# Modeling the impact of maintenance strategies on total cost of ownership

Stein, W.J.

*Award date:*
2009

Veghel, July 2009

# Modeling the impact of maintenance strategies on total cost of ownership

By Walter J. Stein

Student identity number 0516247

in partial fulfilment of the requirements for the degree of

**Master of Science**
**in Operations Management and Logistics**

Supervisors:

Prof. Dr. Ir. G.J. van Houtum, TU/e

Dr. Ir. S.D. Flapper, TU/e

Ir. E. Hessel, Service Development, Vanderlande Industries, Veghel

Ir. K. Kleinveld, Service Development, Vanderlande Industries, Veghel

Ir. M. Broekman, Service Development, Vanderlande Industries, Veghel

TUE. Department Technology Management.

Series Master Theses Operations Management and Logistics

Subject headings: Maintenance modeling, Total Cost of Ownership, Availability, Renewal Process, Conditional Residual Time

# ABSTRACT

This master thesis designs and develops a quantitative model for the analysis of inspection-based maintenance strategies. The developed model calculates the effects of maintenance strategies in terms of expected number of failures and the total relevant maintenance costs, including downtime costs. For capital goods, these cost functions make up for a large fraction of total cost of ownership. The functionality of this model is innovative by applying ‘the time between initial, observable damage and the actual failure’ as a means to calculate the probability that damage on a certain component is observed timely and renewed prior to failure. The developed model can be applied to mechanical products with a serial component structure.

# PREFACE AND ACKNOWLEDGEMENTS

This master thesis report is the result of the final assignment for my master Operations, Management and Logistics at the Technical University of Eindhoven. In the last eight months, I have executed a research in the field of maintenance modeling at Vanderlande Industries.

I would like to thank my first supervisor from the university, Geert-Jan van Houtum, for his guidance in the past eighteen months. I truly have enjoyed his tremendous support and pleasant conversations we have had. During my master course, I have often benefited from his suggestions and feedback. Furthermore, I would like to thank my second supervisor from the university, Simme Douwe Flapper. I have gratefully accepted your constructive comments.

I also would like to thank my daily supervisor, Erlend Hessel. I sincerely appreciate our cooperation, both professionally and personally. Thank you for keeping me sharp and motivated, and providing me with new business in-sights. Furthermore, I would like to thank Katja Kleinveld, Harold Bol and Maarten Broekman for their suggestions and feedback on my ideas.

Obviously, I also would like to thank my colleagues of Service Development: Ruud, Frank, Huub, Harold, Jitske, Bart, Petra, Walther, Herman R., Adrie, Boudewijn, Herman K. and Marian. Thank you all for the pleasant working environment. I really have enjoyed working with you.

Special thanks are in place for my girlfriend, Klaske, for her incredible support and inspiration. Finally, I would like to thank my family and friends for their love and support during my studies.

Walter Stein
July 2009

## EXECUTIVE SUMMARY

Vanderlande Industries (VI) is a Dutch multinational that provides automated material handling systems. VI systems enable the handling of goods in e-fulfillment distribution centers, express parcel sortation facilities or baggage handling at airports. VI systems consist of standard pieces of equipment, called VI sections, such as conveyor belts, sorters, cranes, etc. The core processes of VI customers may depend on availability of their VI systems. Customers are therefore increasingly interested in availability and Total Cost of Ownership (TCO) predictions.

To satisfy these customer demands, VI desires a thorough understanding of the relationships between availability, TCO and maintenance activities to support future maintenance decisions. Previous research showed that maintenance and downtime costs of a baggage handling system can account for almost 70% of the TCO. To provide insight into the effects of maintenance strategies, the following research question has been investigated during this master thesis project:

> *How are the number of technical failures and total relevant maintenance costs of a VI system influenced by different maintenance strategies?*

Optimal maintenance strategies aim to provide optimum system reliability and safety at the lowest possible maintenance costs and downtime costs. There is an inherent trade-off between maintenance costs and availability, which is investigated in this master thesis project.

**Modeling the impact of maintenance strategies on total cost of ownership**

We have developed a quantitative model to analyze the effects of maintenance strategies in terms of Total Relevant Maintenance Costs (TRMC) and expected number of failures. The total relevant maintenance costs are defined as the sum of all costs that are determined by maintenance activities during the lifetime of the system, including labor, material and downtime costs. The model can be used to simulate and analyze any VI section with serial components (such as the Belt Floorveyor or the PosiSorter). The model has been built in Excel, using straightforward, well-known parameters and an intuitive interface.

The functionality of this model is innovative by applying the Conditional Residual Time (CRT) as a means to calculate the probability that a damaged component can be renewed prior to failure. The CRT is defined as the time that elapses between initial, observable damage and component

failure. If an inspection takes place during the CRT, the defect can be observed timely and a preventive action can be taken within the remaining window of opportunity of the CRT.

An essential element of this research is harmonizing maintenance and reliability. Basically, the reliability function of a component determines the number of required renewals in a certain business situation. The maintenance activities ensure that damaged components are replaced prior to failure. The model distinguishes two types of maintenance activities, i.e. preventive maintenance executed in scheduled downtime, and corrective maintenance causing un-scheduled downtime. Generally, corrective maintenance is more expensive than preventive maintenance, due to the unscheduled downtime and corrective maintenance costs that (could) arise with failures.

**Project findings**

At the sites analyzed in this thesis, the majority of the worn parts is replaced during call-out visits. Approximately 10% of the damaged components is replaced preventively under a three-monthly inspection strategy. Thus, the planned inspections do not put a stop to the increasing number of required renewals, and the number of failures at these sites increases faster than necessary. To reduce the number of expected failures, it is inevitable to increase the number of preventive visits.

**Research conclusions**

To answer the research question, the maintenance strategies, called run-to-failure and inspection-based maintenance, are analyzed with the developed model. Using cost parameters and reliability functions founded on historical data, four critical components of the PosiSorter (i.e. diverts, crossings, shoes and merges) are entered into the model. For this system, the pro-active maintenance strategy consisting of eight annual visits outperforms the currently used strategy of four annual visits, by simultaneously minimizing costs and expected number of failures. By doubling the inspection intensity, the expected number of failures decreases by 39%, and the average TRMC consequently decrease by 15% (under the given conditions and cost parameters). Compared to run-to-failure, 28% of the costs are saved with this maintenance strategy. From this, it is concluded that pro-active strategies with increased commitment in terms of resources and inspections can lead to increased reliability and decreased costs. With more than ten annual inspections, the TRMC rises because additional investments in inspections are not paid back by further decreased downtime and emergency costs.

Thus, maintenance strategies determine a significant part of the TRMC and the expected number of failures. Moreover, in addition to inspection frequencies, there are two other important determinants: namely the component lifetime distribution and the CRT of the components. Sensitivity analyses show that maintenance decisions should be based on knowledge of the underlying deterioration processes. Wrong estimations of the component degradation can lead to costly decisions. The CRT also has a large influence on the optimal inspection frequency. Therefore, it is a prerequisite that VI obtains more knowledge on component degradation and the likelihood of observation. After that, maintenance decisions can be supported by convincing arguments based on component degradation knowledge and system maintenance modeling.

**Recommendations concerning data gathering**

A major part of this thesis describes a common problem in reliability engineering, namely the availability of failure data. Getting sufficient data to (manually) extract reliable information is a time consuming and expensive task. After carefully gathering and analyzing the spare parts data, these data are used to estimate the component reliability. VI should ensure that their data is recorded and gathered more properly to optimize processes and further consolidate services.

Fortunately, the necessary data gathering process has started recently, and this future data can be implemented into the developed model. VI is recommended to convert the time-to-failure measures into failure distributions knowledge. This knowledge can be used to analyze reliability, to model maintenance, and thereby to increase system availability.

**Recommendations concerning TCO**

Results of this master thesis underpin that if VI truly wants to predict the TCO of its systems, it is inevitable to expand the knowledge on component reliability and the effects of maintenance strategies. The differences in terms of spare part usage at the seventeen different sites in Italy show that wear of critical components can vary substantially. This leads to large variations in system availability and maintenance and downtime costs.

With the steps recommended in this thesis, VI can enhance the knowledge on maintenance, reliability and the maintenance optimization, and thereby the understanding of the total cost of ownership of their systems. In the end, this makes service account managers more comfortable recommending maintenance decisions towards their customers, who shall appreciate the profitability of a sophisticated maintenance strategy.

# TABLE OF CONTENTS

# LIST OF DEFINITIONS

*Availability*

the probability that a system will be in a condition to perform its intended function when required

*Conditional Residual Time (CRT)*

the time between initial, observable damage and the actual failure is called the *Conditional Residual Time*

*Maintainability*

the ability of a system to be repaired, retained or restored into a condition where it can perform its intended function within a specified period of time

*Position*

a part of the system that requires a working component

*Reliability*

the probability that the system will perform its intended function, within stated conditions, for a specified period of time

*Supportability*

the ability to support customers fast and accurate at minimal costs

*Time-to-maintain*

the total amount of time that elapses while the system is repaired or restored to its operational status

*Total relevant maintenance costs (TRMC)*

the sum of all costs that are determined by maintenance activities during the lifetime of the system, including labor, material and downtime costs

*VI-system*

the actual system delivered to a customer. A system consists of several zones, which consist of a number of mechanical

*VI-section*

standard piece of equipment, such as a standard Belt Floorveyor or a PosiSorter

*VI-component*

an item of a VI-section, such as a motor, a belt, a divert or a shoe, etc.

# LIST OF ABBREVIATIONS

| | |
|---|---|
| BF | Belt Floorveyor |
| BHS | Baggage Handling System |
| BPI | Business Process Intelligence |
| BU | Business Unit |
| CBM | Condition Based Maintenance |
| CC | Customer Center |
| CM | Corrective Maintenance |
| CMMS | Computerized Maintenance Management System |
| CRT | Conditional Residual Time |
| DBM | Detection Based Maintenance |
| ETO | Engineered-to-order |
| FSC | Flow Systems Control |
| LCC | Life Cycle Costs |
| MI | Mobile Inspector |
| MMS | Maintenance Management System |
| MTBF | Mean Time Between Failures |
| MTTF | Mean Time To Failure |
| MTTR | Mean Time To Repair |
| OR | Operations Research |
| PLC | Programmable Logic Controller |
| PM | Preventive Maintenance |
| RMR | Revision, Modification, Retrofit |
| SPO | PosiSorter |
| TCO | Total Cost of Ownership |
| TRMC | Total Relevant Maintenance Costs |
| TTM | Time-To-Maintain |
| TTF | Time-To-Failure |
| TTS | Time-To-Support |
| UBM | Usage Based Maintenance |
| VI | Vanderlande Industries |
| WHS | Warehouse System |

# INTRODUCTION: THE TREND TOWARDS PRO-ACTIVE MAINTENANCE

Companies that buy complex VI-systems require high availability, because their primary processes may depend on these systems. The downtime costs are therefore high, and VI is expected to ensure the system operates smoothly. Not surprisingly, increased system availability has direct impact on business profit, and customer requirements shift more towards costs, reliability and availability.

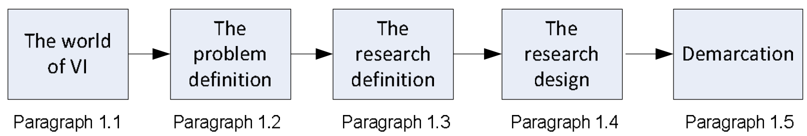
For the systems of Vanderlande Industries, these shifts can become very beneficial. Previous research at Vanderlande Industries showed that maintenance and downtime costs together accounted for almost 70% of the Total Cost of Ownership (TCO) of a baggage handling system (Franssen, 2006). Moreover, an increasing number of customers require TCO estimations, and VI therefore requires a better understanding in the effects of maintenance. The main objective of this research is to provide insight into the consequences of different maintenance strategies on TCO and availability.

More and more companies are replacing their reactive, fire-fighting strategies for maintenance with pro-active, predictive strategies (Swanson, 2001). These strategies require increased commitments in terms of resources, training, integration, but they promise increased reliability and performance.

As we will see, maintenance decisions should be based on knowledge of the underlying deterioration processes, and the costs associated with different aspects of maintenance, e.g. labor, material and downtime costs. In this thesis, we present a mathematical model that calculates, given a number of annual inspections, the expected maintenance costs and expected failures.

# 1 INTRODUCTION INTO THE RESEARCH PROJECT

***This chapter describes the business environment at which this master thesis project has been executed, namely Vanderlande Industries in the Netherlands and her challenges. One of these challenges is investigated in this research. Firstly, Vanderlande Industries is described in Section 1.1. The problem definition is given in Section 1.2, which leads to the research definition, presented in Section 1.3. The research design is presented in Section 1.4, followed by the demarcation in Section 1.5.***




## 1.1 The world of Vanderlande Industries

Vanderlande Industries, further abbreviated to VI, is a Dutch multinational that provides automated material handling systems. Their systems enable the handling of goods in e-fulfillment distribution centers, express parcel sortation facilities or baggage handling at airports. VI, founded in 1949, currently employs around 1,700 employees.

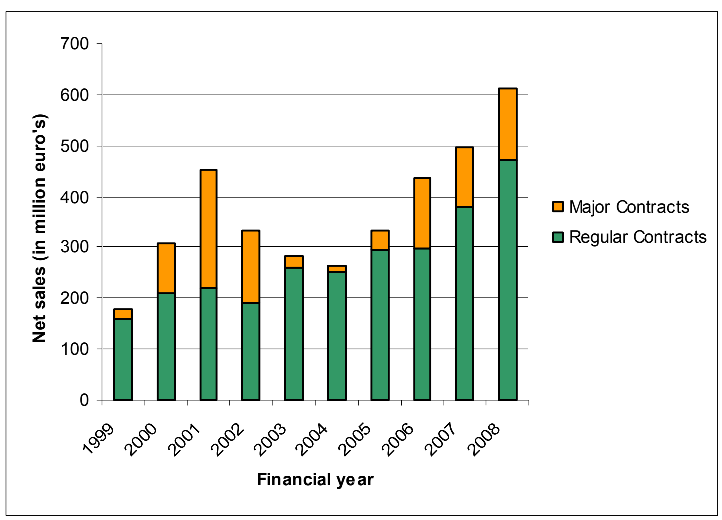



**Figure 1 – The net sales of VI divided into regular and major contracts**

In her financial report, VI distinguishes between regular and major contracts. Major products have a large impact on the financial results (see Figure 1). If one only looks at the total net sales, it seems that the revenue of VI highly fluctuates over the years, which may imply an unstable company or business. However, the regular contracts are stable over time, whereas the major contracts create the fluctuations. Major contracts are for example the baggage handling system in Heathrow London, or the enormous Parcel Express site of UPS in Louisville, USA.

All in all, the company is financially healthy, and the turnover grows. VI management expects growth in 2009 and 2010, in spite of the global financial crisis.

### 1.1.1 Business units

VI consists of four Business Units (BU's): Baggage Handling, Express Parcel, Distribution, and Services:

- BU Baggage Handling - VI designs, builds and services Baggage Handling Systems (BHS) for different sizes of airports. Clients vary from small regional airports, such as Eindhoven Airport, to large major hub airports, such as Amsterdam Airport Schiphol.
- BU Distribution - The distribution systems provide order fulfillment and sortation in distribution centers. These logistic systems provide an optimum of efficiency, labor costs and costs per unit of product handled.
- BU Express Parcel - VI offers a wide range of technologies for the sorting of parcels. The systems provide logistics solutions for customers such as TNT, DHL and UPS.
- BU Services – After commission, the Service department becomes the customer's main contact through the system's operational life-cycle. VI provides all required service facilities to maintain the performance criteria, i.e. productivity, safety, and availability.

### 1.1.2 Engineered-to-order systems

Since each customer orders a different system, VI delivers engineered-to-order (ETO) systems, using modularity for the products. This means that the systems are built upon standard building blocks. The ETO-philosophy impacts the service offered, and the required maintenance activities.

In order to clarify the terminology of this research, the building blocks of VI-systems are defined as follows (see Figure 2):

- A *VI-system* is the actual system delivered to a customer. A system consists of several zones, which consist of a number of mechanical VI-sections and (several) electrical controllers, such as Programmable Logic Controllers (PLC's) or Flow Systems Controllers (FSC's). The sections can be positioned in series or parallel.
- A *VI-section* is a standard piece of equipment, such as a standard Belt Floorveyor (BF) or a PosiSorter (SPO). A section composes several components.
- A *VI-component* can be a motor, a belt, a pulley, a bearing, etc. These either come from the factory or from a supplier. A component can consist of several parts, but this detailed sub-classification is beyond the scope of this research.

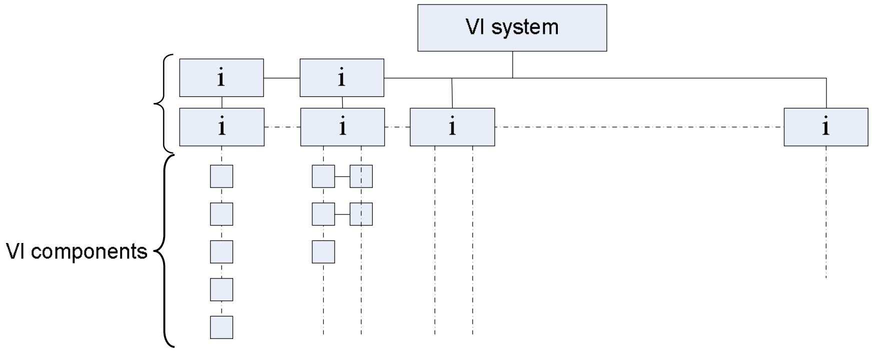



**Figure 2 – A VI system is built with multiple VI sections, which consist of several VI components**

### 1.1.3 Service organization of VI

This master thesis project is executed at the Service Development department of the business unit Services. The service organization consists of three entities: The BU Services, the operating Customer Centers (CC's) and Local Partners. The BU Services is responsible for the development of new service activities and the supply of spares, whereas the CC's and the Local Partners are responsible for the actual executing of the service operations. BU Services supports the execution of service from Veghel. The activities of this BU are split into five categories (Figure 3). This project is executed at the Service Development department of BU Services.

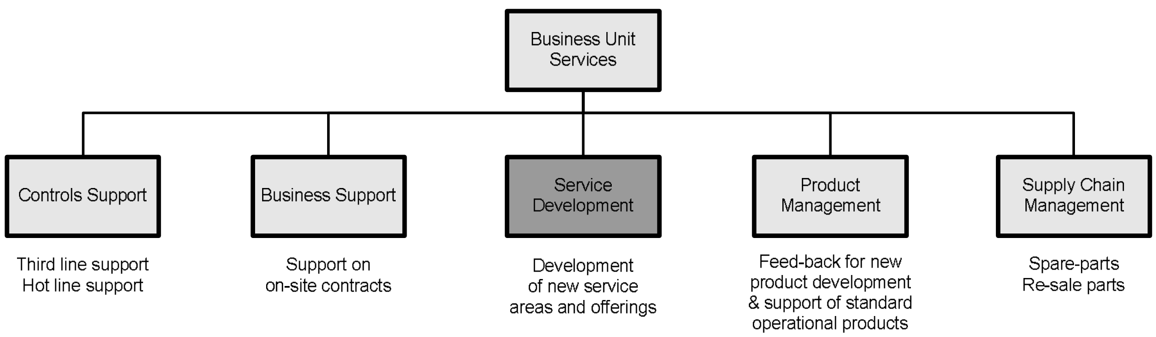



**Figure 3 – The BU Services and the relevant activities for this research**

Because VI's customers are located all over the globe, VI uses Customer Centers (CC's) and local partners for the execution of service activities. Currently, there are nine CC's: Benelux, France, Germany, Spain, UK, USA, China, South Africa and International. A CC generally employs account managers and service engineers, who execute the maintenance activities. In countries without a CC, the customers are serviced through local partners, who are again supported by the CC International. The setup of local partnerships is influenced by (amongst others) geographical constraints, business types and number of systems near the local partner. Local partners are trained and certified by Vanderlande Industries.

