED8, from July 2017 to January 2018

3.4.3 Maintenance performance indicators

An analysis of the preliminary maintenance performance indicators is also relevant to assess the initial performance of maintenance operations, enabling further comparisons with the ones obtained at the end. The performance indicators used at CST plant to assess maintenance operations are the MM - Maintenance Maturity - (3.1), the MTBF - Mean Time Between Failures – (3.2) and the MTTR - Mean Time To Repair – (3.3).

$$MM = \frac{\sum Planned\ Maintenance\ Hours}{\sum Total\ Maintenance\ Hours} \tag{3.1}$$

$$MTBF = \frac{Total\ Working\ Time - \sum Downtime}{Number\ of\ breakdowns} \tag{3.2}$$

$$MTTR = \frac{\sum Downtime}{Number\ of\ breakdowns} \tag{3.3}$$

The MM indicator is a ratio between planned maintenance time and total maintenance dedicated time, allowing to assess the quality of maintenance operations and to give an idea about where maintenance expenses are going. There is no optimal value for this indicator, as a very high ratio may indicate that there are almost no breakdowns, or that too many frequent preventive maintenance actions occur, but it certainly should not assume a low value.

The MTBF indicator enables to assess the reliability of an equipment. It is of particular interest in heavy asset enterprises, like Continental, as an unreliable equipment may prevent from generating revenue. For this indicator, the ideal is to be as high as possible.

Finally, the MTTR indicator is used to evaluate the corrective maintenance teams' effectiveness and efficiency in finding the root cause for a breakdown and correct it. An effort should be put into keeping this indicator as low as possible, but without compromising the MTBF.

These indicators are divided in ED's 7 and 8, allowing the assessment of the two maintenance teams separately.

Preparation and Building – ED7

In ED7, indicators are provided for each machine, and in Table 2 are presented the values for these indicators in the first 3 months of 2018. Data obtained for the maintenance performance indicators suggests, and corroborates, the idea that the *Extruder* is the machine with worst performance levels (very low MTBF for all 3 months), even though the high MM percentage indicates that an effort is being made to increase planned maintenance in that machine. It is also emphasized that, for the machines that have higher utilization (tire building and strip winding), the *Carcass Building Machines* are the ones exhibiting the worse performance, showing a considerably lower MTBF when compared to the *Green Tire Building Machines* and the *Strip Winder*. Data for the machines that with lower utilization also suggests that their performance may be affected by the existence of constant stoppages.

Table 2 - Maintenance performance indicators for ED7, from January 2018 to March 2018

	MM (%)			MTBF (h)			MTTR (h)		
Machine	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar
Carcass Building Machine 01	72%	73%	84%	4.01	4.65	7.49	0.46	0.22	0.18
Carcass Building Machine 02	82%	86%	88%	4.51	3.49	6.29	0.29	0.32	0.51
Green Tire Buil. Machine 01	65%	74%	77%	41.90	17.43	16.25	0.27	0.24	0.14
Green Tire Buil. Machine 02	65%	89%	71%	17.01	12.13	11.20	0.27	0.07	0.23
Extruder	96%	90%	95%	1.10	1.25	2.29	0.54	0.56	0.32
APEX	80%	73%	60%	0.82	5.47	7.20	0.55	0.16	0.16
Bead Winder	74%	85%	64%	4.81	7.78	7.11	0.57	0.06	0.09
Strip Winder	75%	80%	67%	13.31	99.80	51.33	0.26	0.42	0.18
Combicutter	78%	73%	62%	3.28	4.08	4.54	0.46	0.12	0.19

Spraying and Curing – ED8

In ED8, these indicators were grouped: MM is obtained for the whole department, while MTBF and MTTR were grouped according to the process (Spraying or Curing). Table 3 presents the values for these indicators in the first 3 months of 2018.

Table 3 - Maintenance performance indicators for ED8, from January 2018 to March 2018

	MM* (%)			MTBF (h)			MTTR (h)		
Machine	Jan	Feb	Mar	Jan	Feb	Mar	Jan	Feb	Mar
Curing Presses	70%	73%	79%	18.00	19.00	29.40	1.40	1.22	0.38
Spraying Machine				3.50	2.40	5.20	1.01	0.77	0.28

*MM values also include the Final Inspection machinery

Looking at these data, it can be observed that the overall maintenance performance is evolving with a positive trend. Although, there still seems to exist room for improvement, as the year-to-date value for MM, for example, is still below the target value (74% against 75%). The other indicators seem to be behaving quite well, but one always must mind that continuous improvement should always be an explicit goal to every corporation.

4 Methodology

A maintenance plan should always be adjusted to each facility's characteristics and current needs. Therefore, the developed plan cannot be exactly equal to the one existent at the PLT plant.

The ultimate future goal of the company, concerning its maintenance operations, is to combine time-based maintenance policies with condition-based maintenance policies. This would allow to dispatch maintenance actions in the most efficient and effective way possible, following the principles of recent Industry 4.0 trends and attempting to minimize at most downtime and repair costs.

Following this desire, the conducted study attempts to provide a solid progress and basis for this goal, and can therefore be divided in two distinct parts: one that comprises the actual development of the predictive maintenance plan to be implemented in the CST plant; and another one consisting of a more detailed study and modelling of the behavior of one condition monitoring parameter throughout a certain period, with the goal of aiding decision-making concerning the optimal maintenance period. This section presents the used approaches and the way these different policies can be idealized and implemented, describing every step in as much detail as possible, displaying also a few intermediate results.

4.1 Predictive maintenance plan development

Often in the literature, machines are usually treated as holistic entities, and its breakdowns are not assumed to be caused by multiple factors, or due to certain components' failure. This assumption works well if the considered machine is very simple and the causes for failure are always the same. However, this is not the case in real problems, where machines really are composed of multiple components that, because of their distinct functions in the machine, are subject to different levels of deterioration. In this work, several failure modes were considered to occur in the same machine. Therefore, a study of each machine's sub-assemblies' failures was performed, as a basis for the identification of the maintenance actions to be included in the intended predictive maintenance plan, as well as their execution frequency.

4.1.1 Approach overview

Since production in this new manufacturing unit is still not in full-flow, it was more difficult to correctly assess the real maintenance needs of the machines, as well as their optimal execution periodicity. A large portion of existent breakdowns was due to factors that arise in this context: the introduction of new products that still require constant adjustments, the lack of experience in the production process, the existence of newly-formed teams (engineering, process and production) that have been working together for a short period, and the fact that procedures are still in a development phase. Although, an effort was put into identifying those failures that happened due to inefficient machine operation through its mechanical or electrical systems that could be mitigated if more regular maintenance was performed.

In order to do so, it was given a deep look into the breakdown reports of each machine, in an attempt to identify their components that more regularly failed. This task was difficulted by the lack of standardization in the failure reports, increased by the fact that the reports were filled by different people. This led to a one-by-one check of failures in an attempt to group each component's similar types of failure, enabling further and more concrete analysis.

After this identification and preliminary data treatment, it was necessary to understand the causes for those failures, as well as some possible other causes that could lead to failure but had not happened yet. To achieve that, the corrective maintenance personnel and the plant's engineers were consulted, given their experience and knowledge about the machines' operation.

Having the failure causes as a starting point, the actual maintenance actions to be performed were then idealized, having in mind that predictive maintenance actions are to be included in routines, and should be performed preferably while the machine is running (requiring no stoppage). These actions may include not only routine verifications and adjustments, but also certain parameter measurements that impact the machine's overall performance, for which the adequate measuring devices were proposed. The proposed actions were then prioritized, by means of a criticality analysis. A parameter named "Criticality Index" was calculated for each machine subassembly, allowing maintenance actions to be sorted according to it.

Finally, the periodicity of the maintenance actions was estimated. For this estimation, the previously treated data from the breakdown reports was used. However, the number of occurrences even after grouping similar breakdowns, for some cases, was still very scarce. To gather an enough amount of data to enable a statistical analysis, breakdowns were subject to another clustering, based on the corresponding machine subassembly. This clustering was made to facilitate the analysis and making it more significant, allowing conclusions to be drawn based on data and not prejudicing the machines' performance, as it is a more conservative approach.

4.1.2 Identification of failures, causes and maintenance actions idealization

Initially, the most common failures for each machine were grouped, as well as their frequency and total stoppage time. As already mentioned, this data was obtained through the breakdown reports. Since all machines in the plant were analyzed and, thus, the statement of all failures for all those machines would be very extensive, it will only be presented in this section data referring to the *Carcass Building Machines*, shown as an example of the conducted work. The failure modes encountered in the remaining machines are available in the Appendix B.

The five most common failure modes and their frequency percentage in relation to the total number of failures for the *Carcass Building Machine no. 1* are presented in Table 4, and for the *Carcass Building Machine no. 2* in Table 5.

Table 4 - Top 5 most common failure modes and their frequency for Carcass Building Machine no.1

Failure mode description	Frequency
Errors in drum commands	10.74%
Damaged or mispositioned conveyor belts	6.49%
Front nose hits drum or dog ears / tilting error	5.37%
Mispositioned slab conveyor	5.59%
Error in front nose's sensor	5.17%

Table 5 - Top 5 most common failure modes and their frequency for Carcass Building Machine no.2

Failure mode description	Frequency
Errors in PLC/drives	7.44%
Errors in drum commands	7.02%
Reels do not work properly	6.20%
Damaged or mispositioned conveyor belts	5.99%
Diafragms do not expand properly	5.17%

After identifying the most significant failure modes, the causes for those failures were dissected. For this task, the help from the corrective maintenance personnel was of the utmost importance.

The identified causes for some of the failure modes stated in Table 4 and Table 5 are presented as an example in Table 6, being the identified causes for all machines available at Appendix C.

Table 6 - List of causes for some of the identified failure modes for the Carcass Building Machines

Failure mode description	Identified causes
Errors in PLC/drives	• Problems with recipe parameters • System updates • Electrical switchboard temperature too high
Reels do not work properly	• Insufficient lubrication of the reels' guides • Misalignments • Excessive wear in the reel's disc
Damaged or mispositioned conveyor belts	• Positioning sensors not properly adjusted • Conveyor belt "jumps" out of the guide • Excessive wear in bronze connection contact

After the identification of the causes, the monitoring and maintenance actions were idealized. These actions had in mind the existent failure modes, emphasizing the most frequent ones, and were also directed to other machine components that do not fail as often but would benefit from more frequent verifications. These actions attempt to tackle the existing problems and respond to questions such as "What can we do to increase equipment's uptime?" or "How can we mitigate the effect of this failure safely and non-intrusively?".

Furthermore, on another scope, the lack of monitorization was a problem at the beginning, as people only have an idea about what was really happening in the machines. Therefore, we also included parameter monitoring actions, allowing to increase the knowledge about some critical components' current state. The questions to be answered here were such as "How can we monitor the level of deterioration of that component?" or "How can we know if a failure is about to happen and fix it before it does?"

As an example, some of the developed maintenance actions for the *Carcass Building Machines* are presented in Table 7, as well as, if applicable, the tool or measuring device that should be used when performing those actions. The developed maintenance actions for the remaining machines in the CST plant and the remaining actions idealized for the *Carcass Building Machines* can be found in Appendix D.

Table 7 - List of some of the maintenance actions idealized for the Carcass Building Machines

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Front nose	Gap between structure and bearing support	Pachymeter
Conveyor belts	Verification of wear in the bronze contact	
Conveyor belts	Adjust and clean sensors	
Reels	Verification of lubrication in reels' guides	
Reels	Check disc reels' alignment (xx) in homing position	Measuring tape
Reels	Verify positioning of turning reels (xx, yy, zz) in homing	Measuring tape
Dual slab conveyor	Engine consumption of the conveyor	Multimeter
Innerliner knitting zone	Blade and counter-blade cleaning	
Electrical switchboard	Temperature of drives	Thermal camera

Of course, these proposed maintenance actions will always be subject to possible future modifications, as the period during which they were tested was very small (only one month). In addition, they can be changed due to possible machine construction improvements, meaning that some of the maintenance actions may be no longer required. On the other hand, the monitoring actions are also subject to changes. If a conclusion is reached that one of the proposed monitoring parameters does not have a significant impact in the machine's performance, it may be eliminated from the plan, as others that are found to be relevant to measure may, and should, be added.

4.1.3 Criticality analysis

A well-defined maintenance plan is not exhausted by the definition of the maintenance actions to be performed. In fact, especially in cases where the number of actions to be executed is relatively large, it is of utmost importance to prioritize them. In the case of the CST plant at Continental Mabor this need for prioritization is even bigger, since these actions are not to be performed by a dedicated Predictive Maintenance team but, at least in an initial period, by the CM personnel, who also have numerous other tasks to execute during their working hours.

For these reasons, as proposed by Waeyenbergh and Pintelon (2002), a FMECA (Failure Modes Effects and Criticality Analysis) was performed. In this approach, failures are evaluated according to a set of fixed factors that, depending on the component, may have possible severity levels, which are then weighted according to the plant's characteristics, providing a final number, which was called Criticality Index. A distinct Criticality Index was obtained for each considered machine subassemblies, for all machines in CST plant studied.

The first step of this analysis was to define which factors should be evaluated. The same factors should be evaluated throughout the plant to increase standardization and enable comparisons between the different machines and their subassemblies, validating the established prioritization. These factors should consider not only the frequency of breakdown and the time to repair it, but also the consequences associated with that breakdown, such as worker's safety, influence on other machine components' performance or the effect the failure has in the machine subassembly. Bearing this in mind, the factors that were evaluated and their weight in calculation are displayed in Table 8. Weights were computed such that their sum equaled 1.

The second step was to define the number of severity factors and their range limits. The number of severity factors considered was set to three: 1-Good; 2-OK; 3-Bad. Some of these were quantitative (like the ones for frequency and stoppage time), while others were qualitative (such as worker's safety and easiness of failure detection). The range limits and characterization of the severity factors for each of the selected factors are also displayed on Table 8.

The third step was to compute the Criticality Index (CI), for each machine's subassembly (4.1), where W_i is the assigned weight for factor i, and S_i is the severity value (from 1 to 3) attributed to each factor i, for the machine subassembly in question. The obtained values for the CI for all machine subassemblies are available in Appendix E.

$$CI = \sum_{i=1}^{7} W_i S_i \tag{4.1}$$

The severity levels used in this analysis were sorted in ascending order, being 1 the less severe, and 3 the most severe. From here we can conclude that the subassemblies' priority levels are sorted in descending order, meaning that the subassembly with the highest CI value should be the one whose maintenance actions should be given the highest priority (if scheduled for the same date as others). For the *Carcass Building Machine*, the subassembly in this condition is the Electrical switchboard, meaning that their maintenance actions should be performed first.

Table 8 - List of criticality factors evaluated and their corresponding weight and severity ranges

Factor	Weight	Severity scale		
		1	2	3
1 - Maximum registered stoppage time	0.15	t ≤ 1h	1h < t ≤ 3h	t ≥ 3h
2 - Average frequency	0.1	< 1x/trimester	< 1x/month	> 1x/week
3 - If failure occurs, automatic scrap?	0.2	Never	Yes, little	Yes, a lot
4 - Easy to detect a failure?	0.02	Always	Sometimes	Never
5 - Compromises worker's safety?	0.3	Never	It is possible	Always
6 - Influences other components?	0.15	No	Only 1	More than 1
7 - Is the machine a production bottleneck?	0.08	No	Yes, but many	Yes, and only

4.1.4 Periodicity calculation

After idealizing the maintenance actions and prioritizing them according to numerous factors, there is the need to define the periodicities at which the actions should be executed for the plan to be complete. This is one of the most important steps when developing a plan of this kind, as a very low periodicity may produce an insignificant impact on the machines' performance and in their breakdown reduction, and a too frequent periodicity may lead to an unwanted excess of maintenance costs. Therefore, it is of vital importance to find a balance between optimizing maintenance costs, not neglecting the overall machine performance.

In parallel to the used approach in the criticality analysis, periodicities were also calculated separately for each machine subassembly. Although a given machine subassembly may have many distinct failure modes and, therefore, distinct maintenance actions to mitigate their effect, to reduce the number of calculations performed and to gather enough amount of data, all failures from a given subassembly were clustered, independently of their cause for failure.

A cyclical overview of the approach used in the periodicity calculation process is presented in Figure 13, from the raw failure data obtained through the breakdown reports to the final periodicity value attainment. Next, every step of this process will be further explored.

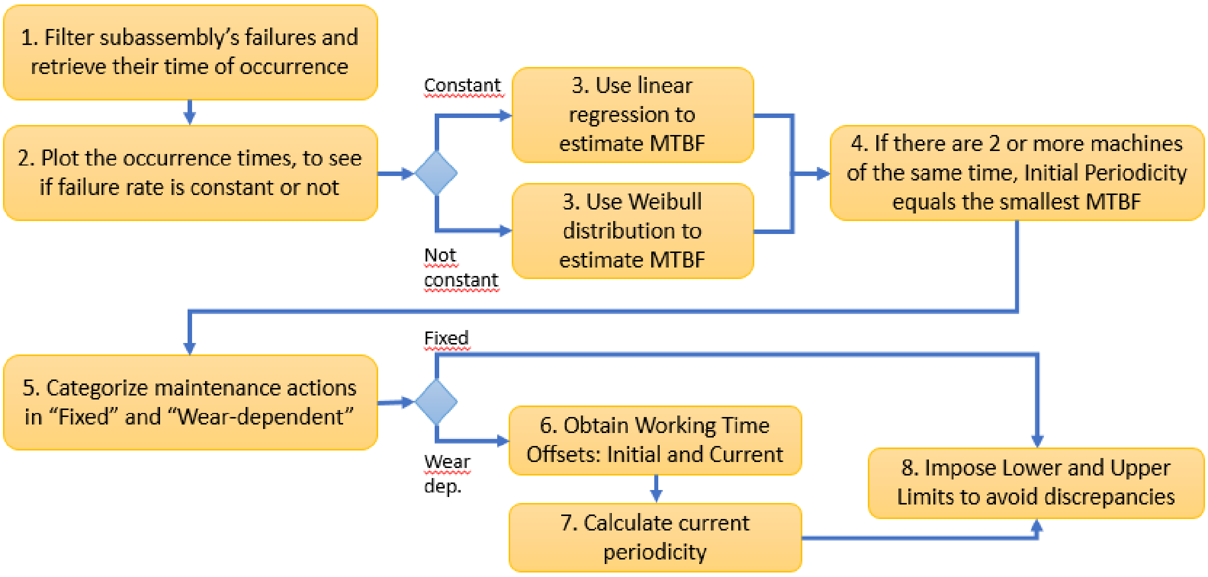

Figure 13 - Periodicity calculation process flowchart

In this section, will be presented the results obtained for the *Carcass Building Machines'* subassemblies as an example. The results for the remaining ones can be found in Appendix F.

The first step in this process was to filter each subassembly's failures and retrieve their time of occurrence. Breakdown reports from April 2017 to March 2018 provided failure data, identifying the type of failure, machine subassembly and failure date to be used. Let t_i define the time of occurrence of failure i, with $i = 1, \ldots, n$ (total number of subassembly failures).

To estimate the time between failures, first t_i was plotted to realize if the failure rate is increasing, decreasing, or remains constant throughout time. The linear trend line given automatically by MS Excel was also plotted, and the R^2 value for its adjustment to data analyzed. The decision about what model should be used to estimate the time between failures was based on the R^2 value obtained for the adjustment of data to the linear model:

- If $R^2 \geq 0.9$, it was assumed that the linear model provided a good adjustment to data, as that linear model was able to explain more than 90% of the independent variable. This also means that the failure rate can be considered constant;
- If $R^2 < 0.9$, it meant that the linear model could not explain a satisfactory percentage of the independent variable, and therefore meaning that the failure rate may not be constant and the model used to translate the failure rate was the Weibull distribution.

Data obtained for some of the *Carcass Building Machines'* subassemblies is presented in Table 9, including the total number of failures observed in each machine, the R^2 value on which the decision was based, and the technique used to model their time between failures. It is important to refer that if the same subassembly in the two machines had different adjusting models by the application of the mentioned decision rule, the used adjusted model for that subassembly in both machines was the most conservative of the two, that is, the Weibull model. This is the case of, for example, the *Innerliner knitting zone* and the *Front nose – structure* subassemblies.

The indicator that allows the estimation of each machine's subassemblies maintenance periodicity is the MTBF. The method used to calculate the MTBF for each machine subassembly was dependent of the shape of the failure rate and, consequently, of the adjusted distribution used. Next, the two methods used (linear and Weibull models) are introduced.

Table 9 - R^2 values and adjusted model used for some of the subassemblies of the *Carcass Building Machines*

Machine subassembly	Number of failures	R^2 value for linear model	Adjusted model used
Conveyor belts (Machine 01)	24	0.9589	Linear
Conveyor belts (Machine 02)	29	0,928	Linear
Front nose - structure (Machine 01)	24	0.9056	Weibull
Front nose – structure (Machine 02)	18	0.8111	Weibull
Front nose – photocells (Machine 01)	21	0.868	Weibull
Front nose – photocells (Machine 02)	14	0.8989	Weibull
Reels (Machine 01)	13	0.947	Linear
Reels (Machine 02)	14	0.9899	Linear
Electrical switchboard (Machine 01)	14	0.9251	Linear
Electrical switchboard (Machine 02)	31	0.9502	Linear

Constant failure rate

As already mentioned before, for the subassemblies in which the linear model was found to adjust itself at a very satisfactory level to the actual failure data, a constant failure rate was assumed. Figure 14 shows a plot of the failure data for one of the subassemblies of the *Carcass Building Machines* (in this case, conveyor belts for machine no. 2) throughout time, being the time variable (in days) the independent variable and the cumulative number of failures the dependent variable.

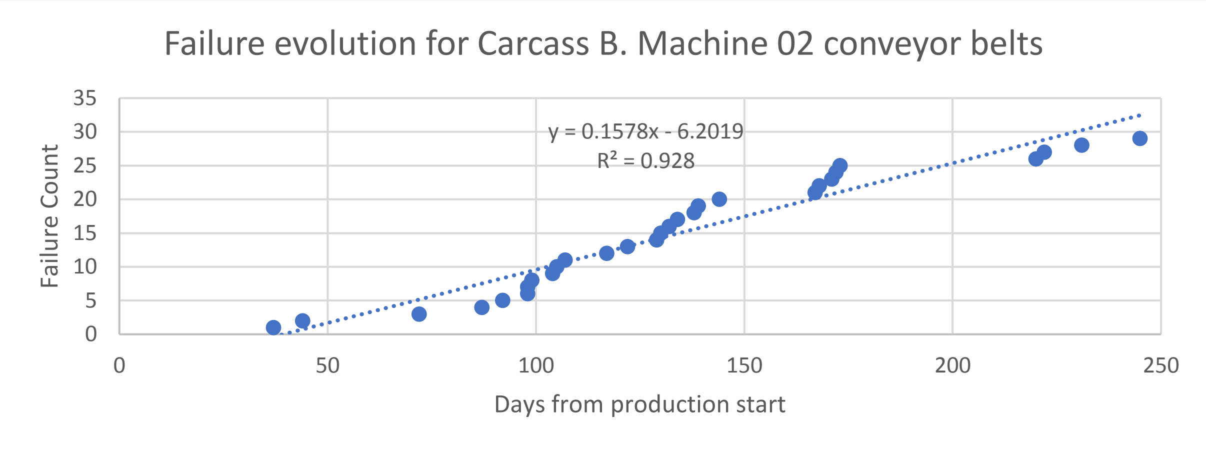

Figure 14 - Failure evolution throughout time for *Carcass Building Machine no.2* conveyor belts

The equation displayed on the graph is the equation for the linear trend line generated by MS Excel. Below the equation is shown the R^2 value of adjustment of data to that trend line. The failure rate, in this case, as $R^2 \geq 0.9$, can be estimated by the slope of the linear trend line, that for this subassembly is equal to 0.1578 failures/day. The MTBF (expressed in days) can therefore be computed using equation (4.2), giving for this subassembly an estimated 6.338 days. In Table 10 the estimated failure rates and MTBF for the subassemblies whose failure rate was considered as constant throughout time are presented.

$$MTBF = \frac{1}{Failure\ Rate} \tag{4.2}$$

Table 10 - Failure rate and MTBF estimations for the subassemblies with constant failure rate

Machine subassembly	Machine no. 1		Machine no. 2	
	Failure rate (failures/day)	MTBF (days)	Failure rate (failures/day)	MTBF (days)
Conveyor belts	0.086	11.623	0.158	6.338
Reels	0.106	9.394	0.060	16.743
Electrical switchboard	0.062	16.248	0.141	7.077

Non-constant failure rate

Figure 15 shows the evolution of failure data throughout time for the *Front nose – photocells* in *Carcass Building Machine no. 1* subassembly. In this case, the data points are well more dislocated from the linear trend line, suggesting a decreasing failure rate. This is confirmed by the R^2 value for the adjustment to that linear trend line, meaning that the failure rate should not be estimated by the slope of the observed trend line.

For the subassemblies which the R^2 of the adjustment to the linear trend line was lower than 0.9, the linear model was a very rough model to estimate the MTBF. For this reason, in these cases failure data were adjusted to a Weibull distribution. The valences of the Weibull distribution were already explored in Section 2, being the most important one the ability to fit every dataset by the estimation of its parameters.

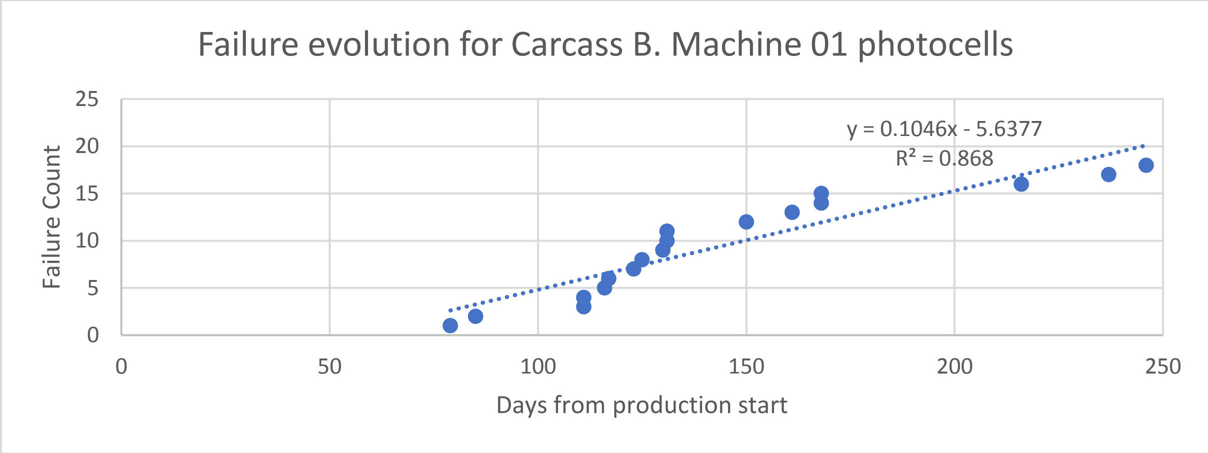

Figure 15 - Failure evolution throughout time for *Carcass Building Machine no. 1* front nose photocells

For every machine subassembly, the parameters for the Weibull model to be used were estimated using the MLE method, described in Appendix A. For the subassembly whose failure data is presented in Figure 15 (front nose photocells for machine no. 1), the obtained Weibull parameters were $\beta = 0.691$ and $\theta = 10.60$. It is relevant to note here that $\beta < 1$, which corroborates the idea from the graph that the failure rate has been decreasing.

After the estimation of the Weibull parameters, the MTBF was estimated from them, using equation (2.3), which for the case of this subassembly was of 13.588 days. Table 11 presents the estimated Weibull parameters for the remaining machine subassemblies for the *Carcass Building Machines*, as well as their estimated MTBF. The MTBF is usually a function of time; however, as it was already stated in Section 2, if it is assumed that the equipment will enter in the useful life part of the bathtub curve, from this moment on its failure rate will remain constant and, therefore, the MTBF value will also remain the same.

Table 11 - Weibull parameters and MTBF estimations for the subassemblies with non-constant failure rate

Machine subassembly	Machine no. 1			Machine no. 2		
	Shape (β)	Scale (θ)	MTBF (days)	Shape (β)	Scale (θ)	MTBF (days)
Front nose – photocells	0.691	10.60	13.588	0.805	15.73	17.737
Front nose - structure	0.749	9.97	11.880	0.721	10.74	13.232
Headstock / Tailstock	1.026	32.33	31.996	0.713	14.47	17.996
Dual slab conveyor	0.654	7.53	10.228	0.674	10.74	14.117
Rolls	0.613	10.60	15.526	1.002	17.73	17.717
Let-off station	1.001	14.77	14.765	1.090	19.53	18.902
Pneumatic sourcing / diafragm	0.709	15.54	19.440	0.655	8.38	11.352
Innerliner knitting zone	1.179	34.11	32.237	0.776	13.44	15.584

Final periodicity value and adjustment to the production level

In Table 11, it can be verified that the estimated MTBF's for the same subassembly on the 2 machines is sometimes quite different. In order to predict the worst scenario possible, giving priority to machine reliability and uptime, the smallest rounded-up number (that corresponds to the most frequent periodicity) was assumed as the "ideal" periodicity for the subassembly in question in both machines. This value was assumed as the *initial periodicity*, for the current production level.

However, the current production level is still well below the installed capacity, as one can attest by reminding Table 1, as most of the machines' working time is still less than 50%. Because the plant is still in an embryonic stage, it is expected for the working time percentage to increase in the future and, consequently, the production level. Therefore, the initial periodicity, estimated above, is expected to become more frequent, especially in the maintenance actions that affect components that are subject to increasing wear and their level of deterioration is strongly correlated with the working time. If, on the other hand, the plant was already producing close to its full capacity, this question would not pose itself, as the calculated periodicities could be considered as final, because normally a production line does not decrease its production level and, therefore, there would not be any need for further adjustments.

Not all maintenance actions are subject to that kind of "working time-dependent" wear. As such, there was the need to categorize the actions that are subject to wear and the ones that are not. This categorization was made action-by-action and not by subassembly, therefore actions for the same subassembly can have different periodicities in the future.

For the actions which did not depend on the production level, the periodicity was assumed as fixed, and equal to the initially estimated periodicity displayed before, independently of the machines' production levels. In contrast, the ones that did depend on the production level due to continuous and accelerated wear from increased working time, require further calculations to be correctly estimated.

First, it was assumed that the deterioration rate remained constant, independently of the percentage of machine working time. This means that if a machine operates for 50% of the available time or if it operates for 90% of the available time, they are subject to the same deterioration per unit of time. This allows to assume that the production level and the maintenance periodicities have a linear correlation: if the production level for a given machine increases, the periodicities of their maintenance actions will decrease in the same proportion, taking into account the initial periodicity and the initial production level.

To achieve this condition, equations (4.3) and (4.4) define a "working time offset" for machine i at the initial production level ($IniWTOffset_i$) and at the current (in the future) production level ($CurWTOffset_i$). The initial working time percentages are the ones presented in Table 1. This accounts for the production level, but the initial periodicity still needs to be considered. The final periodicity calculation for the actions whose components are subject to "working time dependent" wear in machine i's subassembly j is given by equation (4.5). A safety coefficient ($\propto$) was defined to further increase the margin of error, again in a perspective of prioritizing machine reliability and uptime.

$$IniWTOffset_i = \frac{1}{Initial\ Working\ time\ \%_i} \tag{4.3}$$

$$CurWTOffset_i = \frac{1}{Current\ Working\ time\ \%_i} \qquad 4.4)$$

$$CurrentPer_{ij} = InitialPer_{ij} \times \frac{CurWTOffset_i}{IniWTOffset_i} \times (1-\propto) \tag{4.5}$$

In addition to these calculations, to avoid too frequent interventions in the machines and since the worst case is being considered for all the calculations and therefore a large margin for error has been accounted for, there were established maximum and minimum periodicity limits. These limits were established together with the engineering team, whose experience and knowledge regarding the machine breakdown patterns were crucial in this task. The maximum limit was defined for 90 days, while the minimum limit was set to 7 days. This means that even if calculations suggest that, for a given production level, an action should be executed, for example, every 4 days, the attributed periodicity for that action will be of 7 days. Otherwise, if calculations suggest an intervention frequency between the interval of 7 to 90 days, it will be applied.

Table 12 displays the estimated values for the initial periodicities (remember that the initial working time percentage was of 53%, which gives an initial offset of 190%) for some of the maintenance actions designed for the subassemblies of the *Carcass Building Machines* (are the same in both machines, as the smallest rounded number was considered). There are also presented results for the periodicities assuming a current production level (or working time percentage) of 60%, which means a working time offset of 167%.

This was the used approach in ED7. In ED8, on the other hand, the data available for many of the machine subassemblies was scarce. For this reason, the calculation of the periodicity for the maintenance actions was not based on actual failure data. The initial periodicities for the defined actions were assumed after consulting the people that work most directly with the machines, the CM personnel, and the engineers of that department. These initially defined periodicities for those actions can be consulted in Appendix F. However, after this assumption, the calculation of the current periodicities for the *Spraying Machine*'s maintenance actions also followed equation (4.5). For the *Curing Presses*, however, considering that they either work almost non-stop during an entire period or are completely idle, the assumed initial periodicities are already considering a full-time work, so no adjustments to the production level are required.

Table 12 - Initially calculated and current periodicities for some of the maintenance actions for the *Carcass Building Machines*, assuming a current working time of 60%

Machine subassembly	Maintenance action	Initial periodicity (days)	Current periodicity (days)
Let-off station	Engine consumption while unrolling	15	13
Innerliner knitting zone	Visual inspection of blade: color and stretch marks	16	14
Conveyor belts	Adjust and clean sensors	7	7*
Front nose	Gap between structure and bearing support	12	10
Pneumatic sourcing	Verification of correct air pressure in valves' exit	12	12*
Reels	Verification of lubrication in reels' guides	10	10*
Reels	Check disc reels' alignment (xx) in homing position	10	9
Headstock / Tailstock	Check lubrication and wear of the rotary joints	30	25
Electrical switchboard	Temperature of drives	8	8*
Dual slab conveyor	Engine consumption of the conveyor	11	10
Rolls	Check prisons in rolls	16	14

*Maintenance actions that have fixed periodicity, independently of the production level

4.1.5 Monthly plan generation

To complement the developed maintenance plan and to provide the engineering departments a more user-friendly way to generate the monthly plans, an algorithm was developed in MS Excel VBA. In the case of ED7, whose interface is displayed in Figure 20 (in Appendix G), the only inputs needed are the month to which the plan is wished to be generated and the current production levels for that month for every machine (as a % of working time). On the other hand, in the case of ED8, whose interface is presented in Figure 21 (in Appendix G), it is required the month in question, the predicted monthly production level for the *Spraying Machine* and which curing presses will be working on that month. For the *Curing Presses*, this was the used approach, since it is considered that they either work almost non-stop during the entire month or do not work at all, and it is thus worthless to perform maintenance on machines that will not be working during that month.