### 1.1.4 The service offerings of VI

Currently, more than 500 customers enjoy the services provided by VI, ranging from small distribution centers, to the world-largest airports. Obviously, these customers have varying demands, depending on variables such as the size of the system, number of production hours per year, or downtime costs. To satisfy the varying customer demands, VI made their services flexible, built on 'standard packages of services'. The standard packages range from spare parts deliveries, to full-service contracts with on-site VI-teams and service-level agreements. This way, the service contract can be easily adjusted to customer demands. A more detailed description of the service packages and activities can be found in Appendix 2.

The service department of VI has expanded rapidly in the past ten years, and the service activities are likely to continue growing (Figure 4). This master thesis project concerns the so-called 'normal maintenance' which generates approximately 20% of the service sales of VI. Normal maintenance consists of the sales of the call-out services and maintenance inspections. It can be seen that the yearly normal maintenance sales will be approximately 40 million Euro in 2014.

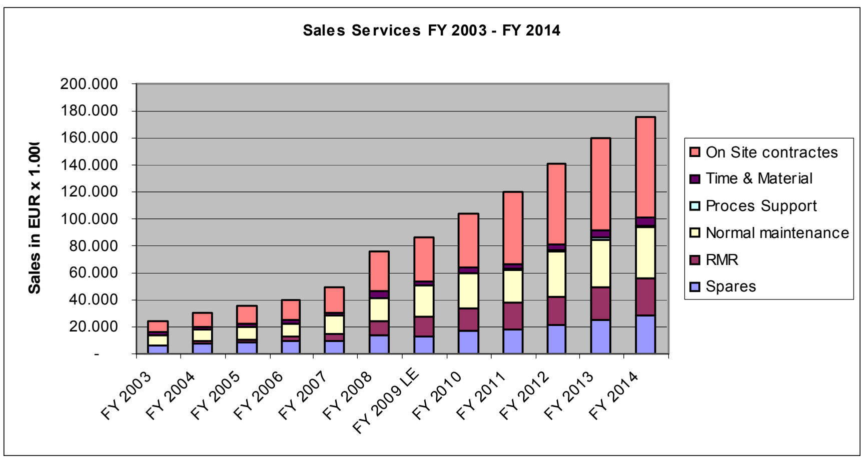



**Figure 4 – The service sales will steadily increase in the next years**

## 1.2 Problem definition

Nowadays, more and more customers of VI require detailed Total Cost of Ownership (TCO) estimations to select the supplier of a (new) system. The concepts *Life Cycle Costing*, *Total Cost of Ownership*, *Product Life Cycle Costing* are all related; these are concepts that try to adopt a long-term perspective for accurate valuation of buying decisions. TCO analyses are likely to be used in non-routine purchases such as capital goods (Ellram and Siferd, 1998), since a majority of the total cost of ownership is expended during the operational phase. These operational costs, including maintenance and downtime costs, are locked up and committed upon during the design and engineering phase by VI, but paid during the usage phase by the customer. This is visualized in Figure 5 (Barringer et al., 1996).

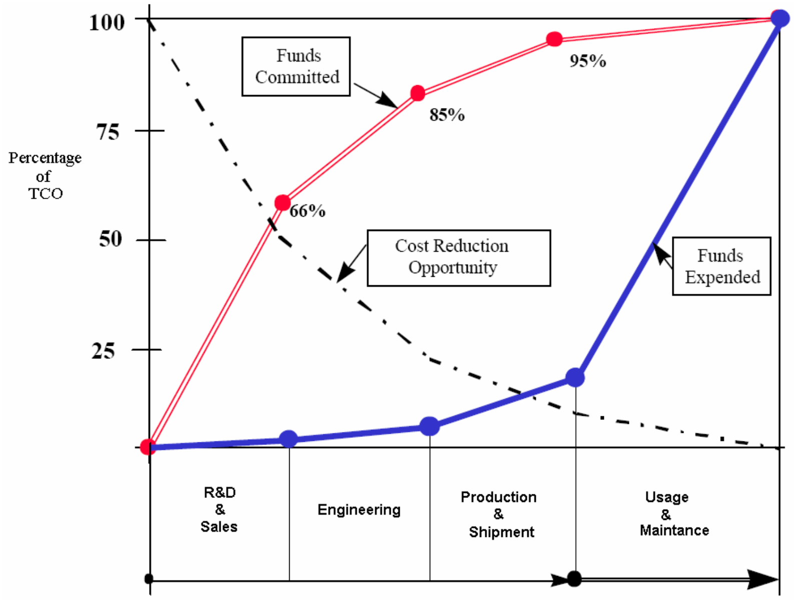



**Figure 5 – A majority of the TCO is committed upon in the design phase, but paid during the usage phase.**

This led to the desire to understand TCO, and many initiatives on these subjects have been set up in the previous years. An important finding was that maintenance and downtime costs together accounted for almost 70% of the TCO of a baggage handling system (Franssen, 2006). Reducing the amount of operational failures, and increasing availability, with better detection and diagnostics could provide a large reduction in the TCO (Franssen, 2006).

Customers of VI are increasingly interested in system availability predictions, because their primary processes depend on the VI system. Generally, system availability increases with an decreasing number of failures, or with an decreasing repair-time. The VI-department called Systems Engineering is very committed to capacity and availability calculations, especially with respect to redundant multi-component systems. At VI, availability also has been subject to many internal researches, such as Van Putten (1999), Franssen (2006) and Vlasblom (2009). Brief summaries of the relevant projects that were executed within VI on availability, TCO, and lifetime estimations, can be found in Appendix 3.

Although maintenance strategies are a major determinant of both TCO and system availability, the influence of maintenance strategies on availability and total cost of ownership has not been subject to an extensive research in VI. Optimal maintenance strategies aim to provide optimum system reliability and safety at the lowest possible maintenance costs (e.g. Wang and Pham, 2006;

and Dekker, 1996). There is an inherent trade-off between maintenance efforts (costs) and availability. Maintenance activities can increase availability and/or decrease total costs; but too much maintenance activities can also decrease availability and/or increase costs. Because these maintenance decisions involve the trade-off of availability and costs, all maintenance decisions should be supported by convincing arguments based on system degradation knowledge and solid system life-cycle estimates.

**This leads to the following company challenge**

VI requires a more thorough understanding of the relationships between availability, TCO and maintenance (or service) activities to support future maintenance (and service) decisions.

Currently, the life-cycle plans and maintenance plans are not based on knowledge or solid calculations, but are based on experience and best practices. Therefore, VI faces two major challenges:

1. The first challenge is to gather sufficient field-data from operating systems at customer sites to sustain claims on the expected system life-cycle. This time-consuming process to gather field-data has recently been started at VI, via modules called Business Process Intelligence (BPI) and Computerized Maintenance Management System (CMMS). At present, this has not generated useful data for this thesis, but it is anticipated that lifetime data will become available in the near future.
2. The second challenge is to use this lifetime data to reduce the amount of operational failures, by applying the proper maintenance strategy for a certain system. The main question is which maintenance strategy to apply to which system, in which situation? For example, when does a three-monthly inspection contract outperform a four-monthly inspection contract?

## 1.3 Research definition

As indicated above, VI needs to enhance its knowledge concerning the effects of maintenance on TCO and availability, in order to support decision making. This company challenge is the subject of this master thesis. TCO, availability and VI-systems are broad terms, and a more precise focus is required.

> **The main research question is**:
> How are the number of technical failures and Total Relevant Maintenance Costs (TRMC) of a VI-section influenced by different maintenance strategies?

- This research focuses on an important fraction of the TCO. The Total Relevant Maintenance Costs (TRMC) are defined as the sum of all costs that are determined by maintenance activities during the lifetime of the system, including labor, material and downtime costs. Other TCO aspects, such as depreciation, spare parts inventory cost, cost of the building or energy costs, are excluded since it is unlikely that maintenance influences these costs.
- This research focuses on the number of technical failures, instead of system or technical availability. System availability (1) is difficult to use, because networks of sections makes the availability calculations complex. Moreover, availability calculations differ per customer, since they can have different desires how the availability of their system is calculated. Technical availability (2) is also difficult to use, because repair-times can vary highly. Moreover, the reasons for downtime are numerous, and are (sometimes) difficult to assign to a specific cause. Focusing on technical failures also mitigates two variables that are out-of-scope to remain focused on maintenance, namely spare parts inventory costs and mean-time-to-repair (which also depends on spare part inventory).
- This research focuses on VI-sections, because the major maintenance decisions at site are often determined from decisions for its critical sections. VI-systems are often complex networks of VI-sections. The availability calculations, executed by the Systems Engineering team, build upon the availability estimations of these sections.

## 1.4 Research design and methodological foundation

In this section, the approach to answer the research question is presented. Studies in the field of Operations Research (OR) often tend to be either research-oriented or design-oriented. The former is based on solid, well-grounded and rigorous work, but is sometimes difficult to implement without company specific solutions. The latter, on the other hand, is highly applicable in a certain situation, but it is sometimes difficult to generalize the findings. The challenge in any OR study is to combine rigor and relevance, to ensure that it can be used in both the academic field and in the particular situation.

Mitroff et al. (1974) create a model that is applicable in operational research and combines normative empirical quantitative research with rigor. Four phases cut an *empirical normative* *research* into appropriate project steps. For the most complete form of research, the researcher must conduct the entire "conceptualization, modeling, model solving, and implementation" cycle. All steps of a cycle are therefore executed in this thesis project.

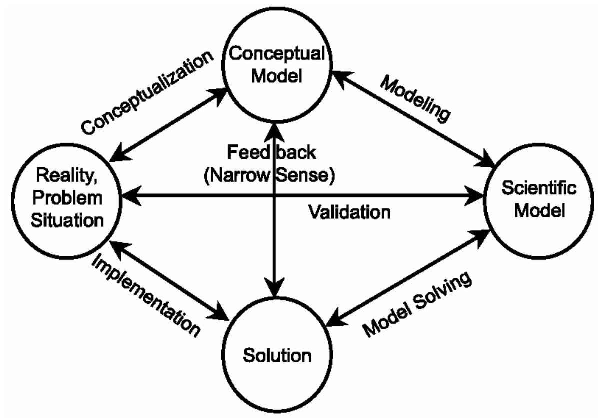



**Figure 6 – Mitroff's model for a an empirical normative research**

## 1. Conceptualization phase

In the conceptualization phase, a conceptual model is made of the problem under study, and all the factors that affect the problem are investigated. This means that decisions (on the variables to include) have to be made, and the scope of the problem and model need to be addressed (Bertrand and Fransoo, 2002). This phase (see Chapter 2) has defined a research area by means of an extended literature review and by interviews with experts in the field of maintenance.

## 2. Modeling phase

In the second phase, the quantitative model is actually built, and the causal relationships between the variables are defined (Bertrand and Fransoo, 2002). This quantitative model should be able to translate the identified input variables into an estimation of decision variables (total relevant maintenance costs and the number of expected failures). The conceptual model remains grounded in academic maintenance theories from a literature review, and is adjusted to match the situation of VI-systems, based on expert's opinions.

## 3. Model solving phase

In the model solving phase, mathematics and economics play a dominant role (Bertrand and Fransoo, 2002). Using the developed model, scenario analyses are executed and different maintenance strategies are evaluated. Inspection-based maintenance frequencies are tested based on historical data at different sites. The variables are also subject to sensitivity analyses, to check the model on robustness.

**4. Implementation phase**

The actual implementation is out-of-scope. Normally, the solution should be implemented after which a new cycle can start (Bertrand and Fransoo, 2002). Due to time limitations, this is unachievable. Nevertheless, to conclude the research, a reflection is given on the presented model, and the limitations of the research and future research possibilities for VI are discussed.

## 1.5 Demarcation

VI systems are engineered-to-order (ETO), because each customer has different requirements. Although VI uses production techniques, such as modularity and commonality to reduce the number of product families, the differences between the systems remain considerable. It is difficult to generalize and standardize formulas with such customer specific products. This leads to some difficulties when it comes to problem solving projects, such as this master thesis project. Therefore, the following demarcations are made for this research:

- Focus on a Parcel Express system

  The product matrix of VI is simply too broad to include everything in this research. Although the second chapter of this thesis will be applicable to all systems at VI, this thesis will focus on the PosiSorter system to concretize research findings (see Appendix 4 for a detailed description). The PosiSorter, further abbreviated to SPO, has a few important advantages. This system has been sold frequently in the past and consists of different critical elements that fail frequently, thus there is a considerable amount of data and knowledge about this product. Another advantage is that the SPO is composed of serially positioned components, which makes the reliability calculations rather straightforward. Most importantly, many SPO sites are sold with a *full-service contract*, which makes the spare parts data reliable (and therefore useful) as opposed to maintenance teams that order spare parts on an ad-hoc basis. Sites with a full-service contract are required to have an adequate administration of the spare part usage for administrational reasons (see chapter 3). Finally, the SPO is often the critical section of a system, thus the maintenance strategy of the SPO is often leading for the maintenance strategy at the entire site.

- On-site maintenance teams versus off-site maintenance teams

  A large difference between current maintenance strategies follows from the choice between on-site teams (such as at Schiphol or at Heathrow) or off-site maintenance teams. It is decided that this project focuses on strategies with the off-site maintenance teams, because there is a desire to sustain claims on these maintenance strategies, and to improve the predictability of these systems maintained by off-site teams. Moreover, this gives the opportunity to compare different sites, which is not possible with the sites with on-site teams, because these are too different in terms of size and complexity.

- Re-sale equipment

  VI systems often also contain equipment of third parties, so-called *re-sale equipment*. For example, a baggage handling system contains X-ray scanners and balances. Although VI is often responsible for the integration of the entire system, the placement and maintenance on the re-sale equipment is executed by a certified supplier. Since it is highly unlikely that VI will ever execute the maintenance on re-sale equipment, this is out-of-scope.

- Miscellaneous

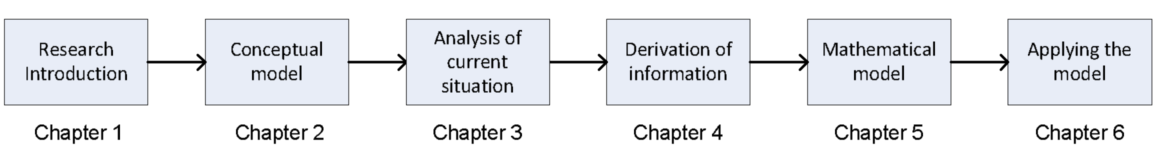
  This thesis is focused on the critical components of the SPO, as identified by the R&D department. Availability of spare parts, tools and engineers are out-of-scope, because these are (more or less) always made available or provided for the customers. Electrical and software issues are out-of-scope as well, because these failures are unpredictable.

## 1.6 Conclusion and outline

The company relevance and main research deliverable can be summarized as follows:

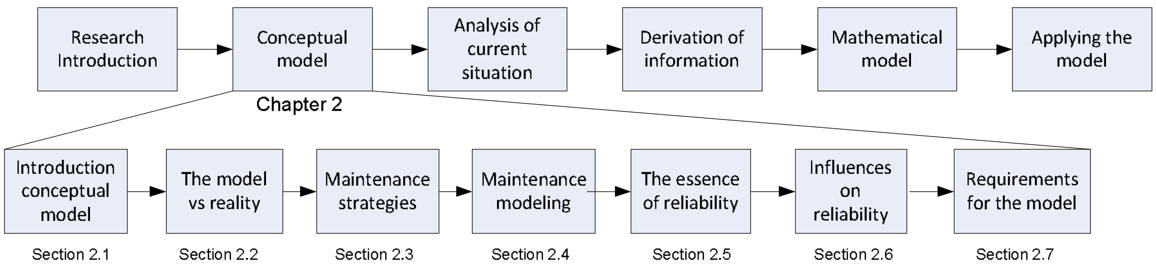
**Company relevance and research deliverable:**
The main objective of this master thesis project is to provide insight into the consequences of different maintenance strategies. A quantitative model is presented, which calculates the expected number of failures and the expected total relevant maintenance costs for VI section, given historical reliability data and different maintenance strategies. With this model, the impact of corrective and inspection-based maintenance strategies is compared for the critical elements of the PosiSorter.

The outline of this thesis is as follows: In the second chapter, the conceptual model is presented, discussing the ins and outs of the model, its goals, and its limitations. The third chapter analyzes the functioning of current situation more thoroughly. In the fourth chapter, the steps to derive information from the available data are explained. This process is essential for the applicability of the field data in the model. In the fifth chapter, the preceding findings are combined into a mathematical model on maintenance efficiency, varying the inspection frequencies on a VI section. In the sixth and final chapter, the different maintenance strategies are compared, and the generalization and implementation of the model is also discussed.



# 2 CONCEPTUAL MODEL OF A VI SYSTEM IN THE FIELD

***In the conceptual model, all factors that affect the research problem are investigated. First of all, the scope of the model and its desired functionality are discussed in Section 2.1. In Section 2.2, the relation between the model and reality is explained. Section 2.3 and Section 2.4 respectively describe the maintenance strategies and maintenance modeling. Section 2.5 explains the importance of reliability, and describes how reliability should be entered into the model. Section 2.6 discusses the factors that influence reliability. Finally, Section 2.7 concludes with the requirements of the quantitative model.***




## 2.1 Introduction

To solve the research problem, a quantitative model that compares maintenance strategies in terms of total relevant maintenance costs and expected number of failures is built in this thesis. In the desired situation, a VI employee can enter the system specifications and costs parameters into a model. The model should automatically calculate the expected costs and the expected number of failures, given differences maintenance strategies. With these results, the VI employee can advise the customer which maintenance strategy would be appropriate, and the optimal decision can be made.

The first step towards a properly functioning model is the conceptual model. The conceptual design discusses the design and the functionality of this model. The general structure (including an input dashboard, a database and an output sheet) of the model is shown in Figure 7.

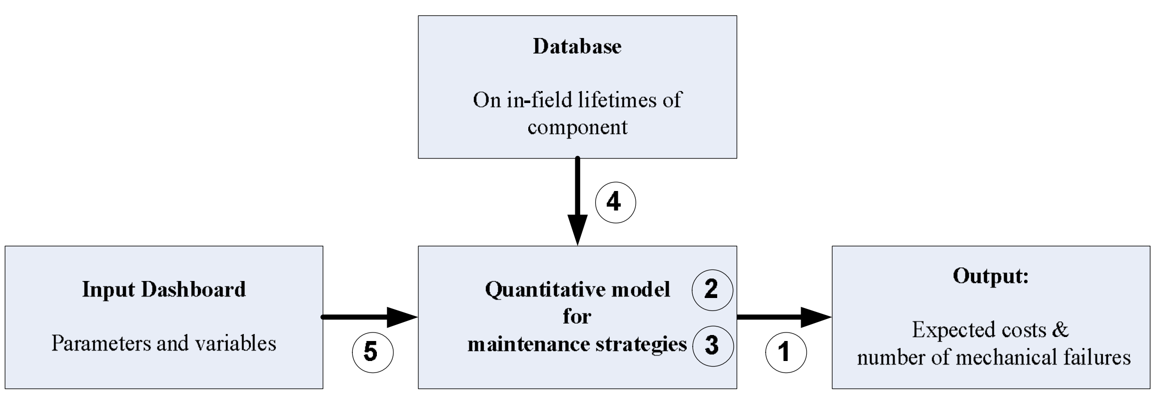



**Figure 7 – Illustration of the general structure of the model**

The underlying research questions, answered in the following sections, follow from this illustration. Questions 1, 2 and 3 concern the working of the model, namely maintenance modeling, availability and cost structures. Questions 4 and 5 follow from this, namely how should reliability be entered, and which are the parameters and variables that should be taken into account. To answer the main research question, the following research questions will be answered consecutively, to be able to model the situation of VI:

| **Foregoing building the model, the next underlying research questions are answered consecutively** | |
|---|---|
| 1. What is the relation between the (output of the) model and maintenance? | § 2.2 |
| 2. What is the essence of maintenance modeling? | § 2.3 |
| 3. What are the potential maintenance strategies? | § 2.4 |
| 4. Which data set, parameter and variables should be included? | § 2.5 |
| 5. Which factors influence the reliability? | § 2.6 |

## 2.2 What is the relation between the model and system availability?

Consider a system that consists of various repairable components. The system will operate until a component fails, whereupon the component is repaired and returned to its operational state. The repair is executed as soon as possible, because unavailability (non-scheduled system downtime) is costly, and needs to be avoided. *System availability* is defined as the probability that a system will be in a condition to perform its intended function when required (Semi-standard, 2004). Long term availability is calculated by dividing the time that the system is in working condition by the total time that the system should be operational. According to Kelly and Harris (1978):

$$\text{System availability} = \frac{\text{System uptime}}{\text{System uptime} + \text{System downtime}} \tag{1}$$

The realization of availability depends on two issues: (1) the inherent reliability of the system and (2) the ability to repair and return the system to operation rapidly and efficiently (Blanchard and Fabrycky, 2006). *Reliability* is defined as the probability that the system will perform its intended function, within stated conditions, for a specified period of time (Semi-standard, 2004). System reliability is mainly determined by the system design in terms of the mean-time-between-failures (MTBF) of the components, by the level of redundancy in the network of components and by the execution of maintenance activities.

In Figure 8, it can be seen that the uptime that elapses between two consecutive downtimes (MTBF) depends on the reliability, whereas the duration of the downtime depends on mean-time-to-repair (MTTR). The system availability has a direct relationship with its reliability and the speed of system repair activities (MTTR). In other words, the technical availability can be increased by a higher MTBF of elements, or decreased MTTR of failures.

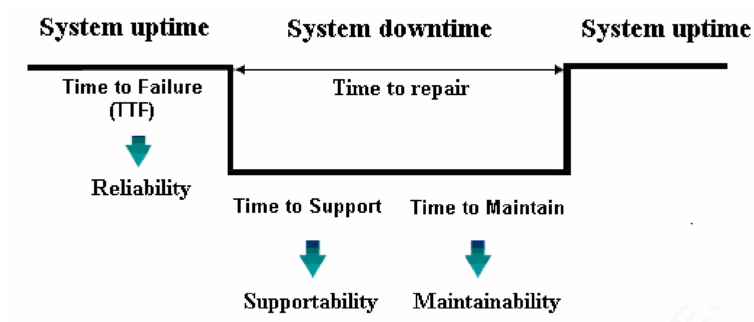



**Figure 8 – Availability depends on reliability, supportability and maintainability**

The MTTR is determined by the supportability and maintainability. *Supportability* refers to the ability to decrease downtime that is caused by waiting for resources, tools, parts or capable engineers. It can constitute a large part of the system downtime, for example when the spare parts are not available. The time-to-maintain is the total amount of time that elapses while the system is repaired or restored to its operational status. *Maintainability* is the ability to restore the system into a condition where it can perform its intended function within a specified period of time (Semi-standard, 2004). In order to decrease MTTR, a company needs to enhance its supportability and maintainability.

Unscheduled downtime of a VI system can have different causes: technical, electrical or operational failures or crashes (see Figure 9). This research considers the technical failures, i.e. broken mechanical part due to wear. Electrical and operational failures are out-of-scope (most electrical failures are solved via the hot-line, and operational failures are unpredictable).

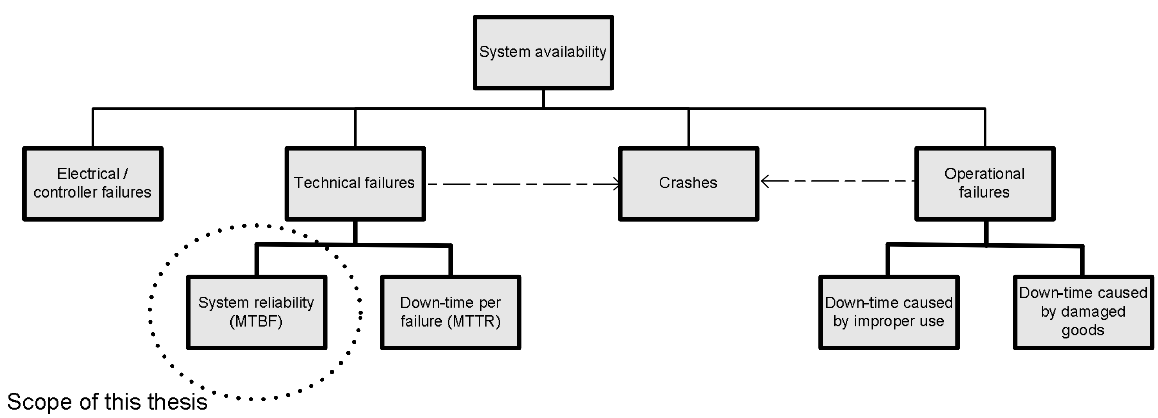



**Figure 9 – Break-down of system availability as used in this thesis**

It can be concluded that when the reliability, supportability or maintainability is low, the system availability will also decrease. Herein, availability is an output, whereas reliability and maintenance are inputs. Increasing availability by improving either the reliability or the maintainability can be costly, but unavailability also entails costs.

## 2.3 What are maintenance strategies, and which should be modeled?

The next underlying research question concerns the functionality of model, namely maintenance. This section presents the definitions of the maintenance strategies used in the remainder of this thesis, and the strategies that can be modeled are discussed.

According to Dekker (1996), a maintenance strategy (or concept or policy) describes what events (e.g. failure or passing of time) trigger what type of maintenance (e.g. inspection or replacement). Proper maintenance management is important to achieve high uptimes or machine availability. Everything around us is subject to inevitable degradation effects due to use and time. This implicates that the maintenance engineer's task is not to prevent degradation, but to slow it down. 'To maintain' is defined as 'cause to continue' or 'keep in existence'. Stoneham (1998) defines maintenance as the process of maintaining an item in an operational state by either preventing a transition to a failed state or by restoring it to an operational state following failure.

Two kinds of maintenance actions can be distinguished.

- *After a failure*: corrective maintenance. Corrective (or restorative, or failure-based) maintenance follows a failure, the operational level can drop below its acceptable level and the operation might be shut down.
- *Prior to a failure*: preventive maintenance. Preventive maintenance is carried out to make an component less vulnerable to causal influences, by restoring the quality to an acceptable level (Stoneham, 1998).

Preventive maintenance can be split up into statistics-based and condition-based preventive maintenance (Mann et al., 1995). With condition-based maintenance, actions between activities is no longer fixed, but executed 'when needed'. Statistics-based maintenance may become profitable when the standard deviation of the failure population is small. Considering the trend of on-line system inspection, the need for condition-based maintenance is evident (Mann et al., 1995). Based on Mann et al., (1995), Stoneham (1998), Bevilacqua and Braglia (2000) and Waeyenberg and Pintelon (2002), the following classification is used in this thesis:

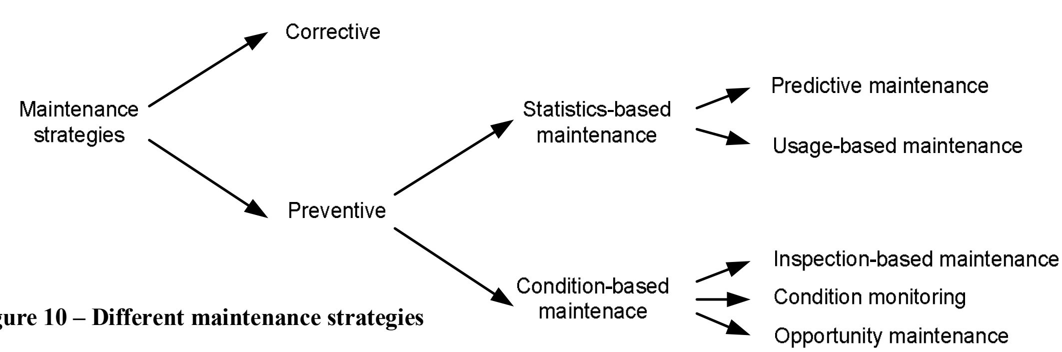



**Figure 10 – Different maintenance strategies**

| | |
|---|---|
| Predictive | The controlled parameters are analyzed to find a possible temporal trend and predict when the controlled quantity value will reach or exceed the threshold values. |
| Usage Based | Maintenance is carried out after a specified amount of time (e.g. 1 month, 1.000 working hours). UBM assumes that the failure behavior is predictable. |
| Inspection-based | Operators or engineers can observe, smell, hear, or feel irregularities. These visual inspections are cost efficient, but suffer from subjectivity and poor accuracy. |
| Condition Monitoring | The system condition is monitored (e.g. with thermography, oscilloscopes, or oil analyzers), and maintenance is carried out each time the value of a given system parameter (nearby) exceeds a predetermined parameter. |
| Opportunistic | OM is executed when a component, within the same system or plant, breaks down and other components are maintained at the same time, and thus with lower start-up costs. |

Currently, inspection-based maintenance is the performed strategies at many customer sites, thus the model presented in this thesis must be able to assess the impact of number of annual inspections and corrective maintenance (i.e. zero annual inspections). For opportunistic maintenance, predictive maintenance and condition monitoring, there is currently not enough information available.

The goal of inspections is to observe damages or defects (hence, condition-based), before an item or system fails. Signals include vibration, unusual noise, excessive heat, surface staining, smell, reduced output, increased variability etc. Inspections are executed regularly, and failures are repaired as they arise. The service consists of a checklist of activities to be undertaken, and a general inspection of the operational state of the plant. Failures that occur between inspections are repaired via corrective maintenance actions or by the customer's technical team.

## 2.4 What is the essence of maintenance modeling?

Basically, a maintenance optimization model is a mathematical model in which both costs and benefits of maintenance are quantified and in which an optimum balance between both is obtained. The difficulty with maintenance decisions is timing (trigger) and content (resources) of an action. The challenge for any maintenance manager is to decide whether the maintenance results are obtained both effectively in terms of contribution to company profits and efficiently in terms of manpower and materials employed (Dekker, 1996).

In general, maintenance optimization models cover four aspects (Dekker, 1996):

1. a description of a technical system, its function and its importance,
2. modeling of the deterioration of the system and possible consequences for the system,
3. a description of the available information about the system and the functions open to management, and

4. an objective function and an optimization technique that helps in finding the best balance.

These steps are also taken into account for the mathematical model.

**The cost structure**

The model presented in this thesis calculates the expected number of renewals on a certain position, based on individual reliability of components. A component can be renewed via replacement or via repair. In most situations at VI systems, the components will be replaced. The term renewal is used in this thesis, because it encompasses both terms for our purpose. In this model, it is assumed that VI only replaces components when the components are clearly damaged, and will soon lead to a failure. Thus components are not replaced preventively based on age or usage, but solely due to observable damage. This implies that the remaining lifetime of a component is neglected. The expected lifetime is twenty to thirty thousand hours, and the remaining lifetime that is neglected can vary between zero and thousand hours (e.g. approximately 3 months).

The number of renewals is determined by the reliability and is independent on the maintenance activities. Depending on the intensity of the preventive maintenance of the maintenance strategy, the component will be renewed prior or after a failure (Figure 11). This distinction, between prior or after failure, has consequences for the kind of maintenance. A renewal prior to failure is preventive, and a renewal after failure is corrective. This leads to two kinds of downtime, i.e. preventive maintenance can be executed during scheduled downtime whereas corrective maintenance leads to unscheduled downtime, and thus to unavailability. For VI systems, scheduled downtime does not decrease technical availability (hence there is no line from scheduled downtime to technical availability). When the MTTR of certain failures are attached to the model, it can estimate the technical availability more precisely in the future.

Generally, corrective maintenance is more expensive than preventive maintenance, due to the unscheduled downtime and corrective maintenance costs that (may) arise with failures. The renewals prior to failure are replaced during scheduled downtime and only incur preventive maintenance costs. The maintenance strategy determines the fixed inspection cost function.

The research area in this field is called maintenance optimization. Optimal maintenance strategies aim to provide optimum system availability at the lowest possible maintenance costs (e.g. Wang and Pham, 2006; Dekker 1996). In order to achieve the latter objective, an appropriate interval for scheduled maintenance must be determined, based upon the expected renewals.

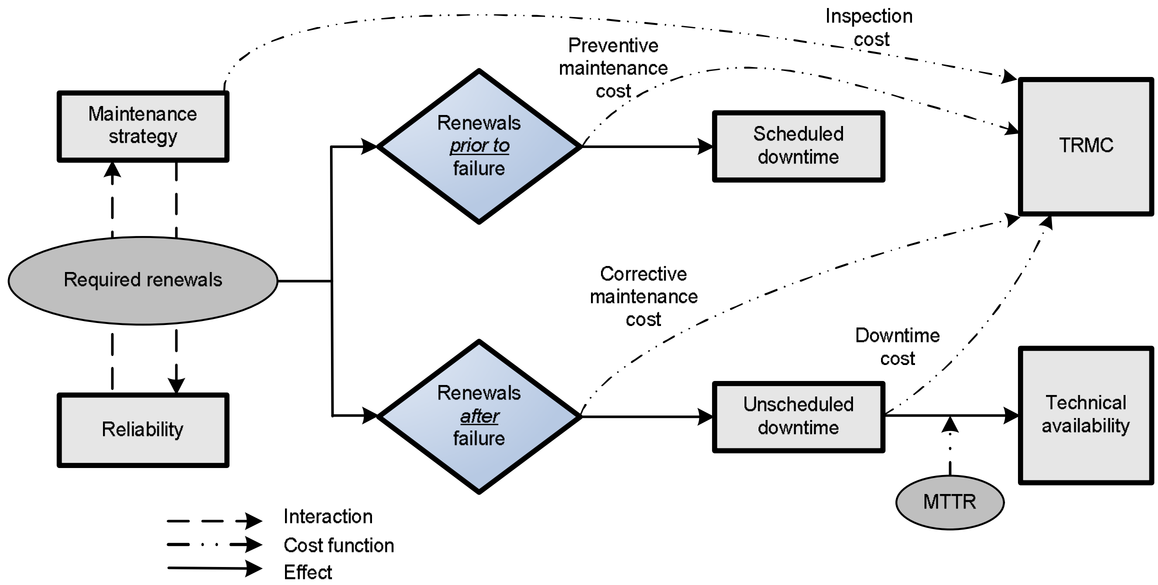



**Figure 11 – Illustration of the mean interactions that have to be modeled for the situation of a VI section**

## The renewal process

VI systems are repairable systems. After failure, repairable systems are brought back to their functioning state. In most situations, the repaired component will be (almost) *as good as new*. If one assumes that the components are as good as new after replacement or repair, one can calculate the expected number of replacements with the so-called *renewal processes*. Renewal processes are a class of stochastic processes, with independent identically distributed variables. Renewal processes play an important role in understanding discrete event systems (such as queuing, processing, inventory controlling or maintenance modeling) and are widely embraced by many authors. The renewal theory can be applied in life-cycle calculations when the components are brought back to a 'as good as new' state (Osaki et al. (2002). This fundamental theory is also used in the maintenance model presented.

To calculate the maintenance costs in the model, the expected number of renewals per position is required. The renewal process is used to approximate the expected consecutive number of failures on a certain position in the system (see Figure 12). Let N(t) be the number of renewals during the time (0,t). The inter-arrival times of the failures $X_1$, $X_2 \ldots X_i$ are identically and independently distributed non-negative random variables (the renewal process is generalization of Poisson processes). M(t) is the expectation of the number of renewals per position of component $x_i$.

$$M(t) = E[N(t)] = \sum_{n=1}^{\infty} n \cdot P\{N(t) = n\} \qquad (2)$$

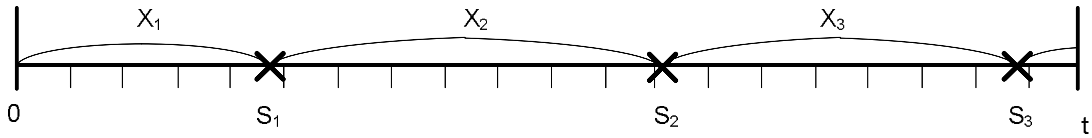



**Figure 12 – $X_i$ is inter-arrival time of the $i^{th}$ renewal on a certain position, at time $S_i$**

**Conclusions**

The renewal function is used in this thesis to translate the reliability function of components into the expected number of renewals on a certain position. When a maintenance action is performed shortly prior to the required renewal, a failure is prevented. This will incur less costs than the situation in which the component is renewed after failure.

## 2.5 How should reliability be entered into the model?

It has been concluded that reliability is an essential input of the maintenance model, to calculate the expected number of renewals. Therefore, the next question is how reliability should be entered into the model.

Since the reliability is vital to the understanding of maintenance modeling, understanding reliability is an important aspect of this thesis. The essence of reliability and the shortcomings of the MTBF are discussed firstly, followed by more fundamental theories on reliability. Subsequently, this section explains the background of reliability engineering and more specifically the possibilities with the Weibull distribution.

### 2.5.1 The essence of reliability

Reliability is an important design characteristic because the other system characteristics (such as TCO, maintenance, spare parts and logistic support) depend largely on the system reliability. The demand for spare parts, for example, heavily depends on the reliability of the products, and thus failing to understand the reliability is likely to result in poor prediction of demand for spare parts. Poor spare part predictions can lead to losses due to overstocking or due to increased downtime.

Reliability is defined as the probability that the system will perform its intended function, within stated conditions, for a specified period of time. Thus, reliability is a function of operating conditions. For example, the reliability of a car can be defined as the probability that it will drive 150,000 kilometers under a real-world usage-profile (Yang, 2007). VI systems also operate at different customers under different conditions. Thus, reliability has to be defined for a certain usage-profile (or user-profile). Within VI, it is widely accepted that when a conveyor runs at a higher speed, the degradation of components will be more severe. However, there is no general overview of the (potentially) influencing factors, nor are there predefined usage-profiles.

### 2.5.2 The reliability function

The reliability function is the basic reliability measure, which gives the probability that a component operates its intended function for a certain period of time without a failure (Kumar et al., 2006). It is a quantitative function of time, that determines whether the component will be defective or non-defective, i.e. the probability that this motor will run at least 1,000 hours is 98.5%, which is used in models, such as warranty calculations or maintenance models.

The reliability function is obtained via the probability density function (pdf, or f(t)) of the lifetime of a component. Examples of continuous random distributions are the normal or exponential distributions. The pdf is commonly used in reliability engineering or life-data analyses because the failure rate function, the hazard rate, and the mean-time function can be determined directly from the pdf. In reliability engineering, the cumulative distribution function (cdf, or F(t)) is the probability that a component will fail before time t, and hence it represents the unreliability function.

$$F(T) = \text{P(failure will occur before or at time t)} = P(TTF \leq t) = \int_0^T f(t) \cdot dt \tag{3}$$

If one knows the reliability functions, one can anticipate the upcoming failures. The reliability function is given by:

$$R(T) = P(TTF > t) = 1 - F(T) = \int_T^\infty f(t) \cdot dt \tag{4}$$

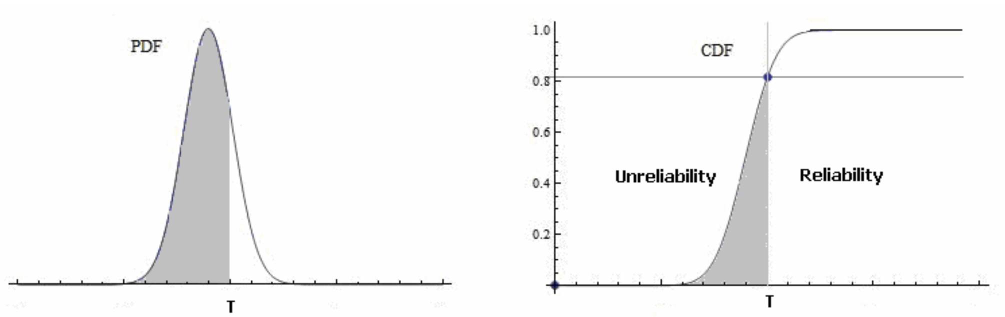



**Figure 13 – The continuous probability function: The probability density function (pdf) and the corresponding cumulative distribution function (cdf)**

It can be concluded that reliability is fundamentally built upon probability theories. Apart from few industries (such as defense, aerospace and nuclear), the knowledge on reliability is very limited among many industries. For many companies, reliability stops with MTBF. Unfortunately, many important product related decisions are made based on this measure of average findings (or predictions), where it would be preferred to take the distributions, that underlay these averages, into account as well (Kumar et al., 2006).