These algorithms were constructed assuming that the user will generate the plan for the next month at the end of the current one. The actions that compose the plan appear chronologically in the Plan Sheet, with their predicted and limit execution dates (set with a 5-day margin). The user should then introduce the actual execution date for each action, and by clicking a button in the Plan Sheet called "Update Plan", the plan is automatically updated, meaning that if an action is executed a day after its predicted execution date, actions similar to that one scheduled to be done later that month will also be considered late. It is also provided a control indicator (percentage of actions executed within limit date) which is also constantly updated whenever the same button is pressed. This indicator allows to check if CM personnel are executing the actions in useful time or if they are neglecting them or having no time to perform them.

4.2 Parameter behavior modelling and maintenance interval estimation

The maintenance plan development and the periodicity calculations underlying it are based on reliability analysis. Usually, a predictive or condition-based maintenance plan intends to go much further, comprising the estimation of optimal inspection intervals and critical maintenance thresholds definition for considered critical parameters for a machine's performance. However, this data collection from installed sensors was yet to be made at the beginning of the project, therefore there was not the possibility to apply those techniques immediately, as they require the existence of large quantities of data, collected during a significant period to understand the machine behavior.

For these reasons, the project focused more in the idealization of routine inspections to the systems and its scheduling though a reliability analysis on their breakdowns, as well as in the definition and proposal of measurement actions that may support a more detailed data-driven condition-based maintenance plan implementation soon.

Notwithstanding, an attempt was made to design a condition-based policy for a machine's critical performance parameter. This study aims to provide a basis for future condition-based studies in the plant and to demonstrate the potentialities that a well-thought and detailed study of the critical performance parameters may have on the overall machine performance.

4.2.1 Approach overview

The second part of the project required the data gathering for a condition monitoring parameter that could assess the deterioration state of a machine's component. After the data acquisition, the parameter evolution throughout time was estimated using a discrete-time Markov Chain, where a discrete number of states was defined, as its probability transition matrix, based on the gathered data.

This probability matrix had, however, to be slightly adjusted, as the time span over which the data was gathered was not large enough to observe all the states specified in the transition matrix. Therefore, some of the transition probabilities, namely the ones to reach the higher deterioration states, were assumed.

A decision rule was set, similar to the one proposed by Grall *et al.* (2002b) and already explored in section 2.8.2. Under this modelling framework a corrective maintenance action takes place if the parameter reaches the state of failure; a preventive maintenance action occurs if the parameter reaches the state immediately before the state of failure ("preventive maintenance" state); and no action is pursued elsewise.

Finally, the evolution of the parameter throughout a large period was simulated, based on the transition probabilities of the Markov chain. For this, the Monte-Carlo simulation technique was implemented in MS Excel. The goal of this simulation was to predict the time it takes for the parameter to reach the states of failure and “preventive maintenance”. This information can be then utilized to set the inspection and maintenance intervals.

4.2.2 Parameter description and data collection

The first step in this study was to select the parameter whose behavior should be studied. Preferably, it should be from a component that is working for as long as possible (for this estimation to be as close as possible to the full-production reality), should be easily measurable at any time, as the frequency for data gathering was not very long, and its deterioration measure evolution should exhibit (not just a condition of failed or not failed).

Bearing these conditions in mind, the selected parameter was the water pressure exit from the Temperature Control Units (TCU) of the *Strip Winder*’s extruder, who are responsible for controlling its components’ temperatures by pumping hot or cold water as required. This component was ideal, as it not only belongs to one of the machines with highest working time percentage as it is a component that must be working all the time, regardless of the machine’s state (working or not), water must keep circulating to ensure that the temperatures of the extruder components remain at the desired level. In addition, the water pressure could be easily monitored at any time, with an analogic manometer that displays its value constantly.

This parameter provides information about the clogging level of the filters installed just before the pressure measurement. These filters capture dirt and impurities from the central water supply for the whole plant, and are important to be kept unclogged, since an insufficient or non-renovation of water in the extruder’s components may cause them to overheat, damaging the materials that are extruded and are then added to the tire. When the registered water pressure drops, it therefore means that the filters are getting more and more clogged.

Data collection took place for nearly a month and a half, with very irregular intervals between data points. This was mainly due to the inability to collect data at weekends and holidays and because data were collected at different hours in each day. To solve this issue, data was normalized, to obtain equally spaced data points.

Data was collected for six different components of the extruder, but ultimately only two of them were chosen to be the object of analysis: the extruder’s head and inferior roll TCU’s.

4.2.3 Condition-based model used

The initial idea for this study was to construct an algorithm based on discrete Markov chains’ probability transition matrix, with the aim of optimizing the critical threshold from which a preventive maintenance action should take place (M), as well as optimizing the inspection intervals based on the measured value. However, after the discrete degradation level states definition for the Markov chains, and by looking at the gathered data, it was realized that this optimization was no longer possible to achieve, as the observation of the higher degradation states was not verified, due to frequently imposed maintenance actions by the engineering team to prevent the component to fail, making the total definition of the matrix and the algorithm construction an impossibility. Another approach was then used to tackle these problems, which will be further described in detail next.

Data normalization process

The first step was to treat the gathered data. As it was already said, the intervals over which data were obtained were very irregular, which is something that is incompatible with the use of discrete-time Markov chains, that entail transitions to be made between equally spaced intervals (e.g. days, weeks, etc.). For this reason, there was a need to normalize the obtained raw data to match Markov chains’ specifications.

Inspection times IT_i were normalized from 0 to 1 - NIT_i -, using normalization equation (4.6). Of course, this does not convert the observed values into equally spaced time intervals. To do so, each normalized and equally spaced instant of time - $NESIT_i$ - was said to be equal to $1/N$, being N the number of registered data points, maintaining then the same sample size. Finally, there was a need to obtain the pressure values for the normalized and equally spaced time data points - $P(NESIT_i)$, which was achieved by linear interpolation (4.7).

$$NIT_i \frac{IT_i - Min(IT)}{Max(IT) - Min(IT)} \tag{4.6}$$

$$P(NESIT_i) = P(NIT_j) + (NESIT_i - NIT_j) \times \frac{P(NIT_{j+1}) - P(NIT_j)}{NIT_{j+1} - NIT_j} \tag{4.7}$$

where:

- $P(NESIT_i)$ is the interpolated pressure value for normalized and equally spaced time i;
- NIT_j is the maximum normalized sampled time j, such that $NIT_j < NESIT_i$;
- $P(NIT_j)$ is the sampled pressure value for normalized sampled time j, such that $NIT_j < NESIT_i$;
- NIT_{j+1} is the minimum normalized sampled time $j + 1$, such that $NIT_{j+1} > NESIT_i$;
- $P(NIT_{j+1})$ is the sampled pressure value for normalized sampled time $j + 1$, such that $NIT_{j+1} > NESIT_i$;

Probability matrix construction and underlying assumptions

After the data normalization process, it was possible to construct the probability transition matrix to model the parameter evolution over time. The probability transition matrix in a Markov chain is what commands the behavior and evolution state of the system characteristic that is being modeled. Given its number (m) of discrete states $(X_0, \dots, X_{m-1})$, it sets the conditional probabilities $P(X_j|X_k)$ of the system transitioning to state X_j $(j = 0, \dots, m - 1)$, given that it is currently on state X_k, subject to the condition described in equation (4.8). State transitions occur whenever the defined transition interval passes. The system's state can either change, if the next observed value is below the current state's lower limit or above its upper limit, or remain the same if that condition does not verify.

$$\textstyle\sum_{j=0}^{m-1} P(X_j|X_k) = 1, \quad \forall k = 0, \dots, m - 1 \tag{4.8}$$

Typically, the probability transition matrix is constructed based on data, being $P(X_j|X_k)$ equal to the number of observed state transitions from X_k to X_j divided by the total observed transitions from state X_k to any state. However, as already stated before, in this case the data collected were not enough to observe sampled values for the higher deterioration states. Thus, assumptions had to be made in order to obtain a probability transition matrix that allowed relevant decision-making conclusions about the optimal maintenance policy:

- Adapting the approach proposed by Marseguerra *et al.* (2002), transitions due to component degradation are only allowed until the state immediately before failure. Failure state is therefore only reachable if a random failure occurs, and it can occur from any degradation state from X_0 to X_{m-2}. Transition probabilities from state $X_k = X_0, \dots, X_{m-2}$ to state $X_j = X_0, \dots, X_{m-2}$ were therefore defined separately from the transition probabilities from state $X_k = X_0, \dots, X_{m-2}$ to state X_{m-1} (failure state). Failure and degradation events are considered as being mutually exclusive;

- Whenever the system reaches the failure or "preventive maintenance" state, it is subject to a corrective or preventive maintenance operation respectively, and its state is returned to "as good as new", i.e., $P(X_0 \mid X_{m-1}) = 1$ (perfect maintenance);
- The system can only remain in the current state or transition to a state of higher deterioration, being the only exception if the current state at a given moment is the failure state;
- Probabilities of reaching the failure state X_{m-1} increase exponentially with the increase of the degradation level, being defined by condition (4.9).

$$\begin{cases} P(X_{m-1} \mid X_k) = 0.002 & if\ k = 0 \\ P(X_{m-1} \mid X_k) = P(X_{m-1} \mid X_0) \cdot e^k & if\ 0 < k \leq m-2 \end{cases} \tag{4.9}$$

The initial probability of 0.002 is an assumed value for this particular case, found to be suitable enough for the number of discrete states specified in Table 13. The resulting generalized probability transition matrix based on these assumptions is presented next (4.10).

$$\begin{pmatrix} P(X_0 \mid X_0) & P(X_1 \mid X_0) & P(X_2 \mid X_0) & P(X_3 \mid X_0) & \cdots & P(X_{m-1} \mid X_0) \\ 0 & P(X_1 \mid X_1) & P(X_2 \mid X_1) & P(X_3 \mid X_1) & \cdots & P(X_{m-1} \mid X_1) \\ 0 & 0 & P(X_2 \mid X_2) & P(X_3 \mid X_2) & \cdots & P(X_{m-1} \mid X_2) \\ 0 & 0 & 0 & P(X_3 \mid X_3) & \cdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & P(X_{m-1} \mid X_{m-2}) \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \tag{4.10}$$

The discrete states in which the markovian process was based on, which in this case correspond to pressure value ranges, are presented in Table 13. It is important to refer that the intermediate states have different ranges between themselves: for example, states 1 and 2 have a range of 0.5 bar, while states 3 and 4 have a range of 1 bar each. The influence of this range difference will be tested later in a sensitivity analysis. The highest and lowest deterioration states' ranges are not required to be equal, as the maximum value for the lowest deterioration state and minimum value for the highest deterioration state are not relevant as they have no impact on the analysis (those values are never reached in reality). Additionally, the upper limit of the highest deterioration state (state 5) is also the failure threshold – L - (3.5 bar), so state 5 is considered as the failure state.

Table 13 - Discrete states to be used in the Markov chain and their upper and lower pressure limits

State no.	Lower pressure limit (bar)	Upper pressure limit (bar)
5	0.0	3.5
4	3.5	4.5
3	4.5	5.5
2	5.5	6.0
1	6.0	6.5
0	6.5	8.0

Monte Carlo simulation and maintenance policy decision-making

The initial aim of the study was to optimize the preventive maintenance threshold – M- and the inspection intervals for this component. However, due to the impossibility to do so, the decision-making of the optimal condition-based maintenance policy was made through simulation, using the Monte Carlo technique, of the parameter behavior using the model previously described. It is important to refer that this technique cannot be applied to the probability transition matrix, but to the cumulative probability transition matrix.

Different preventive maintenance thresholds were set, and their simulated total maintenance costs compared with other maintenance policies, such as time-based maintenance (TBM) and failure-based maintenance (FBM), aiming to find the optimal one, i.e., the one with lower total cost. These different scenarios and their preventive maintenance triggers (the policies' main decision rule) are presented in Table 14.

Table 14 - Description of tested scenarios and their underlying maintenance policies

Scenario description	Preventive maintenance trigger
FBM - Run until failure	None
TBM – 2 weeks	Every 15 calendar days
TBM – 1 month (current policy)	Every 30 calendar days
TBM – 2 months	Every 60 calendar days
CBM – Safety threshold = 4	When system reaches state 4
CBM – Safety threshold = 3	When system reaches state 3
CBM – Safety threshold = 2	When system reaches state 2
CBM – Safety threshold = 1	When system reaches state 1

Maintenance and failure costs depend on multiple factors. The number of machine stoppage hours is one of them. If currently a stoppage can be compensated later easily, in the future when production is in full-flow it will be a lot more difficult, therefore it is a crucial factor. In case of a maintenance operation, it is accounted the time for shutting the machine down, cleaning the filter and reconnect it, while in the case of failure is added the time for repairing and checking the entire system again before resuming it, besides the fact that the cleaning time should be longer if the filter is completely clogged. The cost to consider here is the opportunity of losing production. For this, the average selling price for an agricultural tire was considered. On the other hand, if a filter clogs and the extruder overheats, the material it produces does not have the required specifications and therefore the tire in which that material is applied becomes a scrap. Under these circumstances the plant loses the money it could gain with that tire. Finally, the possibility of substitution of the filter is accounted for, assuming it is higher in a case of failure. The assumed maintenance and failure costs and their calculation steps are described in Table 15 and equations (4.11), (4.12), (4.13) and (4.14).

Table 15 - Inputs for calculation of preventive maintenance and failure costs

Preventive maintenance costs		Failure costs	
Estimated stoppage time (hours)	0.75	Estimated stoppage time (hours)	2
Tires produced / hour (throughput)	8	Tires produced / hour (throughput)	8
Number of scrap tires	0	Number of scrap tires	1
Average selling price (€)	1000	Average selling price (€)	1000
Probability of filter substitution	5%	Probability of filter substitution	20%
New filter cost (€)	400	New filter cost (€)	400
TOTAL COST (€)	**6020**	**TOTAL COST (€)**	**17080**

$$Opportunity\ cost = Stoppage\ time\ \times Throughput \times Selling\ price \tag{4.11}$$

$$Scrap\ cost = Nr\ scrap\ tires\ \times Selling\ price \tag{4.12}$$

$$Replacement\ cost = Filter\ cost \times Replacement\ probability \tag{4.13}$$

$$Total\ cost = Opportunity\ cost + Scrap\ cost + Replacement\ cost \qquad (4.14)$$

It is important to refer that all the variables contributing to the total maintenance and failure costs are assumed as constant throughout the analysis. Thus, the contribution of each cost type to the total maintenance and failure costs is fixed (as they only depend on the number of failures and maintenance operations, respectively). The contributions (in percentage) of each cost type to maintenance and failure costs are presented in Table 16.

Table 16 - Contributions of the different cost types to the total failure and maintenance costs

Cost type	Maintenance cost contribution		Failure cost contribution	
	€	%	€	%
Opportunity cost	6000	99.67%	16000	93.68%
Scrap cost	0	0.00%	1000	5.85%
Replacement cost	20	0.33%	80	0.47%
TOTAL	6020	100%	17080	100%

4.3 Curing presses N_2 pulses analysis

One of the goals for this project was to find critical parameters to the machines' performance that were not being monitored yet and evaluate their behavior in order to understand with higher precision their behavior. By doing so one could understand what was these parameters' evolution and what are the critical values from which one should act (maintenance) or bear in mind that something is not working as it was supposed to (alarm). In the case of the *Curing Presses*, this condition parameter was the number of nitrogen pulses sent to the bladder, which maintain high pressure inside it.

In the curing process, the pressure and temperature inside the bladder are two essential parameters that must be kept at certain values to make sure the quality of the cured tire is not negatively affected. The pressure inside the bladder during the process tends to decrease with time, and to avoid that instant high-pressure nitrogen pulses are prompt into the bladder in order to re-increase the pressure inside it. The number of pulses sent is, therefore, an indicator of possible leaks in the bladder or on the tubes: if the number of pulses in a cycle is well above the expected, it means that a leak is happening.

4.3.1 Automatic chart generation

The presses send data relative to temperature and pressure of the bladder and dome every 5 seconds. The first problem was that this data was not being treated properly, and there was a need to develop a very fast way to chart these parameters for any given period, to be checked every time something odd was detected on a cycle. In order to solve that problem, an automatic chart generator was developed using MS Excel VBA, whose only inputs were the date, the machine in which the cycle occurred and the time period of that cycle, that could be easily defined through the interface presented in Appendix J. The obtained chart for a random curing cycle can be visualized in Figure 16. The Excel sheet containing the code was then put into the company's servers, allowing to generate the chart for any cycle, at any time, at any machine.