### 2.5.3 The shortcomings of the MTBF

The MTBF and the MTTF are the most-widely used measures for reliability and performance for non-repairable items (Lewis, 1996). Also within VI the MTBF is estimated by the R&D department, and used for availability calculations by the Systems department. The MTBF is a convenient measure because it can be calculated easily. However, this is only true when failures occur randomly (assuming a constant failure rate) which is, for several kind of components, often not the case. These misinterpretations are caused by the difference between mean and median. For example, if the data set consists of the values [1,2,3,4,20], the mean equals 30/5 = 6 time-units, but 80% of the sample has failed before the mean of the sample. So, if two suppliers both argue that their products has a MTBF of 500 hours, but one product has an exponentially distributed lifetime, and the other product has a normally distributed lifetime, this will lead to the following failure functions.

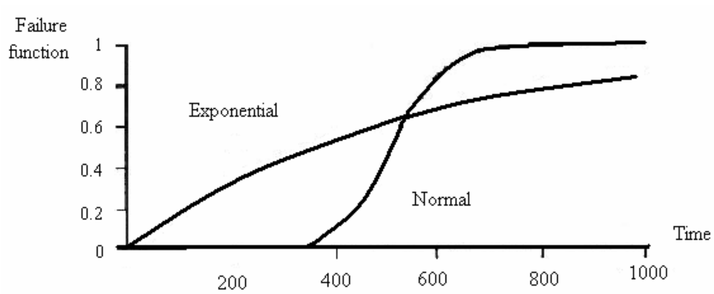



**Figure 14 – The reliability function of two different components, with the same MTTF (from Kumar et al, 2006)**

Obviously, the products with an exponentially distribution have a higher chance of failure in the early stages of the lifetime than the normally distributed failures. Therefore, this thesis uses the distribution of the TTF of components, instead of means such as the MTTF or the MTBF.

### 2.5.4 The Weibull distribution

The Weibull distributions play an important role in the statistical analysis of experimental data due to its flexibility (Kumar et al, 2006) and therefore it often used in the field of lifetime data analyses. This two-parameter continuous distribution has no characteristic shape. Using a shape parameter ($\beta$>0) and a scale parameter ($\eta$>0)[1], it can mimic the behavior of other statistical distributions, such as the normal and the exponential distribution. When $\beta$=1, the Weibull distribution equals the exponential distribution, meaning failures occur randomly or accidentally.

[1] Sometimes the parameters $\beta$ and $\eta$ are replaced by shape parameter k and scale parameter $\lambda$.

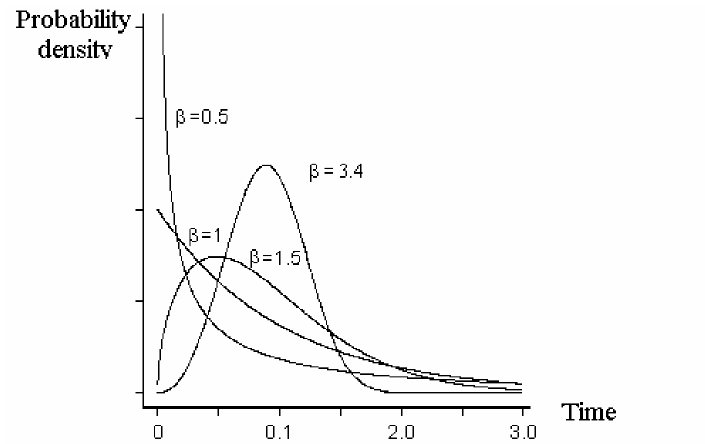



**Figure 15 – For different values of β the Weibull distribution takes different shapes.**

The other β values characterize the 'normal wear failures' with an increasing failure rate. When β = 3.4, the distribution approaches the normal distribution. For the Weibull function, the cdf is given by:

$$F(T) = 1 - e^{-\left(\frac{T}{\eta}\right)^{\beta}}$$

When the parameters of the distribution are known, the reliability function of a component is identified, and then it can be used for maintenance modeling. An easy and useful technique to obtain good estimates of the distribution parameters is called probability plotting (Lewis, 1996).

### 2.5.5 The failure rate

The failure rate, also called the hazard rate, measures the rate of change in the probability that a surviving product will fail in the next small interval of time. The hazard rate is expressed in the expected number of failures per unit of time, for example four failures per 1,000 systems per hour. Generally, there are three trends: the decreasing failures rate (DFR), the constant failure rate (CFR), and the increasing failure rate (IFR). This is often visualized via the bath-tub curve (see Figure 16). This curve represents three classes of failure mechanisms: infant mortality, random

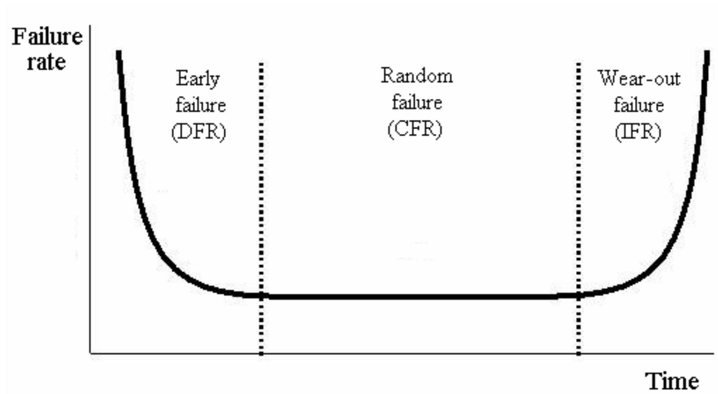



**Figure 16 – The well-known bath-tub curve depicts the time-dependent failure rate**

failures, and aging (Lewis, 1996). Typically, these can be described by Weibull distributions with different shape parameters $\beta$. If $0<\beta<1$, then there is a decreasing failure rate, which normally indicates a quality problem.

Whenever preventive maintenance is considered, one must know which type of failures is actually occurring. Trying to predict a random failure may lead to costly results, whereas predicting wear-out failures may be very beneficial. If the component has an increasing failure rate, then a carefully designed preventive maintenance program can be beneficial to system availability.

At VI, the knowledge on reliability and the component degradation is fairly limited. To test on the reliability, VI uses experiments in which the components run, in a test facility, until they break. However, since the parts are designed to run twenty to thirty thousand hours, these systems are often installed before the tests are finished. Re-testing or expanding experiments is often considered, but hardly ever executed. Reliability can be either measured in the field or tested via stress-tests. Such tests can simulate the stress incurred during operation.

## 2.6 Which factors influence the reliability?

There is no generally accepted list of influencing factors on reliability. In Section 2.2, it is concluded that system reliability is determined redundancy and component degradation. Component degradation is a function of design, maintenance activities, operational influences, and external influences. Based on interviews with VI employees, the following list of influencing factors concerning technical availability is built (see Figure 17).

Technical availability is determined by the MTBF and MTTR, as discussed in Kelly and Harris (1978). Although VI has estimated the MTBF and MTTR of many components, the influences on these averages are not quantified. It is known that the MTTR (on the right side) is affected by the availability of parts, tools, resources (travel distance and training), ease of diagnosis and maintainability. However, the impact of these determinants is unknown.

The failures considered in this thesis concern failure due to wear, or more precisely concern the degradation of the components. Degradation has operational influences, such as operational speed of the system, weight of the packages sorted or transported, the capacity and the number of operational hours ran. The operational influences that need to be taken into account are assessed in the next chapter.

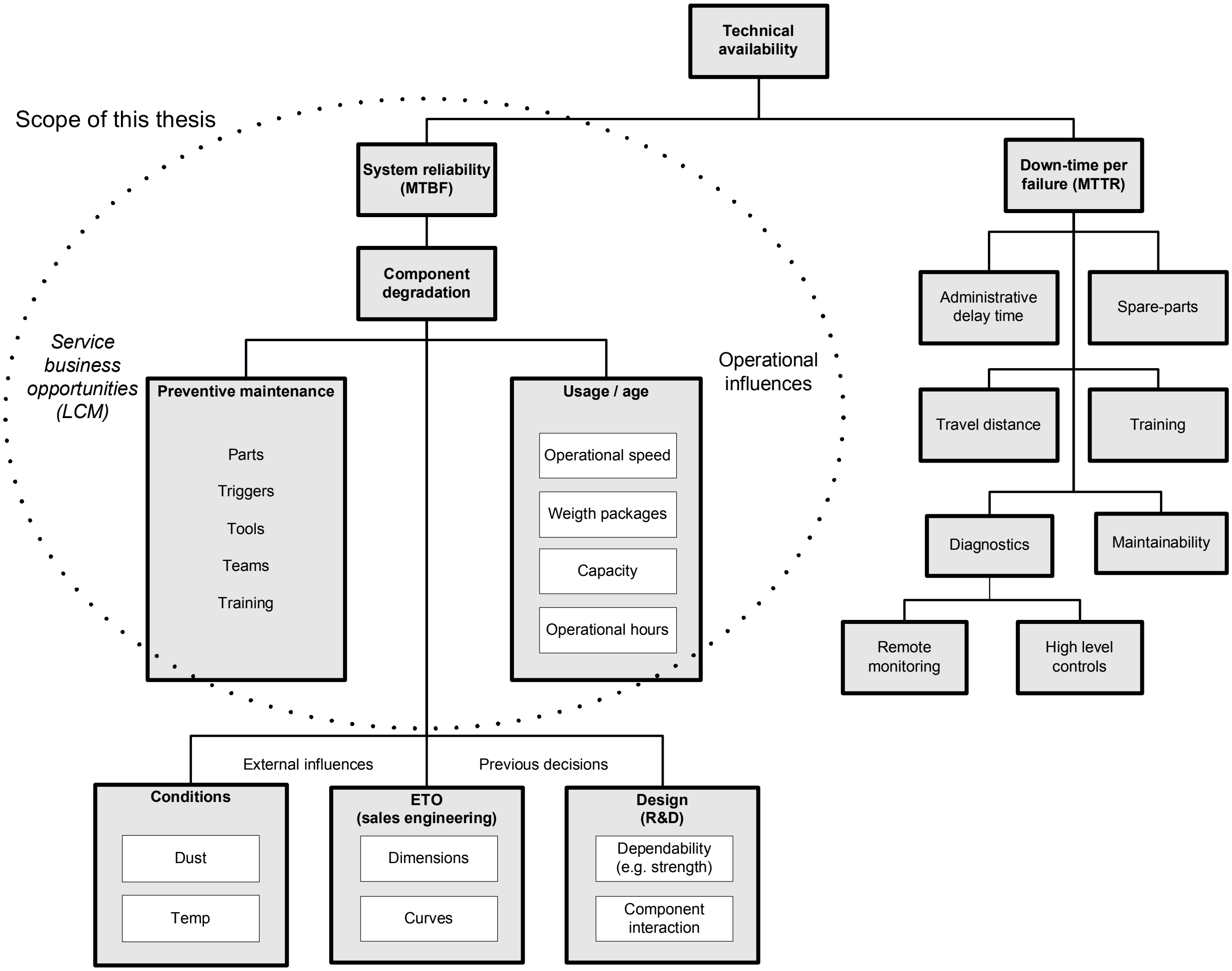



**Figure 17 – Overview of factors that influence reliability (on the left) and MTTR (on the right)**

To increase the corporate knowledge on system reliability, VI should solve this problem by systematically gathering data on the deterioration process per critical component, in different circumstances. However, the amount is potential circumstances is large, thus the best starting point is to gather information on component degradation in certain usage-profiles.

The factors which have a large impact on reliability should play an important role in the determination of the usage-profile. For example, when it turns out that speed and weight of the packages are important, then VI should use four usage-profiles.

## 2.7 Conclusions and requirements for the quantitative model

This chapter has presented the conceptual model, discussing important aspects of availability, reliability and maintenance modeling. The model combines academic theories from a literature review with opinions from experts, to match the situation of VI-systems.

This chapter closes with a short recap, presenting the requirements for the quantitative model. As discussed previously, the model should use an input dashboard, a database and an output sheet. The dashboard should include system specifications and customer specific cost parameters. The model will use the system inputs to look up the right degradation information that belong to a certain environment (on a pre-existing) datasheet based on gather field-data, and calculate the expected system degradation via the renewal function and the cost structure (as presented in this chapter). Finally, the mathematical model balances the risks associated with a failure and the investments in inspections to increase preventive renewals.

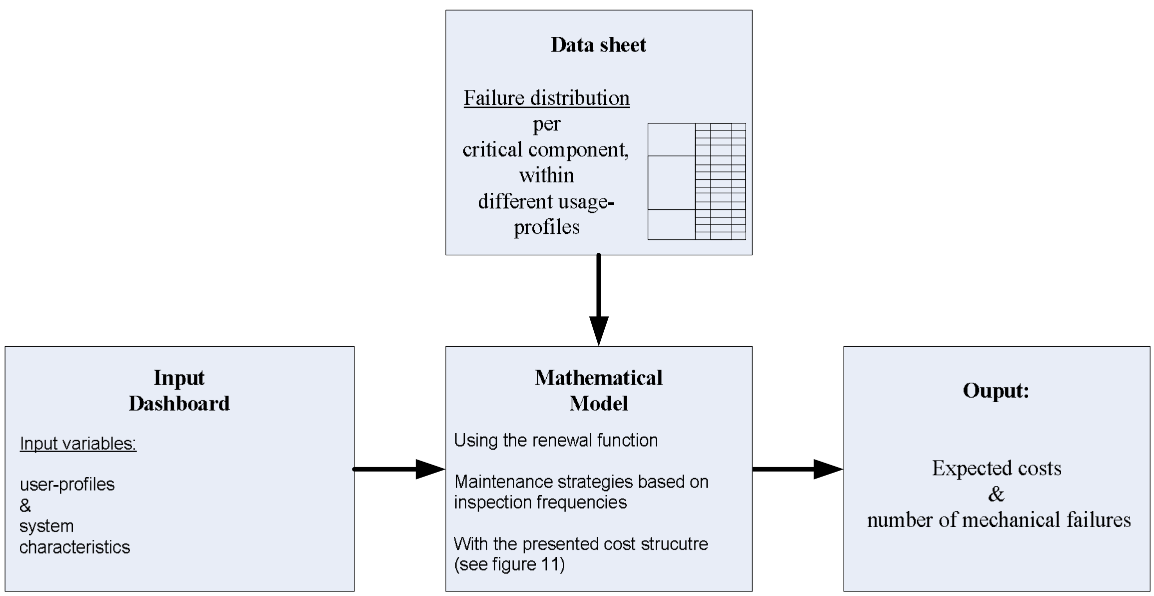
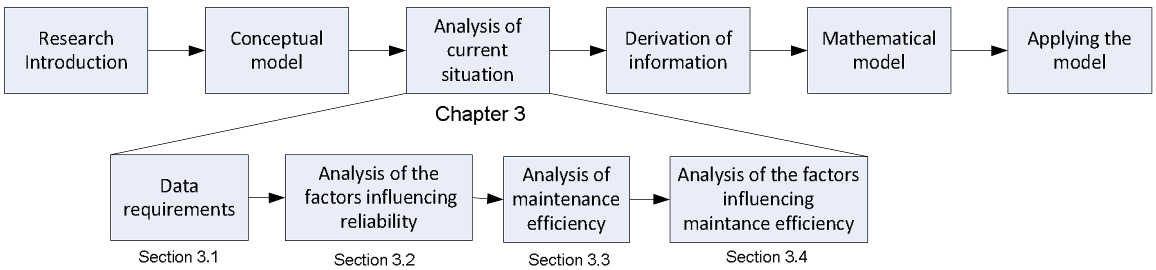



**Figure 18 – The functionality of the quantitative model**

# 3 ANALYSES OF CURRENT SITUATION

***In this chapter, the factors that influence reliability and maintenance efficiency are analyzed. Firstly, the data requirements and the reliability of data sources are discussed in Section 3.1. In the remainder of this chapter, the following three analyses are executed:***

1. *Analysis of the impact of influencing factors on reliability, in Section 3.2*
2. *Analysis of the maintenance efficiency, in Section 3.3*
3. *Analysis of the relation between the influencing factors and maintenance, in Section 3.4*




## 3.1 Data requirements

To execute the abovementioned analyses of the current situation, in-field data is required. This section discusses the data requirements and the method to gather the data, and explains how the reliability of this research has been confined. Within VI, data is not recorded for the purpose of maintenance optimization (yet), but merely as means to store accounting information. As a result, there is a large amount of reliable financial data, but the data on maintenance activities and failures is rather scarce[2]. Since spare parts are an important part of the accounting information, the data on spare part demand is recorded properly and therefore used in this thesis.

To ensure that the spare parts data is reliable and useful, the customer sites are chosen carefully. It has been chosen to use the data of an Italian customer with seventeen SPO sites and full-service contracts. These sites have an adequate administration of the spare parts, because the work orders are recorded properly. A proper administration of work orders is required by the financial department of VI to manage the full-service contracts. Hence the data on spare parts demand at sites with full-service contracts will provide the most reliable data. Another advantage is that these sites are fairly comparable in terms of maintenance, average load and product array, but they differ in terms of age, speed, length, capacity and local maintenance partner. Therefore, these sites can be compared in terms of influencing factors.

[2] The failures are very accurately administered at (amongst others) Schiphol Airport, Munich and London Heathrow, but these sites do not have an SPO system. The argumentation for the focus on the SPO is given in Section 1.5.

To ensure that the spare parts data is correctly interpreted, it is essential to gather and analyze the data systematically by strict rules. Analyzing data without knowing the underlying failure mechanisms can lead to wrong results, thus it is important to distinguish between failures caused by wear-out and failures caused by misuse or accidents. Therefore, all the order-lines used in this thesis are carefully inspected for odd orderings, large quantities and suspect combinations (see also the distinction between wear versus crash in Appendix 5). Some ordered parts are left out of this research when the description is unclear or missing, or when the parts had nothing to do with maintenance (such as keyboards, cables and connectors). For the dataset used in this thesis, this is about 10% of the order lines.

If one assumes that maintenance teams of VI only order spare parts after actual usage, it can be argued that when the demand after crashes or misuse is removed, the rest of the spare part demand is used to replace worn parts. Therefore, *spare parts used to replace worn parts* are a useful measure to estimate component reliability.

**Additional information on analyzed SPO sites**

The seventeen customer sites consist of one SPO, roughly ten to thirty conveyor belts, an FSC controller, around 40 chutes and roller curves, and most sites have a so-called Gappex. The customer has a full-service contract with VI, which means that VI is responsible for the preventive maintenance and the repair after unexpected failures. The service contract is equal for all 17 sites, and includes a maintenance strategy with four inspections per year. When the system fails between the inspections, the system is repaired as soon as possible with an emergency call-out.

The customer pays a monthly fee for the inspections and the accompanying call-out service. For misuse or accidents (such as a broken package or when a fork-lift hits a conveyor), the customer will receive an additional bill with the spare part costs. In Italy, the actual execution of maintenance is outsourced to five local maintenance partners. The partners use work-orders to inform VI on: the reason for the visit; the amount working hours; and an overview of the parts used. They send this work-order to the local VI agent, who is responsible for controlling the work-orders, the payments and the re-ordering of spare parts.

## 3.2 Analysis of influencing factors on reliability

### 3.2.1 The spare parts demand in Italy

The SPO has many components that are critical for its functionality. In this section, the components that have failed on at least four (of the seventeen) sites are analyzed, i.e. the *divert*, the *shoe*, the *crossing*, the *merge*, the *PPI-wheel*, the *photoswitch* and the *valve.* The three most interesting components are the *diverts,* the *crossings* and the *shoes*, since these components cause the most failures.

Figure 19 shows the total spare part demand and the demands for the individual critical components of the SPO, over the period from January 2007 to March 2009[3]. In the past eleven years, VI commissioned one or two systems per year. The sites are ordered on total number of operational hours the system has run. Sedriano (on the right) was opened in 1999 and is the oldest site. Pisa (on the left) has been running the least number of hours. It can be seen that the older sites use more spare parts than the younger sites. These differences are investigated in this chapter.

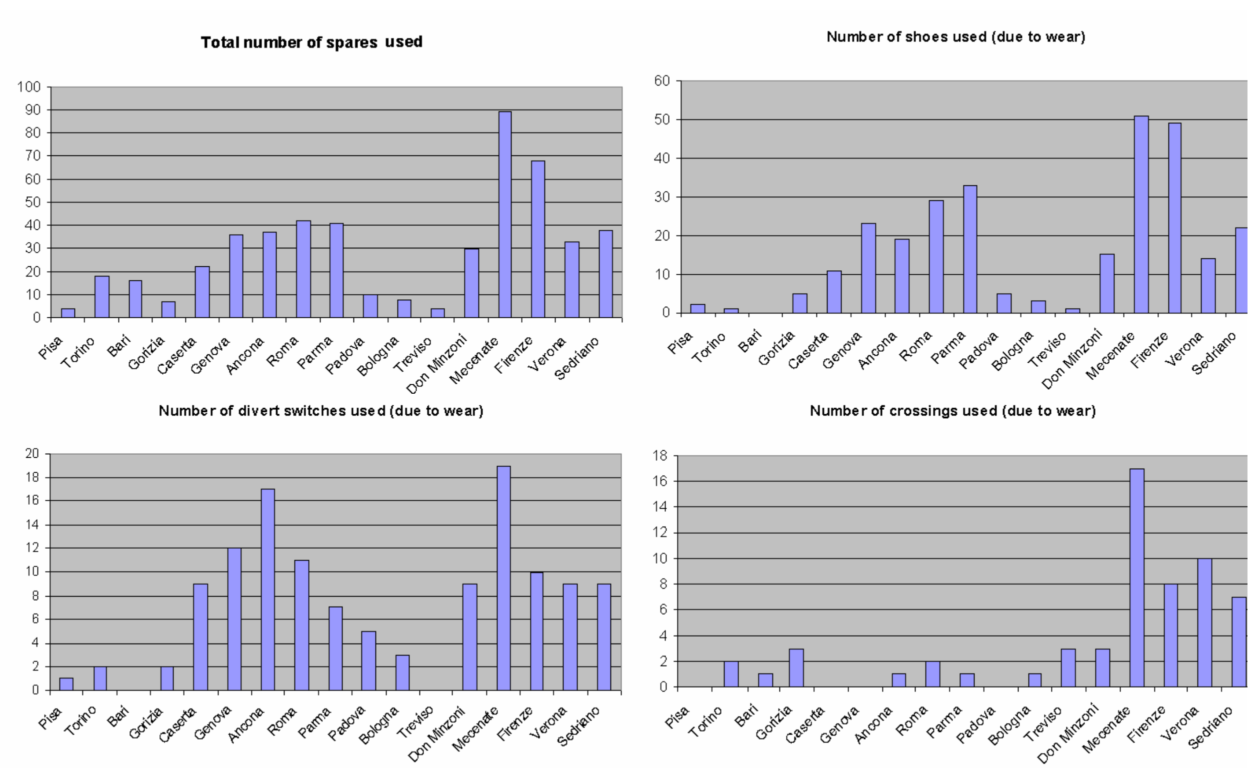



**Figure 19 – Selected demand for the critical components over the period from January 2007 to March 2009**

[3] Older administration is less reliable. In January 2007, a new administrational system has been taken into use. Since then, the spare parts are ordered shortly after usage, and the reliability of the administration has improved.

### 3.2.2 Structure of the analysis

In Section 2.6, the influencing factors (such as speed, capacity and maintenance partner) were introduced. In this section, the impact of these influencing factors on spare part demand is assessed.

Ideally, one would like to test all the situational factors. Although considerable effort has been devoted to obtaining numbers for all situational factors, it became apparent that for a few factors that was unfortunately not possible. Cleanliness or dustiness, for example, is a 'soft' and subjective measure and it was too time-consuming to underpin, because eventually all sites have to be visited for this kind of information. Geographically, this was not possible. Another influencing factor that seemed easy to obtain, weight of the packages, resulted in untrustworthy results, and is also excluded of the analyses.

This analysis consists of a number of regression analyses, using the statistical package SPSS. A regression analysis is the technique to analyze numerical data on causal relationships. A correlation between two variables means that if one variable changes, the value of the other variable will also change. For example, there is a positive correlation between the speed of a car, and its emissions. This means that, on average, pollution increases when a car drives faster. In this case, speed is the independent variable, and emission is the dependent variable.

In this research, five influencing factors have been quantified and entered into the regression analyses as the independent variable. $Y_i$ is the spare part demand due to wear, for the critical components i at the 17 sites, over 27 months. This leads to the following regression equation:

$$Y_i = \delta \cdot [\text{age}] + \alpha \cdot [\text{length}] + \beta \cdot [\text{speed}] + \psi \cdot [\text{capacity}] + \omega \cdot [\text{maintenance partner}] + \varepsilon \qquad (5)$$

<u>Independent, influencing factors:</u>

| | | |
|---|---|---|
| Age | : | The number of hours the SPO has run |
| Length | : | The length of the SPO in meters (equivalents of this variable, such as the number of shoes, chutes or crossings also have been tested) |
| Speed | : | The operational speed of the SPO in meters per minute |
| Capacity | : | The average capacity of the SPO in packages per hour |
| Maintenance partner | : | A nominal variable for the outsourcing of the maintenance to an Italian maintenance partner |

Target variables Yi:

- Demand per site for these critical components: *shoes, crossings, diverts, merges, photoswitches, PPI-wheels* and *valves*[4].
- An aggregation of the spare part demand per site

VI is highly recommended to test the impact of this variable in the future. It may be very interesting and useful for VI to further investigate the impact of these factors. For example, weight differences, dustiness or temperature may well be rather large impact. The R&D employees have plenty ideas to test these situations, but lack time and resources. VI should expand the reliability experiments in the R&D department, where these situations are imitated to compare these influences.

### 3.2.3 Analysis of the demand for the critical SPO parts

This subsection presents the main findings from the statistical analyses (the output results can be found in Appendix 6). From the regression analysis on *demand for shoes*, it is concluded that *age, speed, length,* and *maintenance partner* all have significant influence on the worn shoes. The *demand for shoes* per site is predictable with an accuracy of 70%. It was also concluded that the factor *speed of the SPO* has the highest impact on the *demand for shoes*. This confirms the suggestions of the VI employees that speed and age should have a large impact.

The *divert switches and crossings* are two other critical components of the SPO. Both components have been tested separately on regression with the influencing factors. It turned out that approximately 70% of the demand for both components can be predicted using the variable age (*hours run*). Other variables, that were expected to have an influence on these components, were not significant: *number of chutes, number of crossings, length, capacity and speed* were rejected as predictors by the statistical program. This is remarkable, since these factors are likely to influence the component degradation. An explanation might be that the differences between the sites are too small to find differences via statistical analyses. A second plausible explanation is that the influences of these factors have been diminished by the effects of other factors. For example, that the influence of *age* is so large, that the influence of *speed* cannot be determined. A final explanation might be the influence of factors that could not be entered into this analysis, because their impacts remain unknown. Further research is required to solve this, but these are

[4] There are more parts that are critical (such as the chains, the motor, bearings etc), but since these parts have not failed due to wear, they cannot be included in this analysis (and parts that do not fail, are not interesting for this research).

nonetheless interesting findings for the R&D department (who are responsible for design and testing).

Four other critical components have also been tested. The demand for *merges* shows no relation to age, packages sorted or hours run, neither to maintenance partner. The only variables that had a significant impact are *speed* and *capacity*. The components *photocells, PPI-wheels,* and *valves* also have been tested on predictability, but no significant results have been found. Statistical analyses require sufficient data, and the time-span of the dataset is probably not large enough for these parts.

Finally, an aggregation of the spare part demand has been entered as dependent variable, e.g. the summation of spare parts used for all critical components of the SPO. It is concluded that the variables *age, speed, length, and maintenance partner* each have significant influence on the total demand of spare parts due to wear. This means that these are considered to be the influencing factors with the highest impact.

<u>Based upon these observations, the following can be concluded</u>:

- The age of the system, in terms of hours run, is clearly an essential predictor of the demand of shoes, diverts and crossings due to wear. This means that is very likely that these components have an increasing failure rate. This is important to know, because it means that the number of failures will increase in time, and this influence the efficiency of maintenance activities;
- The demands for shoes, crossings and diverts worn can be predicted with approximately 70% accuracy. The demands for shoes increase when the sites is older (*hours run),* longer or faster *(length and speed).* Demands for *crossings* and *diverts* increase with *age;*
- The demand for other components (e.g. photocells) cannot be analyzed with this dataset;
- It became apparent during this research that it is difficult to quantify and analyze the influence all essential factors. Moreover, some findings are remarkable and since they contradict the judgments of experts. Nevertheless, since knowledge on these variables is important to predict failure behavior, the R&D department should increase effort to analyze these impacts.

## 3.3 Analysis of maintenance efficiency

When a maintenance partner of VI, visits one of the seventeen sites, this can be either a planned visit or an unplanned visit. During *a planned visit,* an inspection (or work from inspection) is executed, whereas during an unplanned c*all-out visit*, corrective actions are executed. The distinction between *planned visits* and *call-outs visits* in the selected work-orders is trustworthy, since they are always entered for administrational reasons.

The relation between planned and call-outs visits is further investigated. The following ratio will be used:

$$\text{ratio} = \frac{(\#\text{ of spare parts used during call-outs})}{(\#\text{ of spare parts used in total})} \tag{6}$$

Recall that the maintenance strategies for all sites are the same, namely four annual inspections, and call-outs when failures occur. Since all maintenance partners have received the same training and maintenance instructions, it can be presumed that the sites are maintained in a comparable fashion. In other words, there should be no differences in the aggressiveness in which parts are replaced preventively. In practice, this means that only observable damaged parts are renewed. Thus, all worn parts are either broken (corrective) or damaged (preventive by inspection). The higher this ratio, the more call-outs were required to keep the system running. This would imply that when the ratio between corrective actions versus the total number of actions decreases, the preventive actions have been effective. In other words, it is argued that high ratios indicate that the planned maintenance was inefficient. The hypothesis is that when sites get older, the number of preventive actions increases, due to increase wearing of parts.

***The spare parts data***

In the previous section, the spare parts data for SPO has systematically been analyzed, whether they were ordered due to wear, or due to crashes. In this section, the parts for the other sections (e.g. conveyor belts) are used as well, but instead of the sophisticated selection method for the SPO parts, less effort demanding thresholds are used for this large dataset. To obtain the required information for this analysis, the following criteria are used to select the useful work-orders:

- parts should be more expensive than 1 euro (which excludes parts as spacers, rings etc);
- demands larger than 10 are excluded (except bearing balls and rollers) [5];
- all orders coming from planned maintenance visits are included.

[5] This rough calculation of used spare parts only assumes that the crashes are more or less equally divided over the different sites. Based on discussions with site managers, the threshold of ten items is chosen.

Figure 20 shows the summation of the spare parts costs to replace worn parts at each site, during the time-span of 2 years and 3 months. The customer sites are sorted on number of operational hours on the X-axis. Gorizia is the youngest site in Italy with an SPO1, and Sedriano is the oldest site with this VI equipment[6]. For example, at Mecenate there have been more than 1,600 spare parts usages to replace the worn parts.

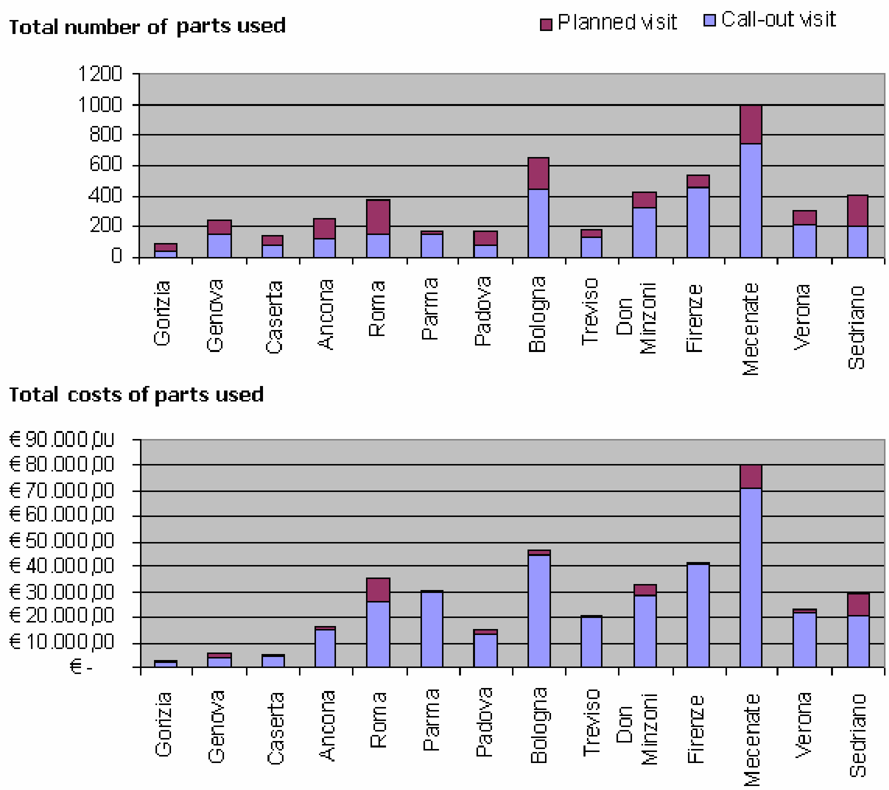



**Figure 20 – Spare parts used to replace worn parts during maintenance actions, sorted on operational hours**

<u>Observations:</u>

- The trend on total costs indicates that, on average, the older sites have more costs on spare parts usage in the same time-span. This confirms that the total demand for spare parts is increasing with age.
- The differences in total number of parts used (between the individual sites) are large, e.g. € 80,000 in Mecenate versus € 23,000 in Verona. Also in Roma and Bologna more parts were used than at other sites.
- The majority of the spare parts are used during call-out visits. The number of parts used during call-outs visits increases with the age of the sites.

[6] Three sites, i.e. Bari, Pisa and Torino, have been deleted from this part of the analysis, since at these locations, the SPO2 is placed. Individual components (such as the divert and crossing) have not been adjusted, but many other components have. Including the SPO2 in this aggregated analysis might therefore bias the results.

***The ratio***

The figure below depicts the ratios on the different sites. Again, this is sorted on increasing age, thus from Gorizia to Sedriano. The linear trend-line (set out by Excel) is also depicted for further analyses. The dots in the figure depict the ratios *(spare parts used in emergencies versus total used spare parts)*. Currently, on average 10% of the damaged components are replaced preventively with a three-monthly inspection strategy. A draw-back of this ratio is that some operational managers call VI faster than other operational managers. However, this does not explain why the average ratios are so high.

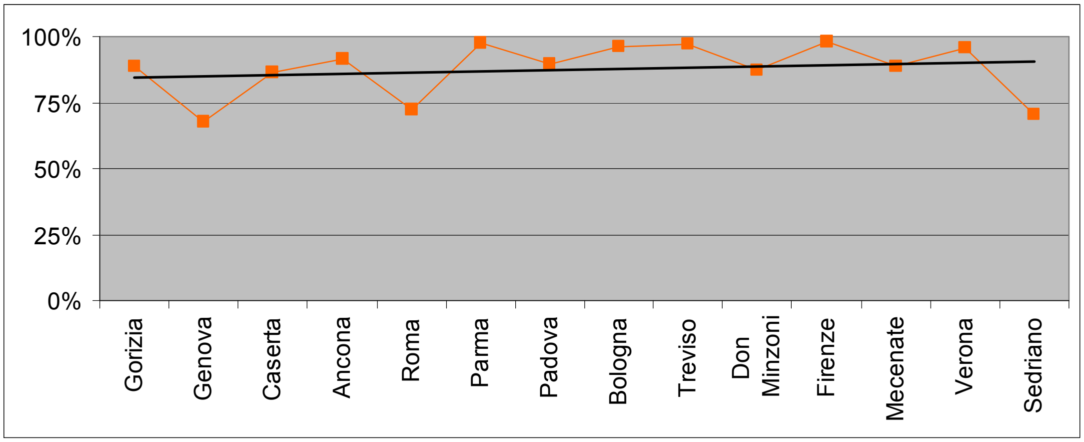



**Figure 21 – The ratio for the 14 sites with an SPO1**

<u>From this, the following can be concluded:</u>

- The differences in total number of parts used (between the individual sites) are dangerously large. This means that using averages to predict costs (either TCO or TRMC) can lead to financial fiascos. This fortifies that it is essential to look at individual components.
- Inspections lead to more replacements when sites get older, but the number of call-outs increases as well. But the preventive maintenance strategies do not lead to a satisfactory decrease in terms of failures, and the maintenance is rather ineffective.

<u>Reflection</u>

The customer center of Italy agrees with these findings, joking that engineers should build a campus next to some sites because of the large amounts of call-outs. This is inevitable with the concept of full-service: there is no incentive for the operational manager to decrease the number of call-outs. Thus the findings concerning the ratios cannot automatically be generalized to other sites. However, the differences are still very large, and in terms of TCO this maintenance construction seems rather ineffective.

## 3.4 Analysis of influencing factors on maintenance efficiency

This section discusses the correlations between the maintenance actions and influencing factors. This is a comparable type of analysis as used in Section 3.2, but dependent variables are split up into *Planned visit, Call-out visit* and *Total number of spares used.*

In regression table in Appendix 6, it can be seen that preventive maintenance correlates positively with *speed, capacity and length* (Block A). This means that a longer SPO (or faster or with a higher capacity) leads to more replaced parts during planned maintenance activities. The opposite is also true; at slower SPO's there are few parts replaced during planned maintenance. This seems to be fine; however, the variables *speed, capacity* and *length* do not correlate with the *total number of spares used*.

The variables, correlating highly with parts replaced during *calls-out* and with the *total parts-used*, concern *age* and *usage* (Block B and C). This raises the question why spare part usage does not correlate with planned maintenance. Simply put, when a site becomes older, the number of replacements during inspections remains equal, whereas the total number of parts replaced increases.

<u>From this, the following is concluded:</u>

- The number of spares used during preventive maintenance increase in a considerable different pace than the number of spares used in call-outs.
- Planned maintenance is wrongly adjusted to the needs of a particular site.

<u>Reflection</u>

Indeed, VI does not increase the levels of inspections, and therefore the relative number of corrective failures also increases. Ideally, the ratio should go down in time. The teams should get to know the sites, increase site knowledge, and increase the number of preventive actions. VI could, for example, execute more planned visits, or apply a more aggressive preventive strategy at older sites. Or VI could make an arrangement with the customer that older sites are visited more frequently than younger ones. Then (approximately) the same amount of fixed revenues can be obtained from the inspection visits, but their system performance is likely to become much higher. The same argument holds for customers such as DHL, UPS, Deutsche Post, etc. Another explanation for the high ratios can be that the maintenance teams require more time to execute the inspections (and work from inspections). The remedy is the comparable: increase length of the inspections.