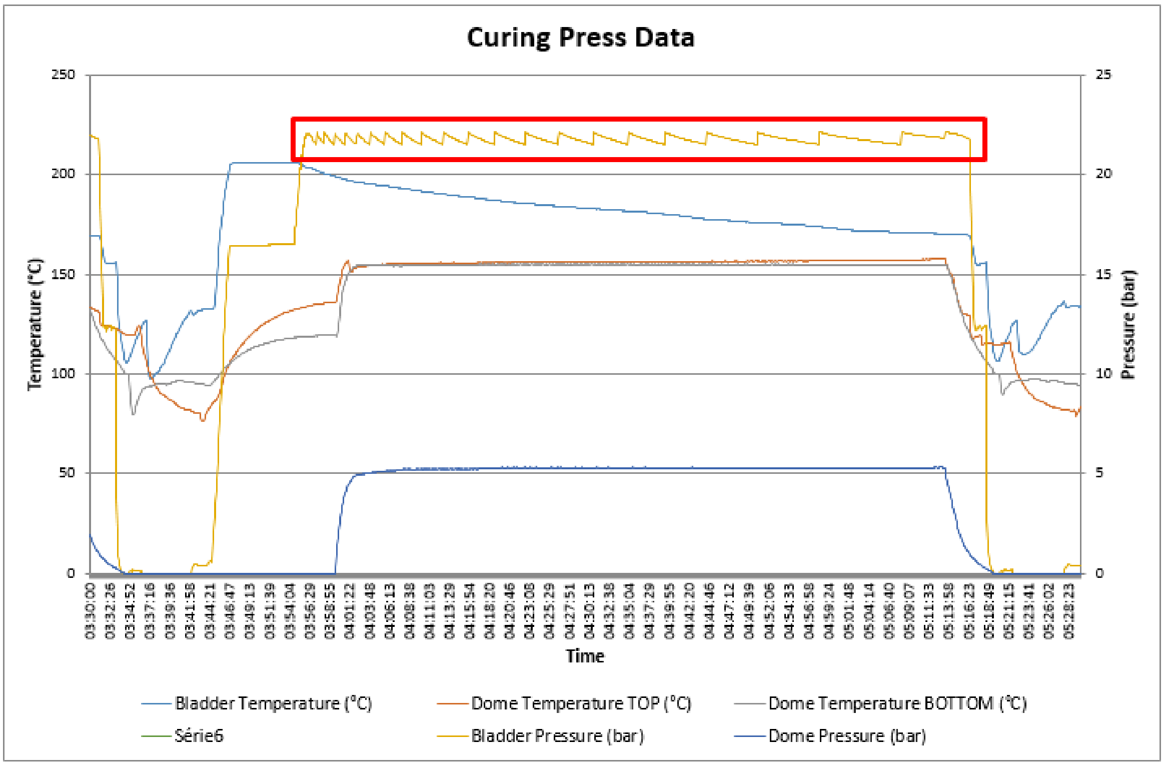

Figure 16 - Curing press data from one curing cycle, obtained from the VBA code developed

The red emphasized zone in Figure 16 represents the curing process itself, where the yellow peaks are the nitrogen pulses that are sent to re-increase the inner bladder pressure during the cycle. The number of nitrogen pulses often depends on the tire type to be produced (tire types are often referred to as tire measures) and of the curing machine type used in the process. There are multiple tire measures to be vulcanized in three types of curing presses: A (104'' – inches - of dome diameter), B (91'' of dome diameter) and D (104'' of dome diameter). Currently there are 1 press of type A, 4 presses of type B and 4 presses of type D. As mentioned before, not all of them work at the same time, and they are not designed to cure every tire measure, being the A's and B's used for the larger tire measures and the D's for the smaller tire measures.

4.3.2 Alarm and maintenance value setting

A vast number of cycles was analyzed, from January to March 2018. To easily obtain the number of pulses of a given cycle without counting them by hand, a VBA macro was coded. For each combination of tire measure and machine type, we retrieved statistics regarding the number of pulses, such as the average, the mode, and the maximum and minimum values observed.

A leak is characterized by a considerably higher number of pulses throughout a set of consecutive cycles. Therefore, isolated cycles with a higher number of pulses, when the immediately before and after cycles register "good" numbers were marked as outliers (due to incorrect data processing or because something specific happened during that cycle) and were excluded from the analysis.

The initial goal with this analysis was to identify cycles with remarkably higher number of pulses than the others, which would indicate the observable number of pulses when a leak was happening. However, even if a clearly identifiable leak is not detected, the obtained values can be assumed as the ones characterizing good cycles, and that any observed values that go above the observed range mean that something is wrong. For these cases, there are two types of possible actions to be pursued: an alarm may be issued, as a message for the engineering team to bear in mind that a cycle has recorded more pulses than the alarm limit and may need a closer monitoring in the upcoming cycles; and the stoppage of the machine, if a cycle has recorded a such large number of pulses that it is even above the defined stoppage limit. These limits, theoretically speaking, are achieved sequentially, as it is expected for a leak to be, at first, small and therefore register a smaller number of pulses, and then to become larger as the machine continues working, prospecting an increase in the number of pulses from cycle to cycle until the stoppage limit is surpassed. The formulas for these limits are found in (4.15) and (4.16) for each measure i to be produced in machine j.

$$Alarm\ limit_{ij} = 1.1 \cdot Mode_{ij} \tag{4.15}$$

$$Stoppage\ limit_{ij} = 1.15 \cdot Maximum_{ij} \tag{4.16}$$

The definition of the above formulas in (4.15) and (4.16) did not follow any theoretical basis, but they have a logical sense. If a cycle’s number of pulses goes a certain margin (assumed 10%) beyond the most observed value, it means that something may be going out of control but may not necessarily implicate a large enough leak to influence the tire quality. On the other hand, if a cycle’s number of pulses goes beyond the maximum registered value by a given margin (assumed 15%), it may indicate that a large leak is occurring, that may damage the tire characteristics and therefore the machine should be stopped to repair the leak.

5 Results

In this section of this thesis the obtained results after applying the described methodologies in Section 4 are presented. First, the impact results from the implementation of the predictive maintenance plan are displayed; afterwards the simulation results from the condition-based model developed for the tested scenarios are presented, as well as a sensitivity analysis on some of its most critical assumptions; and finally results from the curing presses nitrogen pulses analysis are introduced, comprising the definition of the critical alarm and stoppage values for a few tire measure and machine type combinations.

5.1 Time-based maintenance plan implementation

Having already shown some of the intermediate results obtained, crucial for a better understanding of the methodology used, the true impact of the developed maintenance plan has yet to be shown. The way to assess the impact that the plan had on the overall maintenance performance of the plant is to look and compare the selected maintenance performance indicators prior and after the maintenance plan implementation.

5.1.1 Maintenance performance indicators analysis

Even if the period of implementation was only a month, it is relevant to compare the obtained values for the maintenance performance indicators before and after. Table 17 summarizes the resultant performance indicators for May 2018, also presenting the percentage variation in relation to the ones verified at March 2018, for both ED7 and ED8.

Table 17 - Maintenance performance indicators for May 2018 and comparison to the ones from March 2018

	MM		MTBF (h)		MTTR (h)	
Machine	May	+/- (vs Mar)	May	+/- (vs Mar)	May	+/- (vs Mar)
Carcass Building Machines	80.0%	-5.9%	7.08	+2.8%	0.15	-57.1%
Green Tire Buil. Machines	66.3%	-7.3%	28.38	+106.7%	0.22	+15.8%
Extruder	96.8%	+1.6%	2.98	+30.1%	0.09	-71.9%
APEX	83.4%	+23.6%	6.24	-13.3%	0.14	-12.5%
Bead Winder	90.2%	+26.5%	9.23	+29.8%	0.33	+266.7%
Strip Winder	88.6%	+21.3%	24.63	-52.0%	0.09	-50.0%
Combicutter	90.1%	+28.6%	7.67	+68.9%	0.07	-63.2%
Spraying Machine	81.0%	+2.0%	3.50	-32.7%	0.85	+203.6%
Curing Presses			27.80	-5.4%	0.48	+26.3%

Through the observation of Table 17, the improved standardization of maintenance operations can be verified, as the MM values are now very balanced for all the machines. The majority of them experienced an increase in this indicator, proving maintenance operations are now much more organized, and that planned maintenance operations have a very superior weight when compared to CM operations in the total maintenance time expended. Also, good signs are shown in the MTBF and MTTR indicators, as many machines show higher MTBF's (less frequent failures) and lower MTTR's (less severe failures), especially in the machines of ED7. However, it is still very early to evaluate the results from these two indicators, as they normally require more time to mature, therefore these results should be viewed in a conservative perspective, as they may have coincided with a good month.

5.2 Condition-based modelling

In this section are presented the obtained results for the Monte Carlo simulation conducted on the various scenarios, as well as a sensitivity analysis on the condition-based model's most critical underlying assumptions. Prior to the application of the model to real data, however, a simple concept validation was made, based on simulated data, to make sure the model could demonstrate the required trade-off between the number of failures and maintenance operations.

Every scenario presented in Table 14 was simulated throughout 5000 time-intervals, with a warm-up period of 500 time-intervals. It is important to notice that each time-interval does not correspond to one day, since the initially obtained raw data had to be normalized to allow the parameter modelling using a Markov chain. Since the 72 data points collected were gathered within a range of 41 days, and data were then normalized so that they were equally-spaced, each time interval corresponds to $41/72 = 0.569(4)$ days.

5.2.1 Concept validation

In order to validate the conceptual model previously described and verify the existence of a trade-off between failures and maintenance operations, prior to its application to real data, the model was tested using a simulated probability transition matrix. For this concept validation, the number of states (6) and their designations were kept the same as in the used condition-based model. The pressure ranges defined for the discrete states of the Markov chain to be applied to real data are not applicable here, since the probability transition matrix is not generated based on any kind of pressure values data, results obtained have no practical meaning, but are used to understand the policy potential.

The simulated transition probabilities from the degradation states X_k $(k \leq m-2)$ to states X_j $(k \leq j \leq m-2)$ - $P(X_j|X_k)$ - were obtained using the formula proposed by Marseguerra *et al.* (2002), displayed in (5.1). The failure probabilities - $P(X_{m-1}|X_k)$ - were generated according to (4.9), and then added to the simulated probability matrix.

$$P\left(X_j \middle| X_k\right) = \frac{2}{N-k+1}\frac{N-k-j}{N-k} \tag{5.1}$$

where N is the number of degradation states (before failure), i.e., $N = m-1$. Of course, the transition probabilities obtained for the degradation process had to be adapted using (5.2) to respect the inviolable condition stated in (4.8).

$$P\left(X_j \middle| X_k\right) = P\left(X_j \middle| X_k\right) \cdot (1 - P(X_{m-1}|X_k)) \tag{5.2}$$

The final simulated probability transition matrix used for the concept validation is displayed in (5.3). Monte Carlo simulation was performed based on the cumulative probability transition matrix, presented in (5.4).

$$\begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{pmatrix} 0.3327 & 0.2661 & 0.1996 & 0.1331 & 0.0665 & 0.0020 \\ 0 & 0.3978 & 0.2984 & 0.1989 & 0.0995 & 0.0054 \\ 0 & 0 & 0.4926 & 0.3284 & 0.1642 & 0.0148 \\ 0 & 0 & 0 & 0.6399 & 0.3199 & 0.0402 \\ 0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{5.3}$$

$$
\begin{array}{c|cccccc}
 & 0 & 1 & 2 & 3 & 4 & 5 \\
\hline
0 & 0.3327 & 0.2661 & 0.1996 & 0.1331 & 0.0665 & 0.0020 \\
1 & 0 & 0.3978 & 0.2984 & 0.1989 & 0.0995 & 0.0054 \\
2 & 0 & 0 & 0.4926 & 0.3284 & 0.1642 & 0.0148 \\
3 & 0 & 0 & 0 & 0.6399 & 0.3199 & 0.0402 \\
4 & 0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\
5 & 1 & 0 & 0 & 0 & 0 & 0
\end{array} \tag{5.4}
$$

Results after simulation over 5000 transitions, with a warm-up period of 500 were obtained through the Monte Carlo technique. By increasing the policy strictness, it is expected for the number of failures to decrease, but the number of preventive maintenance actions is expected to rise. The goal is to find the policy that better balances these two, considering the assumed maintenance and failure costs of Table 15.

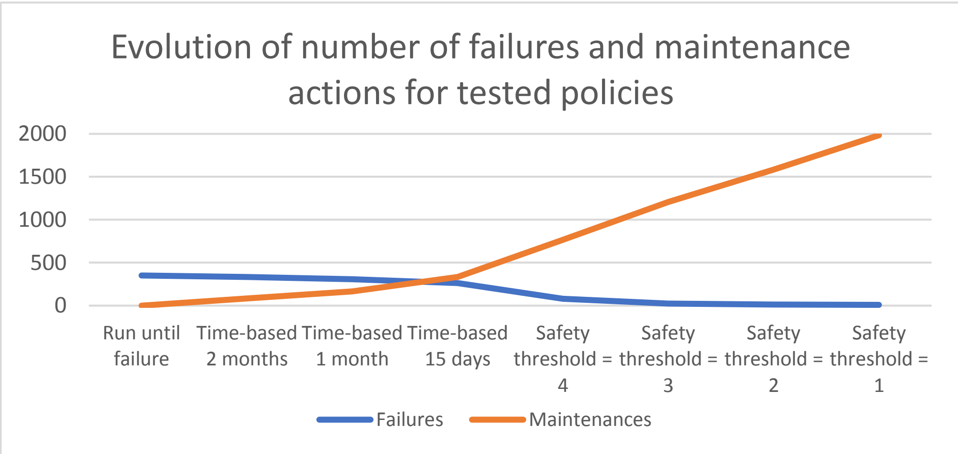

Figure 17- Failure and maintenance trade-off verification

Analyzing Figure 17, it can be concluded that the number of failures decreases as the policies' strictness increases, and the opposite happens with the number of maintenance actions. This was the trade-off that was hoped the model could provide and was tried to verify with this concept validation. A total cost analysis was not the purpose of this concept validation.

5.2.2 Application to real data

Having validated the concept, it is time to apply it to the collected data on the field, that will allow to draw conclusions about what should be the optimal maintenance policy to be followed for the component in question. However, because the obtained data is too polarized in the least degradation states, one additional assumption had to be made. Due to the fact that sudden significant decreases in pressure values (implying sudden "jumps" to higher deterioration states) are not observed (degradation is steady), it was assumed that only transitions to the immediately next higher degradation level take place, besides staying in the current state (meaning that, for $k = 0, \dots, m-2$, only $\{P(X_k|X_k), P(X_{k+1}|X_k)\} \neq 0$). In addition, since pressure values for the higher deterioration states aren't observed, it was assumed that the transition probabilities obtained based on data for the lower deterioration states are kept the same throughout the chain's deterioration states. The probabilities that were used as a reference to explain the parameter evolution in the Markov chain were the ones obtained for the most frequently observed states in data.

As already mentioned, this study was conducted using data from two of the *Strip Winder*'s extruder components: the head and the inferior roll. Next are presented all the assumptions made for each component, as well as the simulation results that led to a decision about the preferable maintenance policy to use.

Extruder head analysis

The probability transition matrix was inferred from the state transition observations of the normalized data. Matrix (5.5) presents the number of observed transitions for the extruder head pressure values. From that matrix, the probabilities $P(X_k|X_k)$ and $P(X_{k+1}|X_k)$, for $k = 0, \ldots, m-2$ were estimated from the observed transitions of the most observed state, that in this case is state 1, with a total of 39 observations. Therefore, $P(X_1|X_1) = 35/39 = 0.8974$ and consequently $P(X_2|X_1) = 1 - 0.8974 = 0.1026$, since it was assumed that only transitions to the next higher deterioration state are allowed besides remaining in the same system state.

$$
\begin{array}{c c}
 & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} &
\begin{pmatrix}
17 & 2 & 0 & 0 & 0 & 0 \\
3 & 35 & 1 & 0 & 0 & 0 \\
0 & 2 & 4 & 1 & 0 & 0 \\
0 & 0 & 1 & 6 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array} \tag{5.5}
$$

Of course, since transitions to the failure state also need to be considered, these observed probabilities are adapted in the final probability transition matrix in order to not violate the condition in (4.8). Thus, a similar exercise to the one used above with simulated data was performed (5.2), and the final probability transition matrix is presented in (5.6).

$$
\begin{array}{c c}
 & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} &
\begin{pmatrix}
0.8956 & 0.1024 & 0 & 0 & 0 & 0.0020 \\
0 & 0.8926 & 0.1020 & 0 & 0 & 0.0054 \\
0 & 0 & 0.8842 & 0.1010 & 0 & 0.0148 \\
0 & 0 & 0 & 0.8614 & 0.0984 & 0.0402 \\
0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\
1 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array} \tag{5.6}
$$

Similarly to the concept validation, the Monte Carlo simulation technique should be applied to a cumulative probability transition matrix, shown in (5.7). Simulation results from 5000 simulated transitions, with a 500 transitions warm-up in each of the tested scenarios for the extruder head component are detailed and presented in Table 18.

$$
\begin{array}{c c}
 & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} &
\begin{pmatrix}
0.8956 & 0.9980 & 0.9980 & 0.9980 & 0.9980 & 1.0000 \\
0 & 0.8926 & 0.9946 & 0.9946 & 0.9946 & 1.0000 \\
0 & 0 & 0.8842 & 0.9852 & 0.9852 & 1.0000 \\
0 & 0 & 0 & 0.8614 & 0.9598 & 1.0000 \\
0 & 0 & 0 & 0 & 0.8908 & 1.0000 \\
1 & 0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array} \tag{5.7}
$$

Considering all the scenarios that were tested, using the proposed model and the cost assumptions for failure and preventive maintenance situations, it becomes clear that a condition-based model is more beneficial than a time-based or failure-based model for this component. Comparing to the policy currently in use (perform preventive maintenance every month), a condition-based model (except for the most conservative scenario) proportions savings of more than 400,000 € for 5000 transitions, i.e., 2847 days, which is just under 8 years of operation. This corresponds to an annual saving of 92,420 € for the optimal policy. Considering that the plant will be operating for way longer than 8 years, one can imagine the savings that can happen over the next 20 or 50 years.

Table 18 - Simulation results and cost analysis for Strip Winder extruder head filter

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	131	0	2237480	0	2237480
TBM – 2 months	115	47	1964200	282940	2247140
TBM – 1 month (current policy)	95	96	1622600	577920	2200520
TBM – 2 weeks	61	192	1041880	1155840	2197720
CBM – Safety threshold = 4	66	83	1127280	499660	1626940
CBM – Safety threshold = 3	32	155	546560	933100	1479660
CBM – Safety threshold = 2	16	248	273280	1492960	1766240
CBM – Safety threshold = 1	9	483	153720	2907660	3061380

The optimal maintenance policy for this component, according to the proposed model, is to set the preventive maintenance threshold at the upper bound of state 3, i.e., to perform a maintenance operation every time the water pressure exit value drops below 5.5 bar. However, due to the number of assumptions that had to be made in the model construction process, setting that threshold at 4.5 bar (lower bound of state 4) should also be looked into as a viable possibility. The expected times to failure and maintenance for these two scenarios are specified in Table 19. The expected time to each maintenance operation can act as a reference for the frequency to which the maintenance team should check the pressure level.

Table 19 - Expected number of days to failure and maintenance for extruder head

Scenario description	Expected time to failure (days)	Expected time to maintenance (days)
CBM – Safety threshold = 4	43.14	34.30
CBM – Safety threshold = 3	88.98	18.37

Extruder inferior roll analysis

A similar approach to the one presented in the analysis of the extruder head was carried out for the extruder inferior roll component, obtaining the probability transition matrix based on observed transitions in the normalized data. The intermediate steps and the final results obtained for this component can be found in Appendix H.

Sensitivity analysis

In order to assess the robustness of the developed model and of the optimal decision obtained through simulation, a sensitivity analysis to a few of the assumed parameters was conducted. In this analysis, the parameters chosen to be evaluated were the ratio between individual failure and maintenance cost, the deterioration and failure probabilities and, finally, the number of assumed states in the Markov chain. For this analysis to be meaningful, when testing a given parameter, the others must be kept the same as before. With the purpose of not making this analysis too extensive, only the extruder head component results will be subject to it.

First, the ratio between failure and maintenance costs was evaluated. The assumed ratio was the one specified on equation (5.8), meaning that the failure cost is 2.84 times higher than the maintenance cost. For this analysis, ratio values of 1.5, 2 and 3 will be tested, and the critical ratio for which the two policies ("Safety threshold = 4" and "Safety threshold = 3") match in terms of total cost. For this, the maintenance cost will be kept constant, but the critical ratio is independent of the actual value of the maintenance cost.

$$Current\ ratio = \frac{Current\ failure\ cost}{Current\ maintenance\ cost} = \frac{17080}{6020} = 2.837 \quad (5.8)$$

Obtained failure, maintenance and total costs for the two most viable scenarios for the cost ratios of 1.5, 2 and 3 and for the critical cost ratio are specified in Table 20. The costs for the remaining scenarios for each of the tested cost ratios can be consulted in Appendix I.

Table 20 - Total cost comparisons between the two most viable policies for different cost ratios

Cost Ratio	Maint. Cost	Fail. Cost	'CBM – Safety threshold = 3'- Total Cost	'CBM – Safety threshold = 4' - Total Cost
Current = 2.837	6020	17080	1479660	1626940
1.5	6020	9030	1222060	1095640
2	6020	12040	1318380	1294300
3	6020	18060	1511020	1691620
Critical = 2.118	6020	12748.24	1341043.5	1341043.5

From Table 20, one can conclude that when the cost ratio increases, the cost difference between the policy that sets the maintenance threshold at state 3 and the one that sets it at state 4 increases. However, when the cost ratio decreases, the opposite happens. The critical ratio value of 2.118 means that setting the critical threshold at state 3 remains the optimal policy if the ratio between failure and maintenance costs is equal or higher than 2.118, i.e., if the failure cost is at least 2.118 times higher than the maintenance cost, whatever its value. If their ratio is found to be lower than 2.118, the optimal policy is to set the maintenance threshold at state 4.

Next, the deterioration probabilities were modified, using that to assess the robustness of the optimal policy obtained. For this exercise, deterioration probabilities $P(X_{k+1}|X_k)$, for $k = 0, \dots, m-2$ were modified from the estimated value of 0.1026 (5.5) to 0.05 and 0.15. The obtained probability matrices for these cases, after the necessary adjustment to obey to unbreakable condition (4.8), can be found in Appendix I.

The results obtained when setting the deterioration probability to 0.05 show that the condition-based maintenance policies (except for the most conservative policy) still perform significantly better than the time-based or failure-based policies (Appendix I). The optimal policy is still the one that sets the preventive maintenance threshold at the upper bound of state 3, however given that deterioration was slowed, the policy that sets the threshold at the upper bound of state 2 has a very similar cost performance (see Figure 18, where $P(X_{k+1}|X_k)$ is represented as "Det. P"), as the number of performed maintenance operations for this threshold is a lot lower than for higher deterioration probabilities, allowing maintenance costs to be lower and compensate the higher number of failures in the other policies.

For a deterioration probability of 0.15, it was expected that the optimal policy would be nearer to the one that sets the threshold at the upper bound of state 4. That, when comparing to a lower deterioration probability, does happen, however the optimal policy found is still the initial one, that sets the maintenance threshold at the upper bound of state 3 (Figure 18), meaning that even for slower and faster deteriorations, this policy is still the optimal one, proving its robustness.

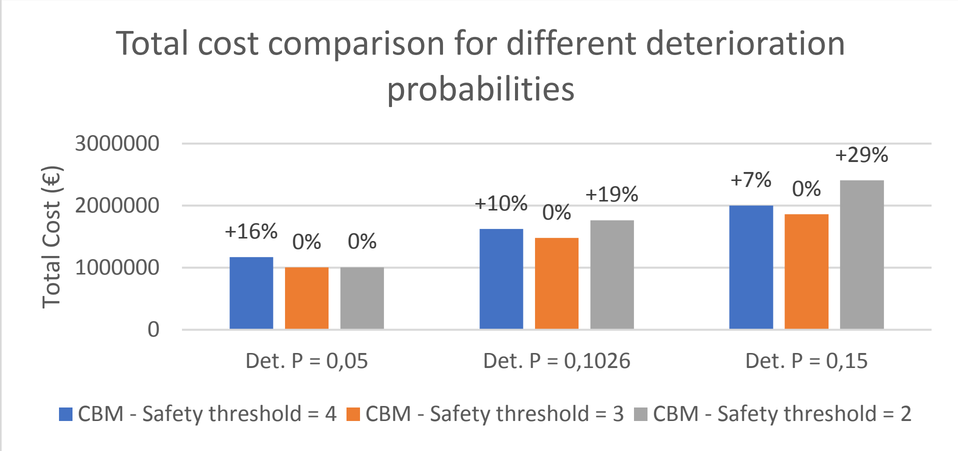

Figure 18 - Total cost comparison, for the three most viable scenarios, for different deterioration probabilities

Besides the deterioration probabilities, the assumed failure probabilities may also have a huge effect on the optimal maintenance policy, especially since their assumption had no underlying data to support it. It was tested a slower and faster evolution for these random failure probabilities than the one used in the model, according to the rules specified in (5.9) and (5.10), respectively. Again, results showed that condition-based policies are considerably better than time-based or failure-based policies (Appendix I). Figure 19 shows the total cost obtained for the three most viable scenarios for the different failure probability distributions.

$$\begin{cases} P(X_{m-1}\,|X_k) = 0.0025 & if\ k = 0 \\ P(X_{m-1}\,|X_k) = 2 \cdot P(X_{m-1}\,|X_{k-1}) & if\ 0 < \ k \leq m-2 \end{cases} \qquad (5.9)$$

$$\begin{cases} P(X_{m-1}\,|X_k) = 0.002 & if\ k = 0 \\ P(X_{m-1}\,|X_k) = \ P(X_{m-1}\,|X_0) \cdot 1.5 \cdot e^k & if\ 0 < \ k \leq m-2 \end{cases} \qquad (5.10)$$

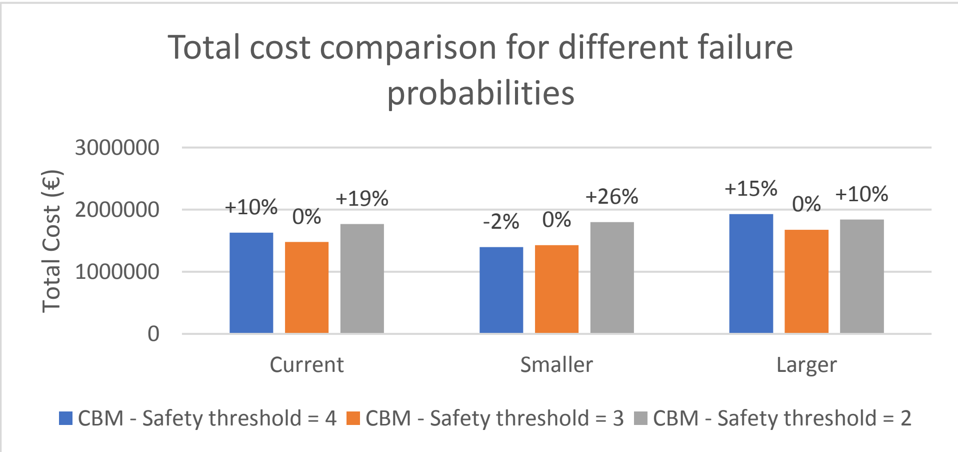

Figure 19 - Total cost comparison, for the three most viable scenarios, for different failure probabilities

Through the observation of Figure 19, it can be drawn that even when the failure probabilities are changed, the initially obtained optimal policy holds up very well, only slightly outperformed by the policy that sets the maintenance threshold at the upper bound of state 4 in the case of smaller failure probabilities. Therefore, this analysis corroborates the idea that the obtained optimal solution is quite robust, as it remains the best one even if changing such important parameters as the deterioration and failure probabilities.

The final evaluation had to do with the number of states considered. Initially, there were considered 5 degradation states and 1 failure state. It is intended to study if an increased segmentation of the pressure values, increasing the number of degradation states of the Markov chain, would be beneficial to the total cost and if it would change the initially obtained solution. The initial ranges choice was one in which the ranges were not all identical, and now one of the intentions is to make them all identical. For this reason, all states, excluding state 0 and the failure state, were assumed to have a range of 0.4 bar. Table 21 summarizes all the states used for this analysis, as well as their pressure value ranges.

Table 21 - Characterization of defined states and their pressure value ranges for the sensitivity analysis

State no.	Lower pressure limit (bar)	Upper pressure limit (bar)	State no.	Lower pressure limit (bar)	Upper pressure limit (bar)
9	0.0	3.5	4	5.1	5.5
8	3.5	3.9	3	5.5	5.9
7	3.9	4.3	2	5.9	6.3
6	4.3	4.7	1	6.3	6.7
5	4.7	5.1	0	6.7	8.0

Since the number of degradation states was increased from 5 to 9, the transition probabilities to a higher degradation state must be higher than the previously obtained ones, since the states' ranges have decreased. Therefore, they were estimated based on the initially assumed ones, multiplying them by $9/5$, being $P(X_{k+1}|X_k) = 0.1846$. This step is arguable, since the normalized real data could be used to set the new probabilities for the newly defined discrete states with an increased accuracy. However, the aim with this analysis is to test the sensitivity of the developed model to a change in the number of states solely, and not to develop a whole different new model. Also, the failure probabilities must be modified, but this time they were estimated through equation (5.11). The obtained transition matrix used in this analysis can be found in Appendix I.

$$\begin{Bmatrix} P(X_{m-1}\,|X_k) = 0.002 & if\ k = 0 \\ P(X_{m-1}\,|X_k) = \ P(X_{m-1}\,|X_0) \cdot e^{k \cdot \frac{5}{9}} & if\ 0 <\ k \leq m-2 \end{Bmatrix} \tag{5.11}$$

Again, the condition-based policies perform better even if the number of discrete states considered increases, as can be proven by Table 22 which proves the viability and robustness of the use of such a policy. The optimal obtained solution in this case corresponds to setting the maintenance threshold at the upper bound of state 4, i.e., to perform a maintenance operation whenever the pressure value drops below 5.5 bar. The obtained solution is the same as the one obtained previously, which is a clear demonstration of the robustness of the initially obtained solution and attests the strength and suitability of the developed condition-based model.

Almost all scenarios evaluated in this sensitivity analysis have a common optimal solution, the same as the initially obtained. This not only proves the robustness of that solution, as whatever conditions are applied it still remains as the optimal one, but also the strength of the developed condition-based model, by the fact that it was able to obtain an initial optimal solution that was not very sensitive and dependent of its underlying assumptions.

Table 22 - Results obtained for the tested scenarios with an increased number of states

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	94	0	1605520	0	1605520
TBM – 2 months	72	47	1229760	282940	1512700
TBM – 1 month (current policy)	59	96	1007720	577920	1585640
TBM – 2 weeks	22	192	375760	1155840	1531600
CBM – Safety threshold = 8	84	12	1434720	72240	1506960
CBM – Safety threshold = 7	68	32	1161440	192640	1354080
CBM – Safety threshold = 6	48	57	819840	343140	1162980
CBM – Safety threshold = 5	44	76	751520	457520	1209040
CBM – Safety threshold = 4	23	118	392840	710360	1103200
CBM – Safety threshold = 3	13	171	222040	1029420	1251460
CBM – Safety threshold = 2	11	252	187880	1517040	1704920

5.3 Curing presses N_2 pulses analysis

Finally, the results retrieved from the analysis of the number of N_2 pulses in the curing cycles, using the approach previously described in Section 4.3 are presented in this section, with the descriptive statistics for few of the tire measures and machine type combinations and their alarm and stoppage found values.

Descriptive statistics

The obtained statistics about the number of N_2 pulses found in the analyzed curing cycles are entirely presented in Appendix J, while Table 23 provides its values for two of the most frequent tire measures produced and, consequently, most observed, in two different machine types (in this case, curing presses of type B and D).

Table 23 - Descriptive statistics on the number of nitrogen pulses for two of the most observed tire measures

Measure	Curing press	Nr of cycles	Maximum	Minimum	Average	Mode
340-85 R28	D01	299	18	15	17.037	17
460-85 R38	B01	222	23	20	21.586	22

Alarm and stoppage limits

Only one leak was clearly identified, having happened in press D03 for measure 420-70 R38, where were registered consecutive cycles of 26, 27 and 28 pulses, while the average was under 21 pulses.

For this reason, for the remaining combinations of tire measure and machine type, alarm and stoppage limits were defined, according to the criteria specified in Section 4.3.2. The alarm and stoppage limit values for the measures previously mentioned are found in Table 24. The alarm and stoppage limits found for the remaining measures can be consulted in Appendix J.

Table 24 - Alarm and stoppage limits for two of the most produced tire measures from January to March 2018

Measure	Curing press	Alarm Limit	Stoppage Limit
340-85 R28	D01	19	21
460-85 R38	B01	25	27

6 Conclusions

In this section, a few final considerations regarding the achievement of the initial objectives, the pertinence of the conducted work to the company and the results obtained are drawn. Some future work perspectives are also suggested, building on the developed work.

6.1 Final Considerations

The main expected goal for this thesis, from the company's perspective, was the development of a predictive maintenance plan to be implemented in the new machines that comprised the new agricultural tire manufacturing facility at Continental Mabor, that could provide a basis for systematizing maintenance activities and at the same time improve, in the long run, the uptime and useful life of the machines. These objectives were achieved, and the analysis was even furthered through the development of condition-based approaches that may prove to be useful in future decisions regarding the choice of the most suitable maintenance policy.

A predictive or condition-based maintenance plan usually relies on sensorial data being collected throughout a significant period, such that it becomes possible to draw conclusions about the optimal policy that should be implemented. However, no sensorial data were being collected prior to the project, and therefore a detailed data-driven condition-based study was not possible.

For this reason, the used approach was very similar to a reliability analysis, where breakdowns per machine subassembly were analyzed, their causes identified and, from there, possible maintenance actions to mitigate those causes idealized. Finally, breakdowns were modeled to find the optimal periodicity for each of the developed maintenance actions. The developed plan is expected to contribute in the long run to the reduction of breakdown frequency, which should in the future reflect in the MTBF. However, as the designed maintenance plan implementation results are only from a one-month period, only the MM indicator has so far suffered an upgrade.

Although the development of this plan was the utmost objective for the company with this project, and the tool from which it will benefit the most, the developed maintenance plan did not result from a pure condition-based approach. In order to complement the analysis and to demonstrate the viability of the implementation of a condition-based maintenance plan instead of a preventive one, data was collected from a condition parameter a critical component of one machine, and a condition-based model based on a discrete state Markov chain was developed to study the parameter evolution. Various policies were tested and compared and the optimal policy, obtained by means of a Monte Carlo simulation. The method was proved to be very robust and viable, as attested by the performed sensitivity analysis, where some of the model's underlying assumptions were changed, and the observed optimal policy almost always remained the same. This also proves the robustness and adaptability of the developed model.