## 3.5 Conclusions concerning the maintenance analysis

The following conclusions can be drawn concerning spare parts demand:

- The age of the system, in terms of hours run, is clearly an essential predictor of the demand of shoes, diverts and crossings due to wear. This means that is very likely that these components have an increasing failure rate. This means that the number of failures will increase in time, and this influences the efficiency of maintenance activities.
- Although the differences between the demands of the different sites are rather large, the wear of components can be predicted with a relative high degree of certainty. The demands for shoes, crossings and diverts worn can be predicted with approximately 70% accuracy, by taking the age of a system into account.
- For the demand of individual components, the results from the statistical analyses contradict the expectations, because many variables, that were expected to influence wear, were rejected as predictor. However, on the aggregated demand, the operational influences do play a role in the spare part usage; especially hours run, length and speed are important predictors.

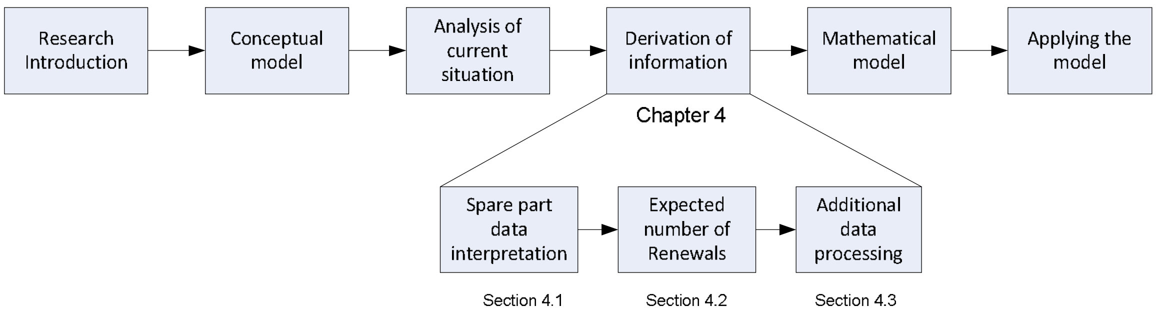
VI should invest in the development of usage-profiles. These usage-profiles should capture the combination of situational factors, for example speed and capacity. Provide the R&D department more time and resources to test the different circumstances.

The following conclusions can be drawn concerning maintenance efficiency:

- Currently, the majority of the worn parts are replaced during call-out visits. Approximately 10% of the damaged components are replaced preventively with a three-monthly inspection strategy. Thus, the planned inspections do not put a stop to the increasing number of required renewals, and the number of failures at the sites under investigation increase faster than necessary. To decrease failures, it is inevitable to increase the number of preventive visits.
- The analyses of this chapter underpin the relevance of this master thesis. If VI wants to predict the TCO of its systems, it is inevitable to increase the knowledge on the effects of maintenance strategies, because average measures as the mean-time-to-failure do not result in accurate cost predictions. The differences in terms of spare part usage (at the seventeen different sites in Italy) show that wear of critical components can vary substantially. This leads to large variations in system availability and maintenance and downtime costs.

# 4 DERIVATION OF INFORMATION FROM THE FIELD DATA

***It is essential that maintenance models are based on valid interpretation of field-data. This chapter describes the steps that were taken to derive the 'expected number of renewals' from the spare parts data, required for the model. Section 4.1 describes how the spare part data is interpreted. Section 4.2 presents how the number of renewals is estimated from the spare part data. Section 4.3 explains which additional steps have been undertaken with the spare part data, and why.***




## 4.1 Spare parts data interpretation

A substantial part of the challenge of this research described in this chapter, namely the transformation from the spare parts data into reliable information on the behavior of the systems. The work-orders have been selected with the sophisticated process of Chapter 3. However, directly fitting the data on failure or lifetime distributions is not possible, and additional steps and assumptions are required. Before the selected data can be applied to the mathematical model, the following is assumed:

- All repairs from inspections have prevented a failure. In the current maintenance strategy of VI, a spare part is solely used when the part is sincerely damaged. Thus, if the parts were not replaced, they would have failed in the near future. Therefore, the data can be used for the TTF approximation, and the residual lifetime is neglected.
- The time-to-repair is neglected in the TTF estimations. This is appropriate since the MTTR is more than ten thousand times smaller than the MTTF.
- Mechanical failures are caused by failures of the more expensive, critical parts. This implies that cheap parts are merely used whenever a critical part is exchanged. By assuming this, the project can focus on the critical parts that fail frequently but irregularly, such as divert switches, crossings and shoes. The cost prices of these components vary between twenty and three-hundred euros. The administration on expensive items is more reliable than the administration on cheap items. Service engineers understand the importance of the administration of expensive parts and (consequently) these work-orders

are completed more accurately. The administration on cheap parts is less reliable and useful. This assumption does not harm the analysis since cheap parts are ordered in large amounts only and are (more or less) always available.

The time-to-failure approximations need to be extracted from the selected spare parts data. The order-date of a particular part is easily converted to a time-to-ordering, with the opening of that site as starting point, but this does not directly measure the time-to-failure, nor does it reflect the true lifetime. There are a few challenges:

1. The number of VI-sites in Italy increases steadily over the years, so the lifetimes of the different components have different starting points in time.
2. The time-span of the data at hand covers a period of two years per site (from January 1, 2007 until March 31, 2009), so the dataset per site is relatively small.
3. The observation periods of the datasets cover only a part of the component's lifetime (see also Figure 22). This is called two-sided censoring.
   a) On one hand, failures prior to the observation period are unknown. Some sites are nine years old before the first failures are documented in this dataset (left-censoring).
   b) On the other hand, not all components are replaced before or during the observation period, so these parts still expand their lifetime (right-censoring).
4. Lastly, parts may have failed more frequently on a certain position. A position is a fixed location in the system that must contain a working component, otherwise the system is down.

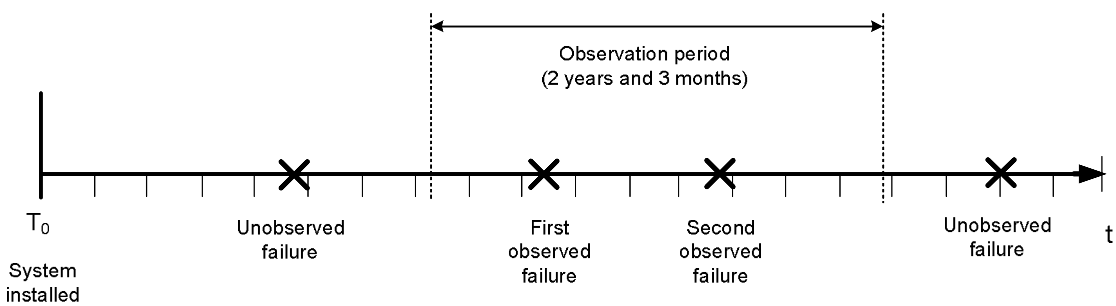



**Figure 22 – Example of consecutive failures on a certain position**

## 4.2 The expected number of renewals

The main goal is to obtain a measure for expected number of renewals for critical components, which will be used in the model (in Chapter 5 and 6). The following method is developed and employed to calculate the expected number of renewals. Firstly, the datasets of the seventeen sites are aggregated into one sample, to resemble a larger observation period. This is possible because it was concluded in the previous chapter that age is the main driver of failures. The lifetime of components of these sites are made discrete for this analysis, using 8 age categories (i=1, 2… 8) of 5.000 hours[7]. These categories allow the summation of positions and the summation of renewals by age, which increases the sample size (and this simultaneously solves the right-side censoring problem).

In these age categories, the numbers of renewals were aggregated and divided by the total number of positions in the field per age category. This is referred to with a(i), which is defined as the probability that a failure occurs in age category i, regardless the number of previous failures on this position. With the available data, a(i) is calculated for four critical components with this formula:

$$a(\mathrm{i}) = \frac{\text{total number of renewals due to wear on positions in age category i}}{\text{total number of positions in the field in age category i}} \qquad (7)$$

All positions in the field are assigned to the age category which overlaps the age of a particular site most. This way, the sites are divided over the age categories, and it is assumed that, on average, this leads to useful estimates of a(i). The total number of renewals, M(i), after age category i is calculated by the summation of a(i). The results for the component called *crossing* are shown in Figure 23. It can be seen that in total 1.08 crossings are (renewed due to wear) per position after 40,000 hours.

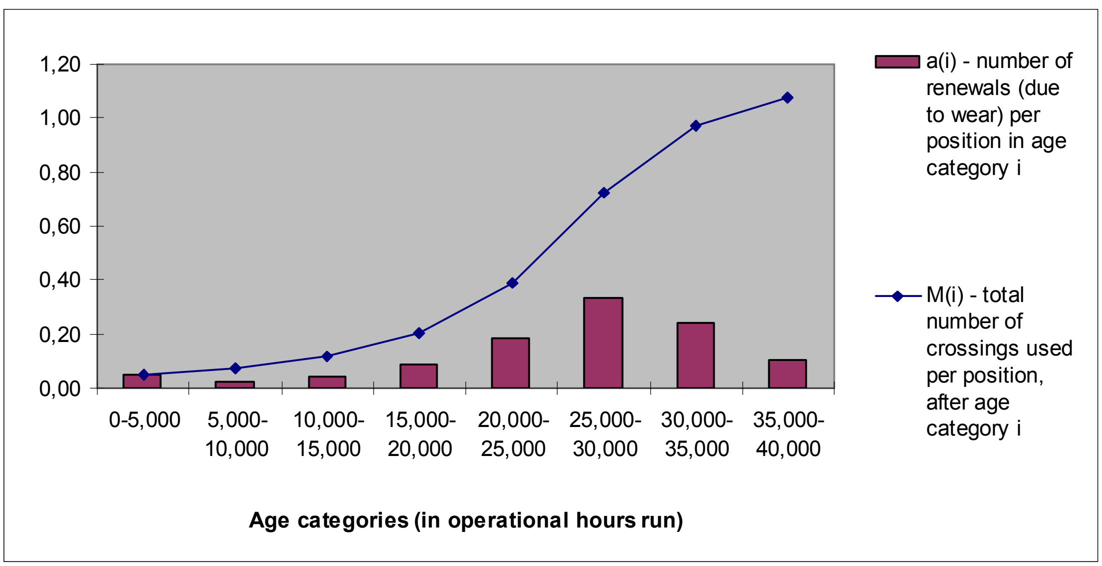



**Figure 23 – The number of renewals per age category i are summed up to obtain the total expected number of renewals per position, after age category i**

[7] This seems large, but (firstly) the spare parts usage of the critical components is limited, and (secondly) some sites are more than 10 years old. This category size keeps the analysis convenient, and suffices for this assessment.

**Table 1 – Calculation of he expected number of renewals for four critical components at t=40,000**

| Component | Name | M(i)= M(t=40,000) |
|---|---|---|
| 1 | Divert switch | 1.46 |
| 2 | Crossing | 1.08 |
| 3 | Shoe | 0.10 |
| 4 | Merge | 0.21 |

Table 1 displays the expected number of renewals after t=40,000 for the four critical components. These results are used in the quantitative model. Readers interested in the model and the findings can proceed to Chapter 5.

## 4.3 Additional data processing

In this section, additional data processing is presented, to illuminate more possibilities with the available data. The goals of this section are to:

1.) Approximate of the failure density function;
2.) Reflect the MTTF on the design goals;
3.) Approximate the Weibull parameters of the lifetime distributions;
4.) Calculate the expected number of failures from the Weibull parameters;
5.) Show an experiment with usage-profiles.

### 4.3.1 Approximation of the failure density distribution

As discussed in Chapter 2, many reliability measures are based upon the failure density distribution. For many purposes, it is useful to know the distribution of the lifetimes. The distribution of time-to-failures is expressed in terms of p(i). p(i) is defined as the probability that the component, commissioned on a certain position at t=0, fails in age category i. This subsection describes how the p(i) measures are obtained from a(i) measures.

As discussed previously, it is likely that some components have failed prior to this dataset. The main difference between a(i) and p(i) is that p(i) is focused on the distribution of the first component placed on a position, whereas a(i) is the result of the probability that multiple consecutive components have failed on that position. Stated differently, p(i) is a discrete approximation of the failure density. To calculate p(i), it is assumed that two consecutive failures have not taken place within one age category. Since the a(i) measures are known, p(i) can be approximated as follows:

$a(1) = p(1)$

$a(2) = p(2) + p(1)\cdot a(1)$

$a(3) = p(3) + p(2)\cdot p(1) + p(1)\cdot p(2) + p(1)\cdot p(1)\cdot p(1)$ … etc.

This can be reformulated into:

$$a(i) = p(i) + \sum_{j=1}^{i-1} a(j) \cdot p(i-j) \tag{8}$$

with $\sum_{i=0}^{\infty} p_i = 1$, because a component will fail maximally once

and a(1) = p(1), because the failure at i=1 is per definition the first failure on a position.

The a(i) variables are known, so formula (8) can be rewritten into:

$$p(i) = a(i) - \sum_{j=1}^{i-1} a(j) \cdot p(i-j) \tag{9}$$

With formula (9), p(i) is calculated for the four components. p(i) approximations for the *crossings* are depicted by the smaller bars in Figure 24.


**Figure 24 – The data is converted into p(i) measures, which is a 'discrete approximation of the pdf'**

The failure probability density is defined as 'the probability that a failure occur in certain time interval' (Kumar et al., 2006), and this section has approximated the percentages of components that fail, given a certain age category. Thus, the p(i) in Figure 24 is a *discrete approximation of the failure probability density function* (pdf) in an age category. For example, the probability that a component fails between 25 and 30 thousand operational hours is approximately 20%, or P(25,000<TTF≤30,000) ≈ 0.2. These results are also used to estimate the Weibull parameters in Section 4.3.4.

### 4.3.2 Mean Time-To-Failure and the design goals

With the p(i) approximations, other reliability measures can be calculated. Firstly, the summation of p(i) are used to approximate the *cumulative distribution function* (see Figure 25), represented by P(i). By adding the age category '40,000+', the percentages sum up to hundred percent.
In the small circle of Figure 25, it can be seen that around 19% of the parts are worn after 20,000 operational hours: $P(TTF \leq 20{,}000) \approx 0.19$. The design goal for the crossings is 20,000 to 30,000 hours (depending on capacity and speed of the site), but this calculation shows that almost 20 percent of the crossings in the field do not reach these goals.

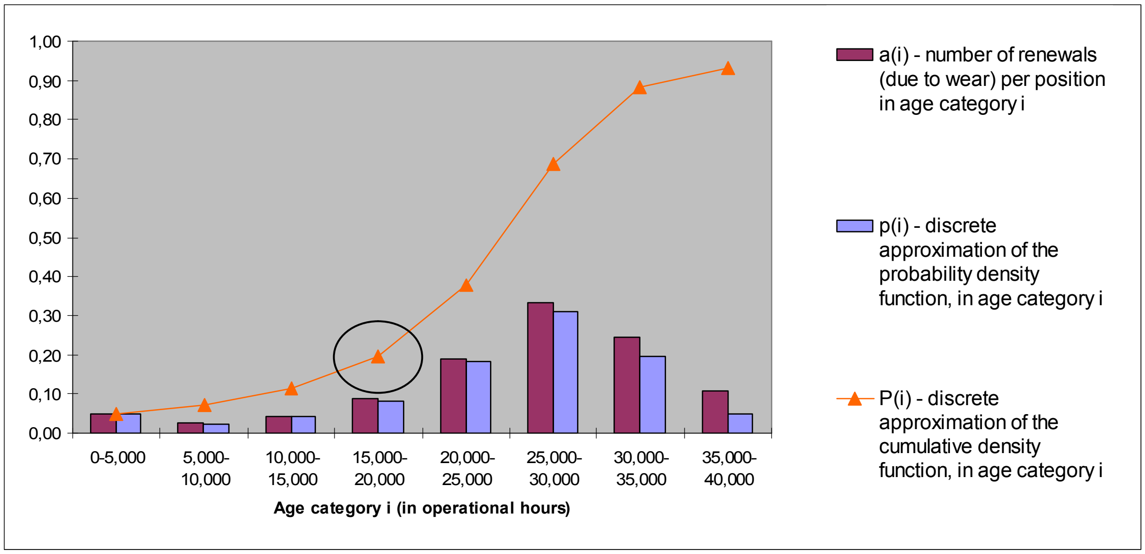



**Figure 25 – 19% of the crossings in the field operate less than 20,000 hours**

And secondly, the MTTF can be calculated and compared to the design goals. When (almost) all components have failed, the expected the mean-time-to-failure (MTTF) can be calculated. In Table 2, it can be seen that the average time-to-failure of the Diverts are also relatively low compared to the design goal of 20,000 to 30,000 hours.

$$E(\text{MTTF}) = \sum_{i=1}^{8} i \cdot p(i) \tag{10}$$

**Table 2 – The MTTF for the divert and the crossing**

| Component | Name | MTTF[8] Via formula 10 |
|---|---|---|
| 1 | Divert switch | 23,523 |
| 2 | Crossing | 28,866 |
| 3 | Shoe | - |
| 4 | Merge | - |

[8] Just 10% of the positioned shoes and the merges in the data sample have failed, thus the mean cannot be estimated properly using this equation.

### 4.3.3 From time-to-failure approximations to Weibull parameters

As discussed in Chapter 1, VI has recently started a process to gather time-to-failure data under different situations. This data should be processed into knowledge. In the future situation of VI, the MTTF or underlying statistical distribution should be known for the components for a certain situation (or per usage-profile). As discussed in Chapter 2, the Weibull distribution is often used in reliability engineering, due to its flexibility in matching a wide range of phenomena (Lewis, 1996). This subsection explains how estimates of the parameters of the lifetime distribution of the components can be determined from TTF data.

In the previous sections, the data has been prepared to be employed in probability plotting. Probability plotting is an easy and useful technique, which yields goods estimates of the distribution parameters, with small sample sizes. Probability plotting can be done manually, or by statistical software. Manual plotting is labor intensive and not always consistent, thus software is preferred. Another advantage of software is that more complicated estimation methods can be used, such as maximum likelihood estimation or least squares.

During this research, a statistical package, called ReliaSoft Weibull 7++ ® has been used. This widely used program (for example by ASML and Philips) only requires the entry of information on time intervals (Time-to-Failure), and whether the part has survived or failed. The data can also be entered in groups; which is useful when the information concerns more parts.

Basically, there were two options to approximate the Weibull parameters with the available data.

- The first option is to plot the TTF estimates of spare parts of a particular site. However, it turned out that this led to suboptimal results. Firstly, the sample was only two years, thus an unknown number of parts failed before (left-side censoring) or after the time interval (right-side censoring). Basically, the unknowns of one particular site are too large. Then maybe 25 parts would have been analyzed, of which maybe 2 or 3 have failed in this dataset, and the other 22 or 23 would have survived. This will result in a rather rough estimation for the lower bound.
- The second option was to combine the results of multiple, comparable sites (as discussed in chapter three). The p(i) are used as indication of the percentage of parts that fail, after they have obtained a certain age: these can be used in ReliaSoft Weibull 7++ ®. The percentage is entered as the group-size, and the average of the age category is entered as TTF (This software also has the option to enter cumulative percentages of failures. This has been tested for the diverts, and this led to the same results).

The second option has been used by a least-squares method. This led to the following results (see Appendix 8 for details and the generated Weibull plots). With the Weibull parameters, the expected long-term average (μ) can be calculated explicitly:

$$E(X) = \eta \cdot \Gamma\left(1 + \frac{1}{\beta}\right) \tag{11}$$

**Table 3 – Estimation of the Weibull parameters of four critical components of the SPO**

| Component | Name | Shape (β) | Scale (η) | Mean (μ) Via formula 11 |
|---|---|---|---|---|
| 1 | Divert switch | 2.0 | 26,600 | 23,570 |
| 2 | Crossing | 2.9 | 33,560 | 29,925 |
| 3 | Shoe | 1.1 | 340,000 | 327,872 |
| 4 | Merge | 1.3 | 137,000 | 129,301 |

Chapter 5 and Chapter 6 use the 'averages operational influences of the sites of the Italian customer' as situation, and the expected number of renewals from Table 1 is used for the numerical experiments. The next two subsections continue on the potential of Weibull parameters, after distributions are fitted upon the data files.