Although the proposed condition-based model to simulate a parameter's evolution throughout time is based on many assumptions that may not entirely correspond to reality, it provides a demonstration that such a model can be applied to the monitoring of components that are continuously subject to wear in the different machines across the plant. It requires, however, a combined effort in the gathering of a sufficient volume of data that allows the construction of a model as much precise as possible, in order to approximate it the most to reality and enable, consequently, decision-making about what should be the most viable maintenance policy to implement for a given component. These decisions may also prove to be very relevant to increase the components' useful life, reduce machines' downtime increasing its availability and, ultimately, maximize savings (in maintenance operations) and revenue (due to the increased availability).

Finally, a different approach to condition-based maintenance was proposed, through the analysis of a parameter that indirectly evaluates if a leak during curing occurs in the presses. This approach consisted in the data processing from sensorial data sent by the presses, identifying the normal performance values and then extrapolating those into obtaining the values from which an alarm should be issued, or close monitoring pursued and the ones from which a machine should be stopped and a CM operation take place.

6.2 Future work perspectives

An expanding and leading company such as Continental Mabor should always put a clear effort to evolve and improve its operations, in every field. In this sense, future improvements and works are suggested, regarding the existent maintenance operations at the CST facility and building on top of the performed work.

First, the periodicity calculations for the maintenance plan were performed under many assumptions, such as calculating the periodicities for the whole subassembly, and not the component focused on each maintenance action. Therefore, these should be adjusted over time according to the experience: if one finds the current periodicity for a given action is too low and frequent, it should be increased for a better resource usage, and vice-versa if the contrary is observed.

Another important aspect worth to look into is the viability of a dedicated predictive maintenance team in the CST facility, as already takes place in the PLT facility. Of course, the performance of the CM team that will be, for now, in charge of the predictive maintenance activities should be evaluated (if they have the necessary time to perform all CM and predictive maintenance activities or if their available time is almost completely dedicated to CM). This evaluation should involve the estimation of costs and working time occupied by the predictive maintenance activities with the dedicated predictive maintenance team and without it (with the CM team in charge of the predictive maintenance activities).

Also, it was noticed during the project that the preventive maintenance checklists to perform at the CST machines are very identical to the ones of the PLT machines, as they were adapted from them. However, the machines in both facilities are quite different, in size and functionalities. For this reason, many of the actions in those checklists are not applicable to the existent machines in the CST plant. Thus, it is suggested that a deeper and detailed look is given by the engineering team, in order to completely tailor them to the functionalities and needs of the existing machines in the plant.

Finally, a project for the implementation of real time sensors in some of the critical machine components that enable real time data collection and online monitoring of these components' deterioration state should be put at the top of the pile. This not only would enable the triggering of maintenance actions only when a certain (previously studied) limit is achieved (which could result in the optimization of resource usage), as it would put the facility as a leading force in a constantly demanding industry through the implementation of Industry 4.0 principles, which is the step companies must take to remain as competitive as possible.

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Appendix A: Weibull parameters estimation methods

MLE method

Given n observations $(x_1, x_2, \ldots, x_n)$, the log-likelihood function of the Weibull distribution is:

$$L(\beta, \theta) = \sum_{i=1}^{n} \ln f(X_i|\beta, \theta)$$

Solving for the optimal solution:

$$\frac{\partial \ln L}{\partial \beta} = -\frac{n}{\beta} + \frac{1}{\beta^2} \sum_{i=1}^{n} x_i^{\theta} = 0$$

Eliminating β:

$$\left[\frac{\sum_1^n x_i^{\theta} \ln x_i}{\sum_1^n x_i^{\theta}} - \frac{1}{\theta}\right] = \frac{1}{n} \sum_{i=1}^{n} \ln x_i$$

This can be solved to estimate θ. Now β can be found in terms of θ:

$$\beta = \frac{\sum_1^n x_i^{\theta}}{n}$$

Appendix B: Identified failure modes

Carcass Building Machine no. 1 (remaining)

Table 25 - Remaining identified failure modes for Carcass Building Machine no. 1

Failure mode description	Frequency
Reels don't work properly	4.25%
Problems with cassettes' coupling	4.03%
Material stuck in rolls	3.80%
Errors in PLC's and drives	3.13%
Mispositioned reels	2.91%
Other	13.19%

Carcass Building Machine no. 2 (remaining)

Table 26 - Remaining identified failure modes for Carcass Building Machine no. 2

Failure mode description	Frequency
Front nose hits drum or dog ears / tilting error	4.13%
Mispositioned slab conveyor	3.93%
Mispositioned reels	3.31%
Error in front nose sensor / photocell	3.10%
Material stuck in rolls	3.10%
Other	16.74%

Extruder

Table 27 - Identified failure modes for Extruder machine

Failure mode description	Frequency
Errors in TCU's	20.62%
Problems in thermic and electric switchboards	13.40%
Errors in opening and closing extruder head	9.28%
Problems with balancers	9.28%
Problems with nozzles and conveyors	8.25%
Errors in the chiller	7.22%
Other	22.68%

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Table 28 - Identified failure modes for APEX machine

Failure mode description	Frequency
Errors in PLC and drives	50.72%
Apex detection sensor misadjusted	10.14%
Problems with the flipper	8.70%
Error in the metals detector	8.70%
Other	21.74%

Bead Winder

Table 29 - Identified failure modes for Bead Winder machine

Failure mode description	Frequency
Errors in PLC and drives	28.16%
Problems with the guiding disc	11.65%
Wire jumps out of the guiding disc	10.68%
Problems in the wire reel	9.71%
Errors in TCU's	8.74%
Problems in wire cutting	5.83%
Other	20.39%

Combicutter

Table 30 - Identified failure modes for Combicutter machine

Failure mode description	Frequency
Torque value not adjusted	18.24%
Le-off station sensors misadjusted	14.71%
Centering problems when rolling	14.12%
Problems with cassettes' coupling	10.00%
Failure in splicing procedure	10.00%
Errors in PLC and drives	8.24%
Other	24.71%

Green Tire Building Machines

Table 31 - Identified failure modes for Green Tire Building Machines

Failure mode description	Frequency
Machine does not initialize cycle	17.09%
Mispositioning / errors in lasers	16.64%
Problems with barcodes	14.56%
Safety sensors / scanners in error	11.39%
Problems with cassettes' coupling	9.49%
Mispositioning of reels	7.59%
Problems with the turret	5.70%
Other	17.72%

Strip Winder

Table 32 - Identified failure modes for Strip Winder machine

Failure mode description	Frequency
Errors in PLC and drives	33.33%
Alpha mispositioned	25.40%
Rubber cutting not accurate	15.87%
Rubber stuck inside the extruder or in rolls	11.11%
Security area sensor error	11.11%
Other	9.52%

Spraying Machine

Table 33 - Identified failure modes for Spraying Machine

Failure mode description	Frequency
Illumination failure	18.87%
Inner layer amends sprayed	16.98%
Problems with barcodes	13.21%
Gantry mispositioned	11.32%
Problems with visualization	9.43%
Pistole nozzle cleaning	9.43%
Other	20.75%

Curing Presses

Table 34 - Identified failure modes for Curing presses

Failure mode description	Frequency
VCL does not load tire, is not centered	57.98%
AGV failure	10.64%
Steam leaks	8.51%
VCL engine failure	5.85%
Hydraulic filter failure	4.79%
Press opening/closing mechanism failure	3.19%
Internal pressure failure	2.66%
Other	4.79%

Appendix C: Failure causes identification

Carcass Building Machines (remaining)

Table 35 - Remaining identified failure causes for the failure modes of the Carcass Building Machines

Failure mode description	Identified causes
Front nose hits drum or dog ears, mispositioning of the front nose	• Sensor errors • Existence of a gap between the bearing and the structure • “Telescopes” are not aligned
Problems with material unrolling, material gets stuck	• Misadjusted loop values • Material adherence to the rolls due to its adhesiveness • Material glues to the counter-blade when knitting
Failure when knitting the innerliner	• Innerliner does not move forward • Blade does not move forward • Counter-blade does not go up
Problems with pneumatic system / diafragms	• Pneumatic failures • One of the diafragms is more stretched than the other, so one of them is filled faster
Dog ears do not advance or back off	• Excessive component weight • Component vibrations make the pneumatic cylinder block
Problems with cassettes’ coupling	• Unevenness of the cassette in relation to its support

Green Tire Building Machines

Table 36 - Identified failure causes for the failure modes of the Green Tire Buildng Machines

Failure mode description	Identified causes
Machine does not initialize new cycle	• IPC failure and replacement need
Reels do not work properly	• Excessive wear in reel’s disc • Mispositioning of the reels
Problems with barcodes	• Worker changes “recipe” before removing the carcass from the drum
Security sensors / scanner in error	• Sensor is very precise, detects the smallest dust • Misalignments
Errors in lasers	• Mispositioning, cause unknown

Strip Winder

Table 37 - Identified failure causes for the failure modes of the Strip Winder

Failure mode description	Identified causes
Errors in PLC’s and drives	• Cooling system failure
Errors in alpha: does not apply the tread / mispositioned	• Tread strip breaks due to too much tension • Tread strip gets stuck in the cooling drum due to its adherence
Problems with tread strip knitting	• Blade is not sharp enough • Problem in pneumatic feeding

Extruder

Table 38 - Identified failure causes for the failure modes of the Extruder

Failure mode description	Identified causes
Errors in TCU's	• Excessively polluted water, making filters clog and valves to jam
Errors in sensors when opening or closing extruder head	• Extruder vibrations misalign sensors
Problems with nozzles and cooling conveyor belts	• Nozzles badly screwd • Excessive dirtiness in the water pump, water does not reach the nozzles
Problems with the chiller	• Oil leaks in the compressors • Accumulated dirtiness inside the deposit
Problems with balancers	• Misadjusted sensors • Programming errors • Support pins corrosion • Loosening of the level sensor bracket
Problems in the heating mills, conveyer belts do not move forward	• Switchboard overheating • Flowmeter does not work properly

Combicutter

Table 39 - Identified failure causes for the failure modes of the Combicutter

Failure mode description	Identified causes
Torque value not adjusted	• Variable material rolls diameters
Failure in amendment process	• Cylinder does not lower • Rubber goes through the cylinder • Amendment table engine uncoupled
Machine does not cut material	• Mispositioned material • Gripper distance not adequate • Misadjusted detection photocell
Material roll not centered	• Material comes unaligned with the cassette
Material not stretched after cutting	• Conveyor belt speed not constant • Material adheres to the gripper or the counter blade

Bead Winder

Table 40 - Identified failure causes for the failure modes of the Bead Winder

Failure mode description	Identified causes
Wire jumps out of guiding disc	• Wire jumps during engine transitions • Disc contacts with the bead rim, damaging it
Problems with wire reel and reel's brake	• Reel's inner shaft breaks • Brake does not work properly
Errors in TCU's	• Excessively polluted water, making filters to clog and valves to jam

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Table 41 - Identified failure causes for the failure modes of the APEX

Failure mode description	Identified causes
Errors in PLC’s and drives	• Electrical switchboard overheating
Failure when applying the apex	• Centering wheel with gap • Programming errors • Dirtiness in the mirror of the disc where the bead settles

Spraying Machine

Table 42 - Identified failure causes for the failure modes of the Spraying Machine

Failure mode description	Identified causes
Inner layer amends sprayed	• Barcode not in the correct position
Excess of “ink”	• Flowmeter not working properly • Ink’s density change with time
Gantry mispositioning	• Programming failures

Curing Presses

Table 43 - Identified failure causes for the failure modes of the Curing Presses

Failure mode description	Identified causes
VCL does not load tire, is not centered	• Construction problems
VCL engine breaks down	• Aggressive start and stop due to the many existent gaps
Steam leaks	• Damaged hoses • Material of hoses and bushings is not adequate • Sealants are not insulating enough and wear out very quickly • Valves should hold the high pressures, but cannot
Internal pressure failures (in the bladder)	• Bladder not properly screwed
AGV failures	• Oil leaks due to insufficient screw of accessories • Problems with wi-fi signal

Appendix D: List of idealized maintenance actions for CST plant

Carcass Building Machines (remaining)

Table 44 - List of the remaining maintenance actions idealized for the Carcass Building Machines

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Let-off station	Engine consumption measurement while unrolling	Multimeter
Let-off station	Verify adjustment of the cassettes’ entrance guides	
Front nose	Cleaning and adjustment of sensors	
Innerliner knitting zone	Verify charge sent to the blade by the generator	
Innerliner knitting zone	Visual inspection of blade: color and stretch marks	
Innerliner knitting zone	Blade temperature	Given by controller
Conveyor belts	Check prisons in rolls	
Conveyor belts	Visual inspection to conveyor belts	
Headstock / tailstock	Visual verification of wear at the dog ears’ guides	
Reels	Verify wear state of the disc and of the turning reels	
Electrical switchboard	Re-set of contactors and circuit breakers	

Green Tire Building Machines

Table 45 - List of the maintenance actions idealized for the Green Tire Building Machines

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Let-off station	Engine consumption measurement while unrolling	Multimeter
Electrical switchboard	Measure switchboard’s drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	
Belt application station	Periodic cleaning and adjustment of safety sensors	
Belt application station	Verify reels’ positioning in homing (xx, yy, zz)	Pachymeter
Belt application station	Check turret’s positioning in homing	Measuring tape
Belt application station	Measure turret’s engine consumption while working	Multimeter

Extruder

Table 46 - List of the maintenance actions idealized for the Extruder

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
TCU's	Electric consumption of TCU's and resistors	Multimeter
TCU's	Cleaning of filters in the feeding pipes	
Extruder group	Verify lubrication mass of the rotary joints	
Extruder group	Verify gap in the scraper knife	
Cooling zone	Verify screw in the nozzles' sockets	Screwing tool
Cooling zone	Measure flow at the exit of pump	Flowmeter
Cooling zone	Verify balancers sensors' alignment	
Chiller	Measure flow at the exit of the deposit	Flowmeter
Chiller	Chiller's filters cleaning	
Electrical switchboard	Measure switchboard's drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	
Heating mills / conveyors	Check safety hydraulic valves	
Heating mills / conveyors	Measure temperature in mills and compare with controller	Thermometer
Heating mills / conveyors	Mills' engine consumption measurement	Multimeter
Extruder head	Check position and alignment of head's sensors	Pachymeter
Extruder head	Extruder engine consumption measurement during work	Multimeter
Hydraulic unit	Manual check of the hydraulic valves	
Hydraulic unit	Verify oil level and register	

Strip Winder

Table 47 - List of the maintenance actions idealized for the Strip Winder

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Electrical switchboard	Verify cooling system	
Electrical switchboard	Measure switchboard's drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	
Tread application station	Periodic cleaning and adjustment of safety sensors	
Tread application station	Cleaning of the tread applicator	Pachymeter
Tread application station	Cleaning of rolls and cooling drum	
Tread application station	Visual inspection of blade (color and stretch marks)	
Extruder	Electric consumption of TCU's and resistors	Multimeter
Extruder	Verify lubricant mass in the rotary joint	
Extruder	Verify gap in the scraper knife	
Extruder	Cleaning of filters in the feeding pipes	

Combicutter

Table 48 - List of the maintenance actions idealized for the Combicutter

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Amendment table	Verify screws of engine	Screwing tool
Amendment table	Engine consumption measurement	Multimeter
Amendment table	Verify pressure at each cylinder's entrance	Manometer
Amendment table	Verify alignment of the inclined plates	Pachymeter
Amendment table	Verify alignment of the cylinders' plates and screw height	Pachymeter
Amendment table	Verify wearing state of the plates' coating	
Cutting station	Verify screw of engine that moves the cutting blade	Screwing tool
Cutting station	Visual inspection of blade (stretch marks, sharpness)	
Cutting station	Clean and adjust material detection photocell	
Cutting station	Measurement of cutting blade's and disc's thickness	Pachymeter
Cutting station	Cleaning of conveyor's and counter-blade's surfaces	
Cutting station	Check conveyor's speed at different points	Velocimeter
Rolling up station	Cleaning and adjustment of the cassettes' centering sensor	
Rolling up station	Cleaning and adjustment of the centering cylinder's sensor	
Rolling up station	Cleaning and adjustment of the cassettes' detection sensor	
Let-off station	Let-off positioning sensors adjustment	
Let-off station	Verify calibration of let-off angle	
Let-off station	Engine consumption measurement while unrolling	Multimeter
Electrical switchboard	Measure switchboard's drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	

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Table 49 - List of the maintenance actions idealized for the APEX

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
TCU's	Electric consumption of TCU's and resistors	Multimeter
TCU's	Verify lubricant mass in the rotary joint	
TCU's	Verify gap in the scraper knife	
TCU's	Cleaning of filters in the feeding pipes	
Electrical switchboard	Measure switchboard's drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	
Apex application station	Cleaning of the mirror of the disc where the bead settles	
Apex application station	Screw, adjustment and cleaning of the station's sensors	
Apex application station	Visual inspection to the gripper's guides and lubricate	
Apex application station	Verify functioning and state of the flipper's spring	
Apex application station	Verify position of the flipper's cylinder	
Apex application station	Verify gripper's basic position	Pachymeter

Bead Winder

Table 50 - List of the maintenance actions idealized for the Bead Winder

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Extruder	Electric consumption of TCU's and resistors	Multimeter
Extruder	Verify lubricant mass in the rotary joint	
Extruder	Verify gap in the scraper knife	
Extruder	Cleaning of filters in the feeding pipes	
Extruder	Monitor noise from the extruder's transmission mechanism	Decibel meter
Electrical switchboard	Measure switchboard's drives temperatures	Thermal camera
Electrical switchboard	Re-set of contactors and circuit breakers	
Bead construct. station	Visual inspection to the blade's state	
Bead construct. station	Visual inspection to the guiding disc's wear	
Wire feeder	Verify noise in the reel's shaft	
Wire feeder	Verify brake's state	

Spraying machine

Table 51 - List of the maintenance actions idealized for the Spraying machine

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
Ink pistol robot	Register pistol pressure for 10 operations	
Ink pistol robot	Check correct functioning of valves before flowmeters	
Ink's pump	Monitor pump's rotation speed	
Entrance zone	Check sharpness and state of sensors, adjust if necessary	
Electrical switchboard	Measure switchboard's drives temperatures (same point)	Thermal camera
Suction system	Register pressure at entrance and exit of the filter	Manometer

Curing Presses

Table 52 - List of the maintenance actions idealized for the Curing Presses

Machine Subassembly	Maintenance / monitoring action	Tool/Measuring device
VCL	Engine consumption measurement while working	Multimeter
VCL	Verify and adjust positioning sensors	
VCL	Clean guides and check safety brake’s state	
VCL	Verify screw of the engine’s coupling to the structure	Screwing tool
Bladder feeding system	Search for incrustations in the pipes’ internal walls	IRIS test
Bladder feeding system	Inspection and cleaning of the traps’ filters	
Bladder feeding system	Ultrasound measurement in the pipes	Ultrasound device
Bladder feeding system	Ultrasound measurement in the valves (look for leaks)	Ultrasound device
Bladder feeding system	Temperature measurement in the dome pipe during cycle	Thermometer
AGV	Verify accessories correct screwing	Screwing tool
Lubrication system	Force automatic lubrication and check for leaks	
Lubrication system	Verify level of lubricating mass in the deposit	
Safety components	Verify & clean transductors’ and pressure switches deposit	
Vacuum	Ultrasound measurement in vacuum pipes	Ultrasound device
Hydraulic circuit	Check and register level of oil in the tank	
Electrical switchboard	Re-set of contactors and circuit breakers	
Mold adjustment system	Visual inspection to the pinion’s wear state	
Opening / closing system	Engine consumption measurement during work	Multimeter
Opening / closing system	Verify and adjust dome positioning sensors	

Appendix E: Calculation of Criticality Indexes

Carcass Building Machines

Table 53 - Criticality Index calculations for the Carcass Building Machine's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
Pneumatic sourcing / Diafragm	1	2	3	1	1	1	2	1.58
Electrical switchboard	3	3	2	3	1	3	2	2.12
Dual slab conveyor	1	2	1	2	1	1	2	1.2
Conveyor belts	2	3	1	1	1	1	2	1.43
Innerliner knitting zone	2	2	2	1	1	1	2	1.53
Headstock / Tailstock	2	1	1	3	1	1	2	1.27
Reels	3	3	2	1	1	1	2	1.78
Front Nose	1	2	1	1	2	3	2	1.78
Let-Off station	1	2	1	1	1	1	2	1.18
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Green Tire Building Machines

Table 54 - Criticality Index calculations for the Green Tire Building Machines' subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
Turret	1	1	2	1	1	1	2	1.28
Electrical switchboard	1	2	2	3	1	3	2	1.72
Reels	1	2	1	2	1	1	2	1.2
Safety sensors	3	3	1	1	2	1	2	1.78
Let-Off station	1	2	1	1	1	1	2	1.18
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

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Table 55 - Criticality Index calculations for the APEX's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
TCU's	1	1	3	1	1	3	1	1.7
Extruder	3	1	3	3	1	3	1	2.04
Electrical switchboard	3	2	2	1	1	3	1	1.9
Apex application station	2	1	2	1	1	2	1	1.35
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Combicutter

Table 56 - Criticality Index calculations for the Combicutter's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
Rolling up station	1	3	1	1	1	3	1	1.5
Let-off station	1	2	2	1	1	1	1	1.3
Angle system	2	1	2	1	1	2	1	1.5
Amendment zone	2	1	2	1	1	2	1	1.5
Electrical switchboard	1	2	1	1	1	3	1	1.4
Cutting zone	2	1	2	3	1	1	1	1.39
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Extruder

Table 57 - Criticality Index calculations for the Extruder's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
TCU's	2	2	3	2	1	3	1	1.97
Nozzles and cooling conveyors	2	1	2	3	1	2	1	1.54
Dancers / Balancers	2	2	3	2	1	1	1	1.67
Chiller	2	2	3	3	1	3	1	1.99
Electrical switchboard	1	2	2	3	1	3	1	1.64
Cutting zone	1	1	3	1	1	1	1	1.4
Heating mills / porkshop	2	1	2	1	2	1	1	1.65
Extruder head	1	2	2	1	1	2	1	1.45
Hydraulic system	1	1	2	3	1	3	1	1.54
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Bead Winder

Table 58 - Criticality Index calculations for the Bead Winder's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
TCU's	1	2	3	3	1	3	1	1.84
Extruder	3	1	3	3	1	3	1	2.04
Wire feeder	1	2	1	1	1	2	1	1.25
Electrical switchboard	2	2	1	1	1	3	1	1.55
Bead construction station	1	2	2	3	1	2	1	1.49
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Strip Winder

Table 59 - Criticality Index calculations for the Strip Winder's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
TCU's	1	2	3	3	1	3	1	1.84
Extruder	3	1	3	3	1	3	1	2.04
Tread cutting zone	1	2	2	3	1	1	1	1.34
Pneumatic feeding	2	1	3	1	1	1	1	1.55
Electrical switchboard	1	2	2	2	1	3	1	1.62
Alpha	2	2	2	1	1	1	1	1.45
Safety sensors	2	1	1	1	2	1	1	1.45
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Spraying machine

Table 60 - Criticality Index calculations for the Spraying Machine's subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
Barcode recognition zone	3	2	3	3	1	3	1	2.14
Entrance zone sensors	2	2	3	3	1	2	1	1.84
Electrical switchboard	3	3	1	1	1	3	1	1.84
Weighting zone	1	2	3	1	1	2	1	1.65
Ink pump	3	1	3	3	1	3	1	2.04
Flowmeters and pistoling	2	2	3	3	1	3	1	1.99
Suction system	1	1	1	3	2	1	1	1.34
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Curing Presses

Table 61 - Criticality Index calculations for the Curing Presses' subassemblies

Subassembly	Severity level for factor no.							CI
	1	2	3	4	5	6	7	
Opening / closing system	3	1	3	1	1	1	2	1.78
Electrical switchboard	3	3	1	1	1	3	2	1.92
Safety devices	2	1	3	3	1	3	2	1.97
Internal pressure system	2	2	3	3	1	1	2	1.99
Steam system	3	2	3	2	1	3	2	2.2
VCL	2	3	1	1	1	1	2	1.43
Weight	0.15	0.1	0.2	0.02	0.3	0.15	0.08	

Appendix F: Initial periodicity calculations

In this appendix, the initially estimated periodicities for the subassemblies of machines from ED7 are presented, as well as some intermediate calculation results, according to its failure rate distribution (constant or not constant).

Green Tire Building Machines

Constant Failure Rate

Table 62 - Periodicity calculation results for Green Tire Building Machines' subassemblies with constant failure rate

Machine subassembly	Machine no. 1		Machine no. 2		Initially estimated periodicity (days)
	Failure rate (failures/day)	MTBF (days)	Failure rate (failures/day)	MTBF (days)	
Turret	N/A	N/A	0.028	35.662	36

Non-constant failure rate

Table 63 - Periodicity calculation results for Green Tire Building Machines' subassemblies with non-constant failure rate

Machine subassembly	Machine no. 1			Machine no. 2			Initially estimated periodicity (days)
	Shape (β)	Scale (θ)	MTBF (days)	Shape (β)	Scale (θ)	MTBF (days)	
Electrical switchboard	0.850	15.30	16.651	1.026	31.81	31.480	17
Reels	0.710	24.45	30.533	1.022	39.16	38.821	31
Let-off station	0.857	25.30	27.387	0.835	22.49	24.755	25
Safety sensors	0.980	55.66	56.133	0.735	23.76	28.776	29

Strip Winder

Constant Failure Rate

Table 64 - Periodicity calculation results for Strip Winder's subassemblies with constant failure rate

Machine subassembly	Failure rate (failures/day)	MTBF (days)	Initially estimated periodicity (days)
Electrical switchboard	0.081	12.317	13
Tread knitting zone	0.035	28.191	29
Alpha	0.057	17.667	18

Non-constant failure rate

Table 65 - Periodicity calculation results for Strip Winder's subassemblies with non-constant failure rate

Machine subassembly	Shape (β)	Scale (θ)	MTBF (days)	Initially estimated periodicity (days)
TCU's / Extruder	1.123	61.52	58.965	59
Safety sensors	0.582	23.06	36.155	37

Extruder

Constant Failure Rate

Table 66 - Periodicity calculation results for Extruder's subassemblies with constant failure rate

Machine subassembly	Failure rate (failures/day)	MTBF (days)	Initially estimated periodicity (days)
Electrical switchboard	0.081	12.317	13

Non-constant failure rate

Table 67 - Periodicity calculation results for Extruder's subassemblies with non-constant failure rate

Machine subassembly	Shape (β)	Scale (θ)	MTBF (days)	Initially estimated periodicity (days)
TCU's	1.123	61.52	58.965	59
Nozzles and cooling conveyors	0.833	18.49	20.368	21
Chiller	0.75	27.24	32.397	33
Extruder head	1.117	28.02	26.907	27
Dancers / balancers	0.706	25.94	32.554	33

Combicutter

Constant Failure Rate

Table 68 - Periodicity calculation results for Combicutter's subassemblies with constant failure rate

Machine subassembly	Failure rate (failures/day)	MTBF (days)	Initially estimated periodicity (days)
Electrical switchboard	0.055	18.335	19
Let-off station	0.049	20.298	21
Rolling up station	0.114	8.739	9
Amendment zone	0.054	18.435	19

Non-constant failure rate

Table 69 - Periodicity calculation results for Combicutter's subassemblies with non-constant failure rate

Machine subassembly	Shape (β)	Scale (θ)	MTBF (days)	Initially estimated periodicity (days)
Cutting station	1.200	44.46	41.822	42

Bead Winder

Constant Failure Rate

Table 70 - Periodicity calculation results for Bead Winder's subassemblies with constant failure rate

Machine subassembly	Failure rate (failures/day)	MTBF (days)	Initially estimated periodicity (days)
Electrical switchboard	0.071	14.103	15
Wire cutting	0.037	27.072	28
Wire feeder	0.050	19.834	20

Non-constant failure rate

Table 71 - Periodicity calculation results for Bead Winder's subassemblies with non-constant failure rate

Machine subassembly	Shape (β)	Scale (θ)	MTBF (days)	Initially estimated periodicity (days)
Extruder	0.647	13.38	18.385	19
Bead construction station	0.801	10.06	11.393	12

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Constant Failure Rate

Table 72 - Periodicity calculation results for APEX's subassemblies with constant failure rate

Machine subassembly	Failure rate (failures/day)	MTBF (days)	Initially estimated periodicity (days)
Apex application station	0.071	14.103	15
Electrical switchboard	0.094	10.657	11
Gripper	0.050	19.932	20

Non-constant failure rate

Table 73 - Periodicity calculation results for APEX's subassemblies with non-constant failure rate

Machine subassembly	Shape (β)	Scale (θ)	MTBF (days)	Initially estimated periodicity (days)
Flipper	0.434	18.11	48.758	49

The periodicities for the Spraying Machine and Curing Presses (ED8) were not estimated through the breakdown reports as the ones for ED7, due to insufficient historical data. The presented periodicity values in Table 74 and Table 75 were assumed based on the CM personnel's experience and knowledge, and are presented individually for each maintenance action.

Spraying Machine

Table 74 – Initially estimated periodicities for Spraying Machine's maintenance actions

Machine Subassembly	Maintenance / monitoring action	Initially estimated periodicity (days)
Ink pistol robot	Register pistol pressure for 10 operations	30
Ink pistol robot	Check correct functioning of valves before flowmeters	30
Ink's pump	Monitor pump's rotation speed	30
Entrance zone	Check sharpness and state of sensors, adjust if necessary	30
Electrical switchboard	Measure switchboard's drives temperatures (same point)	15
Suction system	Register pressure at entrance and exit of the filter	15

Curing Presses

Table 75 - Initially estimated periodicities for Curing Presses' maintenance actions

Machine Subassembly	Maintenance / monitoring action	Initially estimated periodicity (days)
VCL	Engine consumption measurement while working	30
VCL	Verify and adjust positioning sensors	30
VCL	Clean guides and check safety brake's state	30
VCL	Verify screw of the engine's coupling to the structure	30
Bladder feeding system	Search for incrustations in the pipes' internal walls	365
Bladder feeding system	Inspection and cleaning of the traps' filters	30
Bladder feeding system	Ultrasound measurement in the pipes	15
Bladder feeding system	Ultrasound measurement in the valves (look for leaks)	15
Bladder feeding system	Measure temperature in the dome pipe during cycle	30
AGV	Verify accessories correct screwing	30
Lubrication system	Force automatic lubrication and check for leaks	30
Lubrication system	Verify level of lubricating mass in the deposit	15
Safety components	Clean transductors' and pressure switches deposit	15
Vacuum	Ultrasound measurement in vacuum pipes	60
Hydraulic circuit	Check and register level of oil in the tank	30
Electrical switchboard	Re-set of contactors and circuit breakers	365
Mold adjustment system	Visual inspection to the pinion's wear state	30
Opening / closing system	Engine consumption measurement during work	15
Opening / closing system	Verify and adjust dome positioning sensors	30

Appendix G: Interfaces for maintenance plan generation

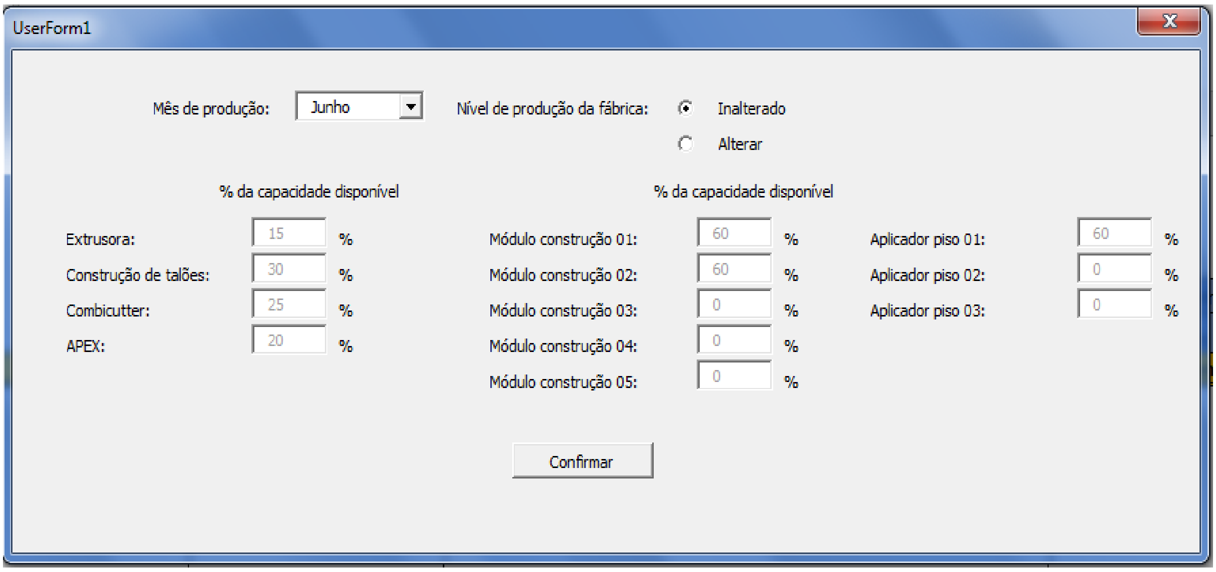

Figure 20 - User interface for the monthly maintenance plan generation for ED7

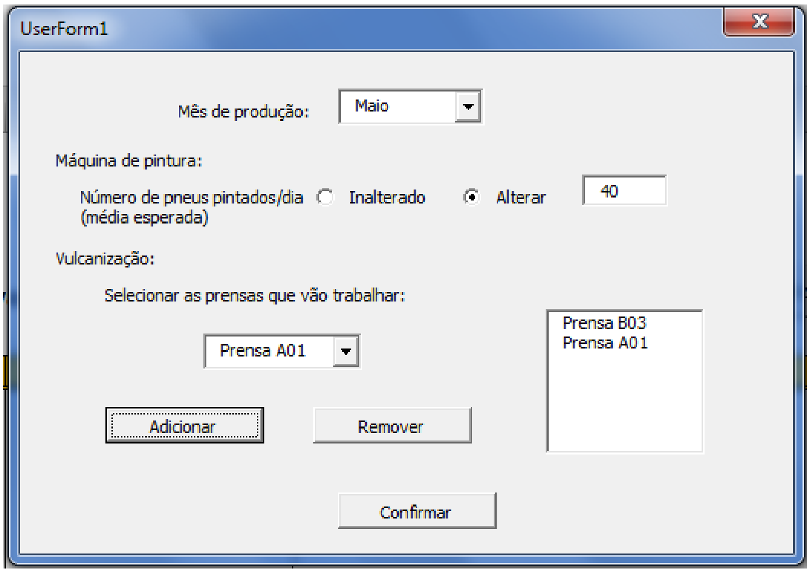

Figure 21 - User interface for the monthly maintenance plan generation for ED8

Appendix H: Extruder inferior roll complete analysis

The number of observed transitions for this component's pressure values is presented in matrix (H.1), where it can be verified that the most visited state is, in this case, state 0, with a total of 54 observations. Thus, analogously to the extruder head component, $P(X_0|X_0) = 52/54 = 0.9630$ and consequently $P(X_0|X_0) = 1 - 0.9630 = 0.0370$.