### 4.3.4 From Weibull parameters to the number of renewals M(t)

The expected number of renewals per position is required to calculate the maintenance costs in the model. In Chapter 6, the summation of a(i) is used. Another method to approximate the expected number of failures on a certain position is via the renewal function. The renewal function cannot be solved analytically[9], and for the Weibull there also are no explicit expressions available. Via a discrete approximation (see Appendix 7 on the renewal function), this function is programmed in Excel for the components of VI (this will be an important part of the tool in the Chapter 6). Below, the behavior and the results for the *'divert'* are given. According to the results of the previous section, the expected lifetime of diverts is 23,570 hours, under the conditions of an average site in Italy.

Firstly, the lifetime expectancies of successive components are shown. Figure 26 shows the pdf of the successive components on a certain position. The renewal function is a counting process, which means it is a recursive function. The function takes the probability that preceding component has failed as the starting point of the failure process of a new component. As a result, the pdf of the second component is flattened with respect to the pdf of the first component.

[9] For example, with the exponential distribution the number of renewals is constantly increasing in time: $M(t) = \lambda t$.

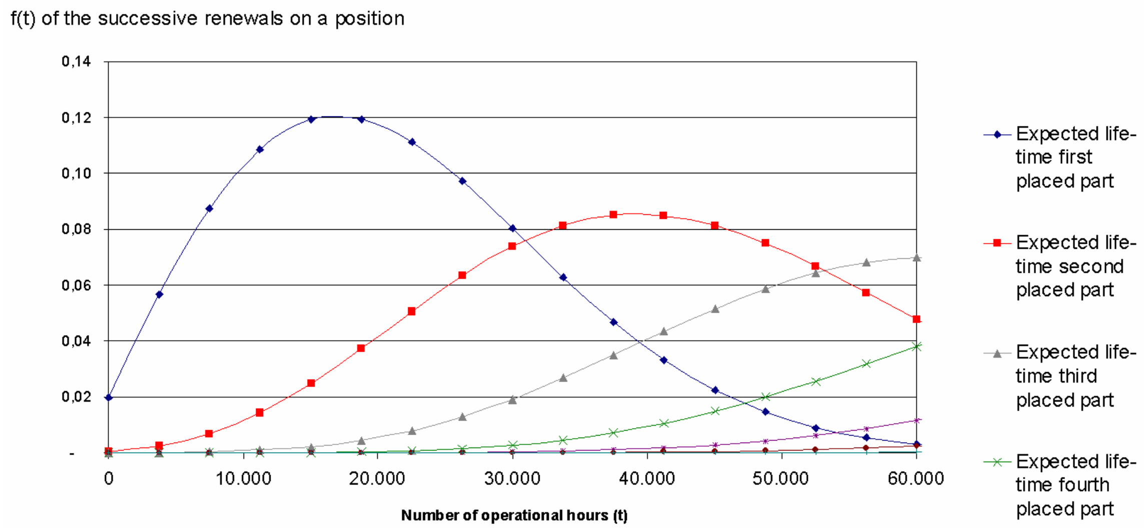



**Figure 26 – The probability density functions of successive components (diverts), each with β=2.0 and η=26,600**

Subsequently, the expected total number of renewals per position $M_i(t)$ can be calculated (Figure 27) for the divert with β=2.0 and η=26,600 and for an imaginary component with β=1.0 and η=26,600. The imaginary component serves an illustrational purpose to compare the divert with an exponentially distributed component with the same scale parameter.

Per position, 1.4 diverts are required in 40,000 hours[10]. It can be seen that the first component is not designed to run for the entire lifetime of the system and renewals are inevitable. It can also be

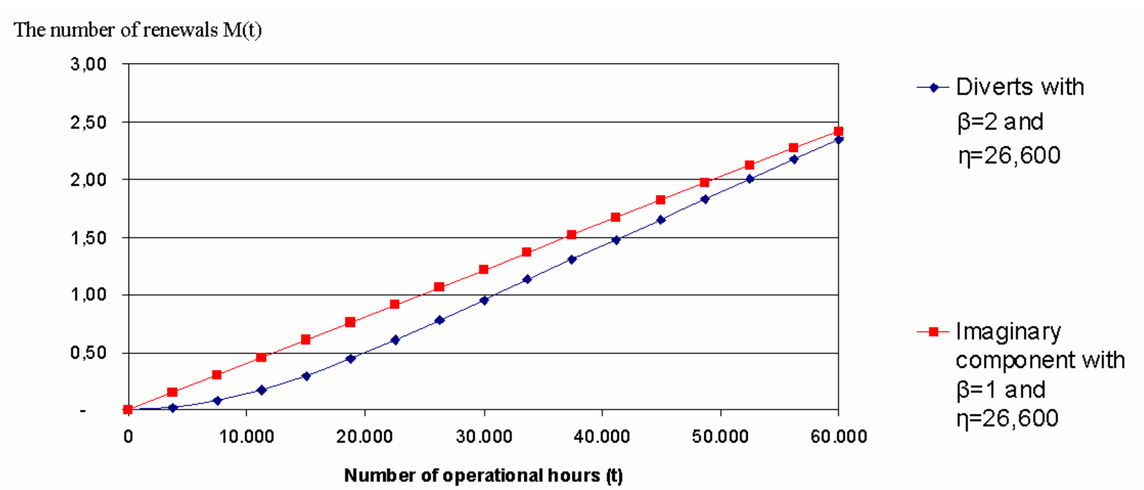



**Figure 27 – The expected number of renewals on a certain position**

[10] The major revisions that VI performed on SPO systems in the past were executed after roughly 42,000 operational hours. This number is rounded to 40,000 operational hours, which is used as the intended lifetime of a system. When a system runs 50 weeks per year, 5 days a week, and 15 hours a day, the approximated lifetime is 11 years.

seen that the number of renewals for the divert is rather flat in the first 15,000 hours, whereupon the slope increases. From this, it is concluded that the number of expected renewals increases: thus the failure rate is indeed increasing.

Table 4 shows a comparison between the two methods to calculate the expected number of renewals, based on the same data. It can be seen that via the Weibull parameters a slightly lower estimation is obtained (on average 8% lower). The differences appear to be larger when β increases. [11]

**Table 4 – Results on the expected number of renewals of the components**

| Component | Name | M(t=40,000) Based on Weibull | M(t=40,000) Based on the summation of a(i) |
|---|---|---|---|
| 1 | Divert switch | 1.40 | 1.46 |
| 2 | Crossing | 0.99 | 1.08 |
| 3 | Shoe | 0.09 | 0.10 |
| 4 | Merge | 0.19 | 0.21 |

### 4.3.5 Experiment with usage-profiles

In the Sections 2.6 and 3.5, the use of so-called 'usage-profiles' has been advocated. These profiles should distinguish the main drivers of component degradation, for example a sorter running at full capacity versus a sorter running at low capacity. An experiment with 'usage profiles' has been executed, to assess whether it is likely that 'usage profiles' will provide a solution for VI[12].

The demands for *crossings* have been analyzed in two profiles: *high speed & high capacity* (132 m/min and appr. 6,000 packages per hour) versus *low speed & low capacity* (120 m/min and 5,100 appr. packages per hour). The demands on the sites Ancona, Parma and Roma have been aggregated for the high speed/capacity profile. And the demands on the sites Bologna, Caserta and Don Minzoni have been aggregated for the low speed/capacity profile. The sites have been chosen in such a way, that the average number of hours run was comparable (to decrease the potential bias resulting from this factor). This leads to the following findings:

---

[11] This is probably due to the effect of the tail of the Weibull distribution, which has a large influence on the parameters that results from Weibull fitting, but do not influence the summation of a(i).

[12] As opposed to statistical regression analyses, Weibull fitting does not necessarily required large samples. If one has little knowledge on the shape factor, small samples will already gain considerable confidence on the lower bound of the scale factors, because the shape is can be estimated in a reliable way.

**Table 5 – The resulting Weibull parameters for different usage situations**

| Situation | Name | Shape (β) | Scale (η) | Mean (μ) Via formula 12 |
|---|---|---|---|---|
| High speed/capacity | Crossing | 2.73 | 33,320 | 29,642 |
| Low speed/capacity | Crossing | 2.90 | 81,580 | 72,744 |

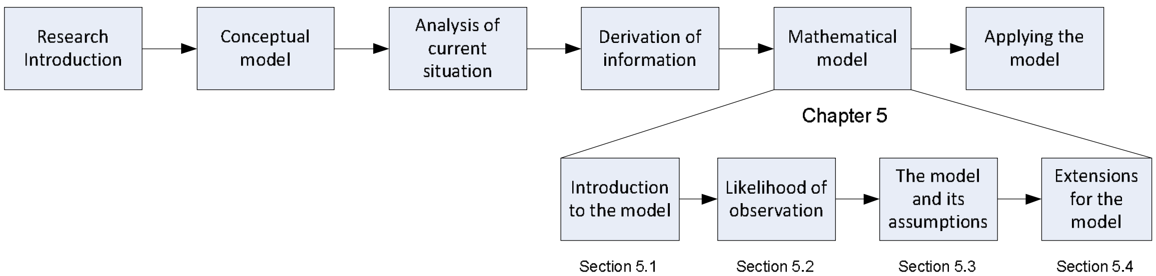
Two observations are important:

1. The lifetimes of 'crossings on less intensively used sites' can more than twice as long, compared to intensively used crossings.
2. The shape parameters are comparable in both situations. If a component is being used in different situations, it is likely that the shape parameter in the different instances will be different, and only the scale parameter will be different. Thus, making assumptions on the shape parameter of a component, the scale parameters that belong to a certain situation can be found (with considerable confidence) with a small data sample. This method is often referred to as 'weibays', or 'weibest' (Kumar et al., 2006).

Obviously, differences in scale parameters can lead to differences in expected number of failures, and thus to different required (near optimal) inspection frequencies. Therefore, the use of usage-profiles may be very interesting for VI.

# 5 MATHEMATICAL MODEL ON INSPECTION EFFICIENCY

***In this chapter, the developed mathematical model is presented to support the decision on number of annual inspections (z). Firstly, the situation in which the maintenance is applied is summarized in Section 5.1. In Section 5.2, the underlying theory of the model is described. In Section 5.3, the model and the underlying assumptions are discussed. In Section 5.4, potential extensions for the model are given.***




## 5.1 Modeling maintenance strategy based on inspections

The model presented in this chapter simulates the effects of maintenance strategies, in terms of expected TRMC and expected number of failures. The maintenance strategies consist of z annual inspections per year (z = 0,1,2…). When z = 0, the maintenance strategy is 100% corrective. Many VI-systems are sold with four annual inspections (z = 4). During an inspection, all components are inspected visually, e.g. see, smell and hear.

Failures occur via a simplified multi-stage degradation process, which is simplified to the stages *good, damaged,* and *failed*. During the stage *damaged*, the failure can be prevented via visual inspections. All damages observed during the inspections are replaced (renewed) prior to failure by a preventive maintenance action. When failures occur between inspections a more expensive, corrective, emergency call-out is used to repair the system. Moreover, failures incur downtime costs, to account for operational losses, customer dissatisfaction and subsequent emergency deliveries or financial claims. The probability that a failure is observed (see Section 5.2) drives the cost differences.

## 5.2 The likelihood of observation

The challenge, associated with isolating the marginal effect of a specific inspection interval on costs, is to determine the probability that a random damaged component is detected timely (prior to failure). To define this likelihood, a measure is required for the condition of the component. Knezevic (1987) describes Relevant Condition Parameters, such as crack length, thickness, depth of tire treads, etc, to observe or measure the condition. For the VI systems, one would like to use a more general measure, applicable to more systems.

Let $Y_i(z)$ = P(damage on a random component i is observed timely, given z annual inspection)

A timely observation means that damage on a particular component is observed (and renewed) prior to failure. Hence, a failure is avoided by inspection. The first instance where the presence of a random damage can reasonably be recognized by an inspection is called the initial, observable damage. The time between initial damage and the actual failure is the Conditional Residual Time (CRT). If an inspection takes place during the CRT, the presence of the defect can be observed and a preventive action may be taken within the window of opportunity in the remaining conditional residual time. Originally, the CRT is defined in the Delay Time Model by Christer (1999). However, this paper goes beyond the situation of VI, and the theory is simplified to suit this thesis.

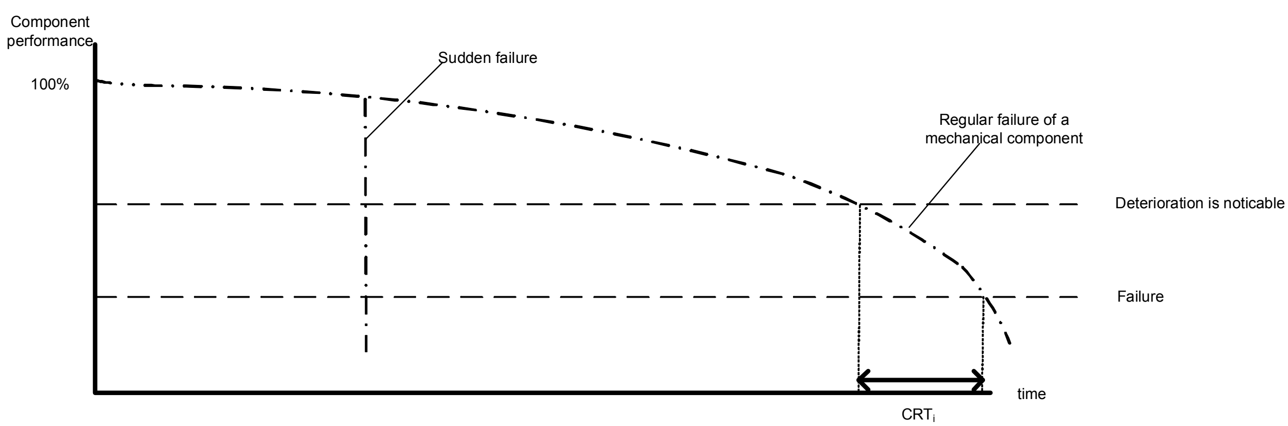



**Figure 28 – The time between observable damage and actual failure leaves an opportunity to replace the component prior to failure**

The CRT is used as indicator for the likelihood that damage is observed by inspections. For a component with a $CRT_i$ (in months) and z annual inspections, the likelihood of observation can be approximated by:

$$Y_i(z) = \text{MIN}\left\{\frac{\text{CRT} \cdot z}{12}; 1\right\} \tag{12}$$

When the CRT = 1 month, and z = 6 inspections per year, 50% of the failures will not be observed nor prevented, since the frequency is too low. If the CRT is large, then it takes a long time before the actual failure occurs, thus the likelihood of observation (during inspection) increases. The ratio cannot become higher than 1. When all components fail immediately, the CRT is (almost) zero and, in this case, inspections are utterly ineffective. Most components of VI have a CRT of 1 to 3 months. Thus, the CRT determines the likelihood that damage is observed prior to failure.

## 5.3 The mathematical model and assumptions

Consider a multi-component product that is composed of i different kinds of components, numbered 1,2… I, with $x_i$ positions per component i (see Figure 29). Many VI-sections (such as the Conveyor Belt of the PosiSorter) have a serial structure, where the VI-section is down when one component fails. Parallel networks and redundancy within VI-systems are out-of-scope, since VI has enough experience and knowledge with these structures.

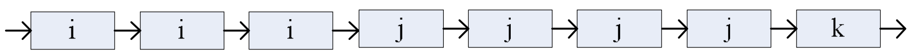



**Figure 29 – Example of a simple VI-section with $x_i = 3$, $x_j = 4$ and $x_k = 1$**

The system is exploited during its lifetime [0,T]. The model initially[13] uses the expected number of renewals per position $M_i(t)$ based on the summation for a(i), as described in Section 4.2. The total number of renewals in the system, during lifetime T, is:

$$\sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot x_i \tag{13}$$

The mathematical model requires the following additional assumptions:

1. An important assumption of the renewal process is that after the repair or replacement, the component is 'as good as new'. This is not always the case, but it is expected that the majority of the repairs are successful.
2. New components have not been improved or modified.
3. The failing components do not influence the failure rates of other components, thus there are no interactions between the renewal processes of the different positions (mutual independency). For diverts, crossings and carriers this is a valid assumptions, since these components do not interact. For shoes, however, assuming that all interactions are accounted for in the lifetime distribution is inevitable.
4. The time-to-repair does not influence the time-to-failure distributions of the components. This also seems appropriate since the average downtime is more than thousand times smaller than the average time-to-failure.
5. Inspections can be executed during planned downtime. This assumption is appropriate in the situation of a VI system, because VI systems only run between 12 to 20 hours per day.

[13] The tool presented in Chapter 6 will also allow the entry of component lifetime distributions, in terms of the Normal distribution or the Weibull distribution, to ease implementation and enhance future possibilities.

6. Only one part is renewed during call-outs. A call-out is an opportunity to inspect other components. This elegant strategy, called Opportunity-Based-Maintenance (OBM) is out-of-scope, because it requires that the production manager will allow longer downtimes to use the opportunity to inspect other components. Production managers often disagree with this, thus OBM will be difficult to implement.

The model contains the following parameters:

| | |
|---|---|
| $C_{insp}$ | fixed costs per inspection (regardless the number of inspected positions) |
| $C_{prev}$ | preventive cost function accounting for costs (e.g. additional labor costs) |
| $C_{emer}$ | emergency costs are the costs that come along with a corrective maintenance action (e.g. call-out costs or hotline support) |
| $C_{down}$ | downtime costs represent costs incurred for system unavailability (e.g. operational losses, customer dissatisfaction and subsequent emergency deliveries or financial claims) |
| $C_i$ | the material costs per component i |
| $M_i(T)$ | expected number of renewals per position of component i, at T |
| $Y_i(z)$ | likelihood of timely observation of a damaged component i with inspection frequency z |
| $x_i$ | number of positions of component i |
| y | number of years (which equals T divided by the yearly number of operational hours) |
| z | number of annual inspections |

<u>The mathematical model</u>

Since $Y_i(z)$ is the probability that a damaged component is observed timely, $1-Y_i(z)$ is used as the probability that the damage leads to failure. The hypothesis is that the number of failures decreases with an increasing number of annual inspections (convexity).

As opposed to the number of failures, the number of renewals does not depend on the maintenance strategy. That is, the number of renewals is independent of the maintenance strategies. $M_i(T)$ is the expected number of failures on a certain position of i in (0,T). This way, the influencing factors are taken into account.

The expected total relevant maintenance cost (TRMC) is the summation of inspection costs, plus the costs for preventive replacements upon inspection, plus the replacement upon emergency call-outs, plus the downtime costs, during (0,T).

TRMC (z) =

Inspection costs (z) + Preventive maintenance costs (z) +

Emergency costs (z) + Downtime costs (z) (14)

Inspection cost (z) $= y \cdot z \cdot \mathrm{C}_{\mathrm{insp}}$ (15)

$$\text{Preventive maintenance cost (z)} = \sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot Y_i(\mathrm{z}) \cdot (C_{prev} + \mathrm{C}_{\mathrm{i}}) \cdot x_i \quad (16)$$

$$\text{Emergency cost (z)} = \sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot (1 - Y_i(\mathrm{z})) \cdot (C_{emer} + \mathrm{C}_{\mathrm{i}}) \cdot x_i \quad (17)$$

$$\text{Downtime cost (z)} = \sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot (1 - Y_i(\mathrm{z})) \cdot \mathrm{C}_{\mathrm{down}} \cdot x_i \quad (18)$$

This can be simplified to TRMC (z) =

$$y \cdot z \cdot \mathrm{C}_{\mathrm{insp}} + \sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot \left\{ Y_i(\mathrm{z}) \cdot (\mathrm{C}_{\mathrm{prev}} + \mathrm{C}_{\mathrm{i}}) + (1 - Y_i(\mathrm{z})) \cdot (\mathrm{C}_{\mathrm{emer}} + \mathrm{C}_{\mathrm{i}} + \mathrm{C}_{\mathrm{down}}) \right\} \cdot x_i \quad (19)$$

The expected number of failures =

$$\sum_{i=1}^{I} M_{\mathrm{i}}(T) \cdot (1 - Y_i(\mathrm{z})) \cdot x_i \quad (20)$$

## 5.4 Potential extensions

There are many potential additions to this model. This section presents three examples.