The same failure probabilities as before were assumed (4.9) and the same adjustment to the matrix was made, in order to not violate the condition referenced in (4.8). The final obtained probability transition matrix for the extruder inferior roll is presented in (H.2), while the cumulative probability transition matrix used in the application of the Monte Carlo technique is presented in (H.3).

$$\begin{array}{c} \\ 0\\1\\2\\3\\4\\5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 52 & 2 & 0 & 0 & 0 & 0 \\ 3 & 15 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{H.1}$$

$$\begin{array}{c} \\ 0\\1\\2\\3\\4\\5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 0.9610 & 0.0370 & 0 & 0 & 0 & 0.0020 \\ 0 & 0.9577 & 0.0369 & 0 & 0 & 0.0054 \\ 0 & 0 & 0.9487 & 0.0365 & 0 & 0.0148 \\ 0 & 0 & 0 & 0.9243 & 0.0355 & 0.0402 \\ 0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{H.2}$$

$$\begin{array}{c} \\ 0\\1\\2\\3\\4\\5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{pmatrix} 0.9610 & 0.9980 & 0.9980 & 0.9980 & 0.9980 & 1.0000 \\ 0 & 0.9577 & 0.9946 & 0.9946 & 0.9946 & 1.0000 \\ 0 & 0 & 0.9487 & 0.9852 & 0.9852 & 1.0000 \\ 0 & 0 & 0 & 0.9243 & 0.9598 & 1.0000 \\ 0 & 0 & 0 & 0 & 0.8908 & 1.0000 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{H.3}$$

Simulation results from 5000 transitions, with a 500 transitions warm-up in each of the tested scenarios for the extruder inferior roll component are detailed and presented in Table 76.

Table 76 - Simulation results and cost analysis for Strip Winder extruder inferior roll filter

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	71	0	1212680	0	1212680
TBM – 2 months	50	47	854000	282940	1136940
TBM – 1 month (current policy)	38	96	649040	577920	1226960
TBM – 2 weeks	23	192	392840	1155840	1548680
CBM – Safety threshold = 4	49	25	836920	150500	987420
CBM – Safety threshold = 3	36	42	614880	252840	867720
CBM – Safety threshold = 2	16	90	273280	541800	815080
CBM – Safety threshold = 1	10	182	170800	1095640	1061380

In the case of the extruder inferior roll, the optimal maintenance policy found with the proposed model is a condition-based policy, like it was observed for the extruder head. This time, the optimal condition-based maintenance policy recommends the setting of the preventive maintenance threshold at the upper bound of state 2, i.e., to perform a preventive maintenance operation whenever pressure drops below 6 bar. It is observed a difference when comparing this threshold to the one obtained for the extruder head, which can be explained by the fact of the assumed degradation probabilities are higher in the case of the extruder head, promoting a faster deterioration, which increases a lot more the number of maintenance actions if the threshold is too low, consequently increasing the total maintenance costs incurred.

In parallel to the extruder head component, another policy besides the one found to be optimal may be of interest to consider, that in this case is to set the preventive maintenance threshold to whenever state 3 is reached, i.e., to only perform a maintenance operation when pressure drops below 5.5 bar. This is so because the model is based on many assumptions that may not correspond integrally to reality, and the cost differences observed are not very large. In Table 77 the expected times to failure and between maintenance operations for both policies for the extruder inferior roll component are presented. Analogously, the expected time to maintenance can be regarded as a reference to when to check the pressure values.

Table 77 - Expected number of days to failure and maintenance for extruder inferior roll

Scenario description	Expected time to failure (days)	Expected time to maintenance (days)
CBM – Safety threshold = 3	79.09	67.79
CBM – Safety threshold = 2	177.95	31.64

Appendix I: Sensibility analysis full data

Cost Ratio Analysis

Complete results relative to the extruder head component for all the tested scenarios for the cost ratios between failure and maintenance costs of 1.5, 2, 3 and for the found critical one, are presented in Table 78, Table 79, Table 80 and Table 81, respectively.

Table 78 - Obtained cost results for the tested scenarios for the extruder head, with a cost ratio of 1.5

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	131	0	1182930	0	1182930
TBM – 2 months	115	47	1038450	282940	1321390
TBM – 1 month (current policy)	95	96	857850	577920	1435770
TBM – 2 weeks	61	192	550830	1155840	1706670
CBM – Safety threshold = 4	66	83	595980	499660	1095460
CBM – Safety threshold = 3	32	155	288960	933100	1222060
CBM – Safety threshold = 2	16	248	144480	1492960	1637440
CBM – Safety threshold = 1	9	483	81270	2907660	2988930

Table 79 - Obtained cost results for the tested scenarios for the extruder head, with a cost ratio of 2

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	131	0	1577240	0	1577240
TBM – 2 months	115	47	1384600	282940	1667540
TBM – 1 month (current policy)	95	96	1143800	577920	1721720
TBM – 2 weeks	61	192	734440	1155840	1890280
CBM – Safety threshold = 4	66	83	794640	499660	1294300
CBM – Safety threshold = 3	32	155	385280	933100	1318380
CBM – Safety threshold = 2	16	248	192640	1492960	1685600
CBM – Safety threshold = 1	9	483	108360	2907660	3016020

Table 80 - Obtained cost results for the tested scenarios for the extruder head, with a cost ratio of 3

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	131	0	2365860	0	2365860
TBM – 2 months	115	47	2076900	282940	2359840
TBM – 1 month (current policy)	95	96	1715700	577920	2293620
TBM – 2 weeks	61	192	1101660	1155840	2257500
CBM – Safety threshold = 4	66	83	1191960	499660	1691620
CBM – Safety threshold = 3	32	155	577920	933100	1511020
CBM – Safety threshold = 2	16	248	288960	1492960	1781920
CBM – Safety threshold = 1	9	483	162540	2907660	3070200

Table 81 - Obtained cost results for the tested scenarios for the extruder head, with the critical found cost ratio

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	131	0	1670018.8	0	1670018.8
TBM – 2 months	115	47	1466047.1	282940	1748987.1
TBM – 1 month (current policy)	95	96	1211082.4	577920	1789002.4
TBM – 2 weeks	61	192	777642.4	1155840	1933482.4
CBM – Safety threshold = 4	66	83	841383.5	499660	1341043.5
CBM – Safety threshold = 3	32	155	407943.5	933100	1341043.5
CBM – Safety threshold = 2	16	248	203971.8	1492960	1696931.8
CBM – Safety threshold = 1	9	483	114734.1	2907660	3022394.1

Transition probability analysis

The modified final transition probability matrices, assuming a transition probability of 0.05 and 0.15, maintaining the same failure probabilities defined in (4.9) and after the adjustment to not violate the condition referenced in (4.8), are presented, respectively, in (I.1) and (I.2). The obtained results for all the tested scenarios for each assumed probability (0.05 and 0.15) are displayed in Table 82 and Table 83, respectively.

$$\begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{pmatrix} 0.9481 & 0.0499 & 0 & 0 & 0 & 0.0020 \\ 0 & 0.9449 & 0.0497 & 0 & 0 & 0.0054 \\ 0 & 0 & 0.9360 & 0.0492 & 0 & 0.0148 \\ 0 & 0 & 0 & 0.9118 & 0.0480 & 0.0402 \\ 0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{I.1}$$

Table 82 - Obtained cost results for the tested scenarios for the extruder head, with degradation probability of 0.05

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	86	0	1468880	0	1468880
TBM – 2 months	65	47	1110200	282940	1393140
TBM – 1 month (current policy)	52	96	888160	577920	1466080
TBM – 2 weeks	27	192	461160	1155840	1617000
CBM – Safety threshold = 4	58	30	990640	180600	1171240
CBM – Safety threshold = 3	36	65	614880	391300	1006180
CBM – Safety threshold = 2	16	122	273280	734440	1007720
CBM – Safety threshold = 1	10	251	170800	1511020	1681820

$$\begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{pmatrix} 0.8483 & 0.1497 & 0 & 0 & 0 & 0.0020 \\ 0 & 0.8454 & 0.1492 & 0 & 0 & 0.0054 \\ 0 & 0 & 0.8374 & 0.1478 & 0 & 0.0148 \\ 0 & 0 & 0 & 0.8158 & 0.1440 & 0.0402 \\ 0 & 0 & 0 & 0 & 0.8908 & 0.1092 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \tag{I.2}$$

Table 83 - Obtained cost results for the tested scenarios for the extruder head, with degradation probability of 0.15

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	166	0	2835280	0	2835280
TBM – 2 months	144	47	2459520	282940	2742460
TBM – 1 month (current policy)	122	96	2083760	577920	2661680
TBM – 2 weeks	95	192	1622600	1155840	2778440
CBM – Safety threshold = 4	66	83	1127280	872900	2000180
CBM – Safety threshold = 3	30	155	512400	1348480	1860880
CBM – Safety threshold = 2	19	248	324520	2082920	2407440
CBM – Safety threshold = 1	9	483	153720	3979220	4132940

Failure Probability Analysis

The modified transition probabilities, assuming slower and faster random failure evolutions are, respectively presented in (I.3) and (I.4). The obtained results for all the scenarios tested under these conditions are displayed in Table 84 and Table 85, respectively. Note that here the original degradation probabilities were maintained.

$$\begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{pmatrix} 0.8952 & 0.1023 & 0 & 0 & 0 & 0.0025 \\ 0 & 0.8929 & 0.1021 & 0 & 0 & 0.0050 \\ 0 & 0 & 0.8885 & 0.1015 & 0 & 0.0100 \\ 0 & 0 & 0 & 0.8795 & 0.1005 & 0.0200 \\ 0 & 0 & 0 & 0 & 0.9600 & 0.0400 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \quad (I.3)$$

Table 84 - Obtained cost results for the tested scenarios for the extruder head, with slower random failure evolutions

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	100	0	1708000	0	1708000
TBM – 2 months	80	47	1366400	282940	1649340
TBM – 1 month (current policy)	68	96	1161440	577920	1739360
TBM – 2 weeks	42	192	717360	1155840	1873200
CBM – Safety threshold = 4	46	102	785680	614040	1399720
CBM – Safety threshold = 3	27	161	461160	969220	1430380
CBM – Safety threshold = 2	18	248	307440	1492960	1800400
CBM – Safety threshold = 1	13	483	222040	2907660	3129700

$$\begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{pmatrix} 0.8956 & 0.1024 & 0 & 0 & 0 & 0.0020 \\ 0 & 0.8901 & 0.1017 & 0 & 0 & 0.0082 \\ 0 & 0 & 0.8775 & 0.1003 & 0 & 0.0222 \\ 0 & 0 & 0 & 0.8433 & 0.0964 & 0.0603 \\ 0 & 0 & 0 & 0 & 0.8362 & 0.1638 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \quad (I.4)$$

Table 85 - Obtained cost results for the tested scenarios for the extruder head, with faster random failure evolutions

Scenario description	Failures	Maint. Actions	Total Failure Cost (€)	Total Maint. Cost (€)	Total Cost (€)
FBM - Run until failure	146	0	2493680	0	2493680
TBM – 2 months	130	47	2220400	282940	2503340
TBM – 1 month (current policy)	108	96	1844640	577920	2422560
TBM – 2 weeks	74	192	1263920	1155840	2419760
CBM – Safety threshold = 4	89	68	1520120	409360	1929480
CBM – Safety threshold = 3	47	145	802760	872900	1675660
CBM – Safety threshold = 2	22	243	375760	1462860	1838620
CBM – Safety threshold = 1	9	483	153720	2907660	3061380

Increase in number of states

For the analysis with the states provided in Table 21, the used probability transition matrix is presented at (I.5).

$$\begin{array}{c} \\ 0\\1\\2\\3\\4\\5\\6\\7\\8\\9 \end{array}\begin{array}{c} \begin{array}{cccccccccc} 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 \end{array} \\ \begin{pmatrix} 0.8956 & 0.1024 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0020 \\ 0 & 0.8943 & 0.1022 & 0 & 0 & 0 & 0 & 0 & 0 & 0.0035 \\ 0 & 0 & 0.8920 & 0.1019 & 0 & 0 & 0 & 0 & 0 & 0.0061 \\ 0 & 0 & 0 & 0.8879 & 0.1015 & 0 & 0 & 0 & 0 & 0.0106 \\ 0 & 0 & 0 & 0 & 0.8809 & 0.1006 & 0 & 0 & 0 & 0.0185 \\ 0 & 0 & 0 & 0 & 0 & 0.8685 & 0.0993 & 0 & 0 & 0.0322 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.8471 & 0.0968 & 0 & 0.0561 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8097 & 0.0926 & 0.0977 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.8297 & 0.1703 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array} \quad (I.5)$$

Appendix J: Curing presses data analysis tools

Curing press data visualization interface

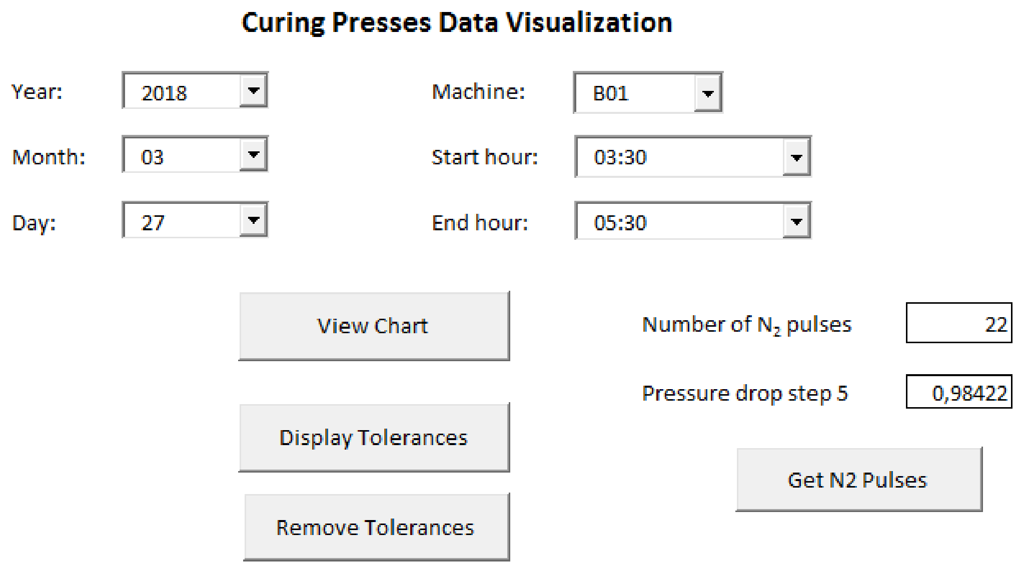

Figure 22 - Curing presses data visualization user interface

Descriptive statistics on the observed data

Table 86 – Descriptive statistics regarding the number of N_2 pulses for all measure-press observed combinations

Measure	Curing press	Nr of cycles	Maximum	Minimum	Average	Mode
280-85 R28	D03	4	16	15	15.25	15
320-85 R28	D03	231	16	14	14.589	15
340-85 R24	D02	76	16	14	14.855	15
340-85 R28	D02	10	22	18	21.300	22
380-70 R24	D01	24	21	15	18.583	17
380-85 R24	D01	152	22	19	20.763	21
420-70 R24	D02	68	21	10	18.485	19
420-70 R28	D03	299	28	15	20.824	21
420-85 R24	D01	11	23	22	22.273	22
420-85 R28	D01	165	23	18	19.115	19
460-85 R34	B01	6	21	16	20.000	21
460-85 R38	B02	49	23	21	22.082	22
480-70 R24	D01	6	22	21	21.500	22
480-70 R38	A01	6	21	20	20.167	20
520-70 R34	A01	101	22	17	20.683	21
520-70 R38	B01	83	22	20	21.169	21
520-85 R38	A01	10	23	21	22.000	22
520-85 R38	B03	267	23	18	21.255	21

Defined Alarm and Stoppage values

Table 87 - Alarm and stoppage limits for the remaining measure-press observed combinations

Measure	Curing press	Alarm Limit	Stoppage Limit
280-85 R28	D03	17	19
320-85 R28	D03	17	19
340-85 R24	D02	17	17
340-85 R28	D02	25	26
380-70 R24	D01	19	25
380-85 R24	D01	24	26
420-70 R24	D02	21	25
420-70 R28	D03	24	27
420-85 R24	D01	25	27
420-85 R28	D01	21	27
460-85 R34	B01	24	25
460-85 R38	B02	25	27
480-70 R24	D01	25	26
480-70 R38	A01	22	25
520-70 R34	A01	24	26
520-70 R38	B01	24	26
520-85 R38	A01	25	27
520-85 R38	B03	24	27