### 5.4.1 Continuous monitoring

Continuous monitoring can be an effective tool to increase the likelihood of observation prior to failure. Monitoring devices can be very simple, such as copper electrodes that give a warning light, or they can be very complex, such as x-ray tools. Some relay on monitoring of a system. For mechanical equipment, the most common monitoring techniques are wear particle analysis, thermographic analysis or vibration analysis. This model has the potential to assess (continuous) monitoring options or investments. In this case, $Y_i(z)$ does not depend on the inspections (or the CRT), but on the sensitivity of the monitoring equipment. $Y_i(z)$ may even approach one, which would imply that almost all damaged components are observed timely. An additional cost function, $C_{monitoring}$, should be added to the cost equation. Then, monitoring investments can be analyzed with this model with relatively little effort: fix the number of annual inspections; create a small test bed (i.e. systematically enter different investment costs and different values for the likelihood of observation) for the monitoring investment; and analyze the effects of an investment on the TRMC. When the downtime and corrective maintenance cost surpass the monitoring costs, this may be very beneficial for the customer.

### 5.4.2 Training and maintenance by the customer's technical department

The model can be extended to include whether the inspection or maintenance action is executed by VI or by the customer. In this case, a binary [0;1] can be entered per component into the calculation whether the customer is able and willing to do this. Additional training costs can also be entered. For the customer this is a relevant maintenance cost, since it may decrease their costs in the long-run.

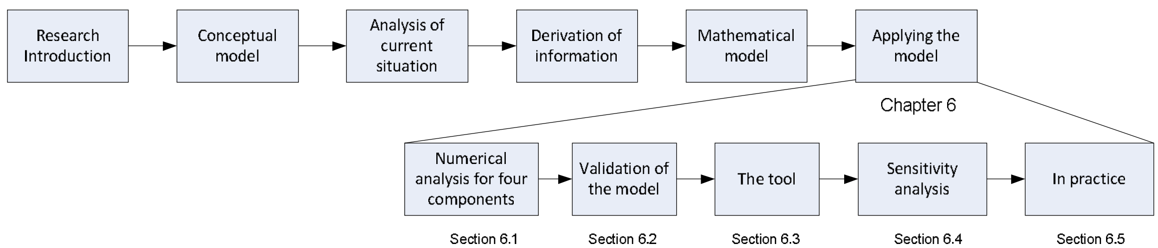
### 5.4.3 Imperfect maintenance and increased reliability due to maintenance

Most optimal preventive maintenance policies, minimizing cost and maximize availability measures, assume 'that after pm the unit is as good as new'. This is an important assumption of the renewal function. But actually, this assumption might not be true due to faulty procedures, e.g. wrong adjustments, bad parts, or damage done during maintenance (Nakagawa, 2006). There are a few methods in the literature to model this problem. Extended preventive maintenance models consider imperfect repair and discussed the optimal policies which minimize the expected cost and maximize the availability (e.g. Wang and Pham, 2006; Nakagawa, 2006). Another example of an imperfect maintenance model is that of Brown and Proschan (1983), which assumes that a failed unit is as good as new with a certain probability. Premise of either of these models is the availability of data on imperfect maintenance. Before this is investigated, it may be useful to assess the impact of imperfect maintenance at the systems of VI.

In this thesis, planned maintenance visits are a means to renew a damaged component prior to failure. Maintenance also slows down degradation, namely by tightening and cleaning. Currently, this cannot be modeled, since there is no information. However, modeling or investigating the increased reliability by cleaning and tightening would be rather interesting, since the effects of these activities are unknown.

# 6 APPLYING THE MODEL

***In Section 6.1, the developed model is applied to an average Italian site. The model is validated with an extrapolation of the raw data in Section 6.2. The model is programmed into an Excel-based tool, which is presented in Section 6.3. Section 6.4 discusses the sensitivity of the model in relation to its variables. Section 6.5 discusses the generalization of this thesis and the steps for implementation at VI.***




## 6.1 Numerical analysis for four components

In this section, four components are entered into the model, to analyze the effects of the maintenance strategies. The number of positions per component ($x_i$) is determined by the average positions installed in Italy (to allow for the validation in the next section). The values for the CRT (in months) are estimated based upon expert interviews. The system is used 50 weeks a year, 5 days a week, and 15 hours a day, and the expected lifetime is 40,000 hours, or equivalently 11 years. The required (component specific) input parameters are given in Table 6.

Additionally, the following cost functions that have been determined (the calculations can be found in Appendix 9).

- $C_{emer}$ = € 360 per failure
- $C_{prev}$ = € 40 per preventive action during inspections
- $C_{down}$ = € 1,000 per failure
- $C_{insp}$ = € 960 per system inspection

**Table 6 – The component specific input data for the four components**

| i | Name | $x_i$ | M(t=40,000) (sum of a(i)) | Mean (in operational hours) | $CRT_i$ (in months) | $C_i$ |
|---|---|---|---|---|---|---|
| 1 | Divert | 45 | 1.46 | 23,570 | 1.5 | € 83 |
| 2 | Crossing | 19 | 1.08 | 29,925 | 1.0 | € 212 |
| 3 | Shoes | 1,170 | 0.10 | 314,872 | 0.5 | € 17 |
| 4 | Merges | 46 | 0.21 | 129,301 | 3.0 | € 36 |

The cost functions are also input parameters of the model, so they can be adjusted for each customer. Here, it has been chosen to use conservative cost measures. It is likely that (for example) the downtime costs are much higher for certain customers, but the goal is to seek a bottom line that applies to many situations.

**Results**

Table 7 shows the results based on these parameters. It can be seen that the maintenance strategy, consisting of eight annual visits, minimizes the TRMC. If one compares the current strategy of four annual inspections with the strategy of eight annual inspections, it can be concluded that (under these conditions) the expected number of failures decreases by 39%, and the average total maintenance costs decrease consequently by 15.7%. Compared to run-to-failure, 28% of the costs are saved with eight annual inspections. For z ≥ 10, the TRMC increases, because additional investments in inspections are not paid back with further decreased downtime and emergency costs.

**Table 7 – The expected number of failures and TRMC after 40,000 hours**

| Maintenance strategy | TRMC | Total number of failures | Average yearly costs |
|---|---|---|---|
| Corrective maintenance | € 319.997 | 221 | € 29.091 |
| 4 annual inspections | € 266.793 | 149 | € 24.254 |
| 6 annual inspections | € 246.169 | 117 | € 22.379 |
| 8 annual inspections | € 225.512 | 86 | € 20.501 |
| 10 annual inspections | € 227.293 | 71 | € 20.663 |
| 12 annual inspections | € 229.074 | 56 | € 20.825 |
| 24 annual inspections | € 281.553 | - | € 25.596 |

## 6.2 Validation of the model

There are a few techniques to validate a model. The most common type of validation is to compare the quantitative output of the model with reality (Van Aken et al., 2007). The output, in terms of expected number of renewals[14], can be verified with the spare part demand for these four components. This is done via an extrapolation of the spare parts data. The parameters entered into the model are based on the averages of the seventeen Italian sites, which makes it possible.

[14] The expected number of *renewals* does not depend on the maintenance strategies, thus the number of failures with the corrective maintenance strategies resembles the total number of renewals. The CRT also has no influence on the number of renewals with the corrective-based maintenance strategy.

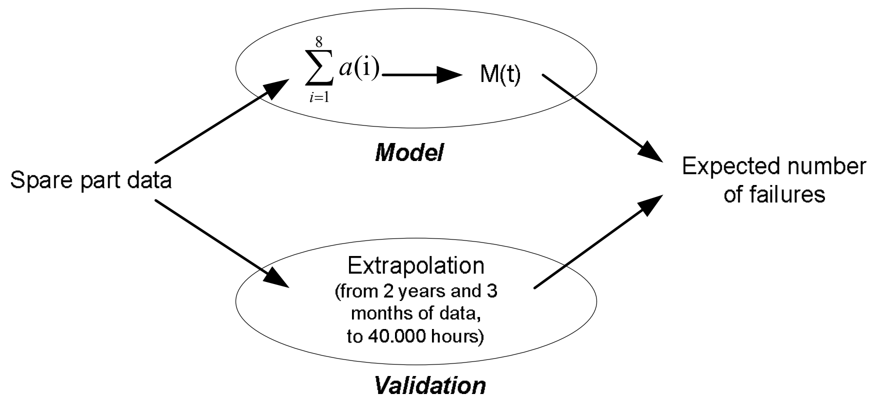



**Figure 30 – The spare parts data is extrapolated to validate the results of the model**

The demands for these four components sum up to 41 parts per site (in the data set of 2 years and 3 months). The average operational hours at site is calculated using 50 weeks per year, 5 days per week and 15 hours per day. Via extrapolation, the total expected number of renewals per site, over 40,000 hours is:

$$41 \times \frac{40.000}{2.25 \cdot 50 \cdot 5 \cdot 15} = 195 \qquad (21)$$

This is seven percent lower than the total number of expected failures with the corrective-based maintenance strategy in Table 7, i.e. 209 expected failures. The most plausible (and likely) explanation for this difference is the inclusion of the three new sites (Bari, Pisa and Torino). These sites (may) have a larger impact on the extrapolation (i.e. they decrease the expected number of failures in the extrapolation) than on the M(t) calculation, because their spare part demands are relatively low compared to the 14 other sites. It is concluded that, irrespective of the seven percent difference, the model is valid and represents the failure behavior of the average Italian site.

## 6.3 The tool

The model is used to build an Excel-based tool, using straightforward, well-known parameters and an intuitive interface. The tool is built as discussed in Section 2.7: with an input sheet; a sheet with reliability information; and a sheet with all the calculations. For reasons of convenience, the outputs are also presented on the input sheet (see Appendix 10 for an impression of the sheet with the input and output).

**Input parameters**

On the input sheet, the characteristics of the serial system and its specific parameters are filled in. For the individual components in the system, the $x_i$, and $C_i$ are required. For the system, the operational hours and the intended lifetime are entered. The cost functions can be customer specifically (e.g. inspection and downtime costs), so these are also entered onto this sheet.

**Time-based increase of the inspection frequencies**

In the previous sections, it is assumed that one maintenance strategy is used during the entire lifetime of a system. If many VI components in a system have an increasing failure rate, it may be justifiable that the frequency of periodic inspections is increased after a certain number of operational years. Figure 31 show the expected number of renewals per position of the four components (based on the Weibull distributed lifetimes). For this reason, an optimal flexible maintenance strategy is also created in the presented tool. With this flexible strategy, the service account manager and the customer can adjust the inspection frequencies over three consecutive horizons, and discuss even more options.

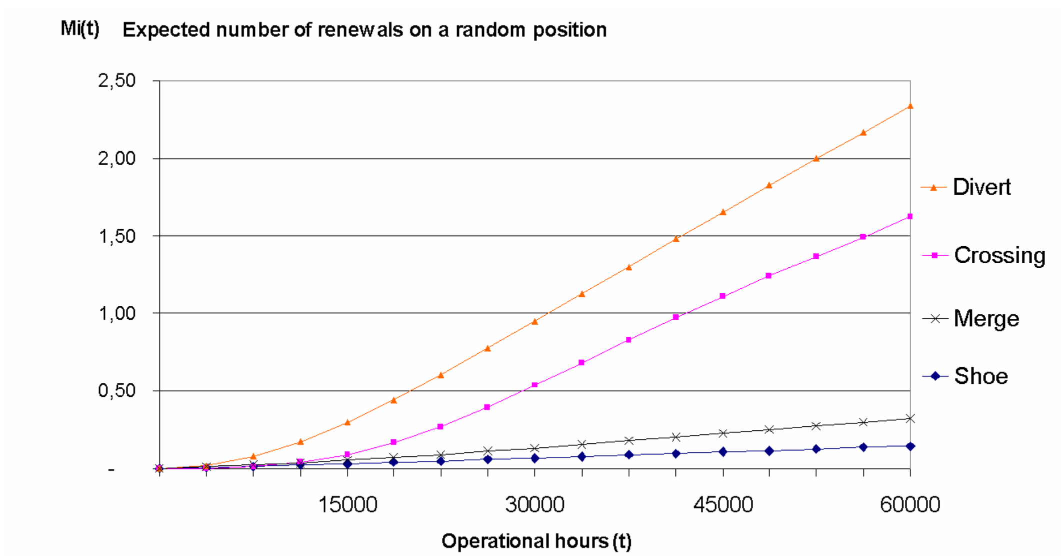



**Figure 31 – Increasing failures on a few positions can justify the increase of frequency of inspections**

**Enter reliability**

The reliability of a component should be based on a certain knowledge database. As discussed previously, VI is currently gathering this data. The reliability of components (given a certain business environment) can be entered in two ways: manually (as the summation of a(i)) or via the distribution parameters of the lifetime estimations of components (Weibull or Normal distribution parameters). In the former case, a number of expected renewals (as discussed in Section 4.2) is selected. In the latter case, $M_i(T)$ can be calculated by a renewal process as discussed in Section 4.3, given the inputs $\eta_i$ and $\beta_i$, that belong to distribution of component i.

**The output**

Next to the previously presented outputs of the TRMC (see Table 7), the tool also presents the expected number of failures for a component during the proposed lifetime (see Figure 32). Obviously, given that inspections avoid failures, the failures are also the highest with this strategy, equaling the total number of renewals. Using the other strategies, an increasing percentage of the renewals are executed preventively, and hence number of failures decrease. This figure can be used to assess whether increasing or decreasing the number of inspections will have an impact on the expected number of failures. Moreover, this figure can also display the effectiveness of the flexible strategy.

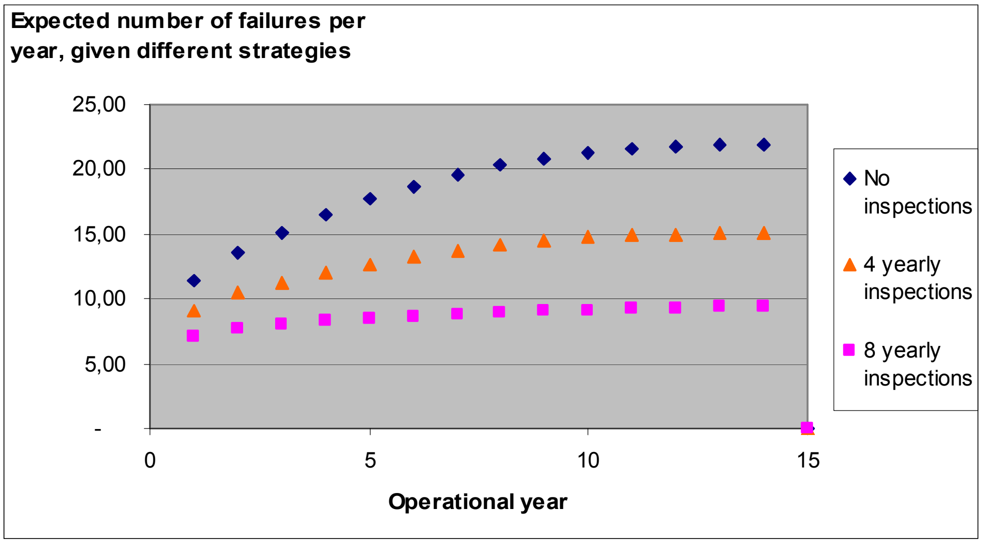



**Figure 32 – The output of the model for four components**

## 6.4 Sensitivity analysis of maintenance strategies

In the previous sections, the situation of an SPO was simulated by four components. In this section, one imaginary product is analyzed, with 50 serial positions of one component. The sensitivity of the outputs of the model are analyzed on component reliability and CRT. Moreover, it becomes apparent that the choice for a particular maintenance frequency depends on many parameters.

The test bed consists of the following parameters:

| | |
|---|---|
| $\eta$ | = {25,000; 50,000} |
| $\beta$ | = {1; 1.5; 2} |
| CRT | = {1; 2} months |
| z | = {0; 4; 6} annual inspections |

And with the following parameters:

| | | |
|---|---|---|
| $C_{downtime}$ | = | € 500 |
| $C_{emergency}$ | = | € 360 |
| $C_{inspection}$ | = | € 500 |
| $C_{item}$ | = | € 200 |
| $x_i$ | = | 50 positions |
| T | = | 40,000 hours |

In Table 8, the results of this comparison are presented. The following can be concluded:

- Block A: When the components have a long lifetime (η = 50,000) and failure rate is increasing (β = 1.5 or 2), the most favorable strategy is actually run-to-failure, because the expected number of failures remains low during the system lifetime. This would includes several VI-components.
- Block B: When the CRT = 1 month, and the scale parameter is 25,000 or lower, the current maintenance strategy (z = 4) can be dangerously expensive. When the CRT = 1, the likelihood of observation is just 33%. The strategy with six annual inspections does not lead to significant improvements. In this case, it would be better to test z = 12, improve the component reliability, or invest in another observation method.
- Block C: When the CRT is 2 months, all failures are avoided with six annual inspections, and consequently the total expected costs are lower. The distribution of the component has become less important, because the results in Block C are more or less comparable: The costs differences are less than 10%, and all expected failures are zero.

The most important learning from these sensitivity analyses is that many parameters have a rather large impact. This also confirms that the choice of maintenance strategy (in terms of inspection frequency) should be based on solid knowledge of component degradation.

**Table 8 – The expected number of failures and TRMC for the sensitivity analysis (T=40,000 hours)**

| | | | | CRT = 1 | | | | CRT = 2 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Run-to-failure (z=0) | | Four annual inspections (z=4) | B | Six annual inspections (z=6) | | Four annual inspections (z=4) | C | Six annual inspections (z=6) | |
| η | β | TRMC | Failures | TRMC | Failures | TRMC | Failures | TRMC | Failures | TRMC | Failures |
| | 1 | € 90.063 | 89 | € 88.330 | 59 | € 87.463 | 45 | € 64.603 | 30 | € 51.873 | 0 |
| 25.000 | 1,5 | € 84.841 | 84 | € 84.484 | 56 | € 84.305 | 42 | € 62.133 | 28 | € 50.779 | 0 |
| | 2 | € 81.314 | 80 | € 81.886 | 54 | € 82.172 | 40 | € 60.465 | 27 | € 50.040 | 0 |
| | 1 | € 43.370 | 43 | € 53.940 | 29 | € 59.226 | 21 | € 42.517 | 14 | € 42.091 | 0 |
| 50.000 | 1,5 | € 34.144 A | 34 | € 47.146 | 22 | € 53.646 | 17 | € 38.154 | 11 | € 40.158 | 0 |
| | 2 | € 28.744 | 28 | € 43.168 | 19 | € 50.381 | 14 | € 35.599 | 9 | € 39.027 | 0 |
| Average | | € 60.413 | 60 | € 66.492 | 40 | € 69.532 | 30 | € 50.579 | 20 | € 45.661 | 0 |

## Sensitivity analysis on the downtime costs

Clearly, with the large fluctuations in the number of expected failures, the parameter downtime cost has a large influence. Table 9 shows the results of the next sensitivity analysis, namely €500 costs per failure versus €1,000 costs per failure. It can be seen that size of the downtime cost can change the preferred inspection frequency. This leads to rather straightforward decisions, but the effects are still interesting. When the CRT is larger, the impact of the downtime costs decreases. This also means that when that downtime cost increase, it can become profitable to increase in methods to increase the likelihood of observation. When the downtime increases, the number of annual inspections should also increase. Although the differences with CRT =1 month remain relatively low, the TRMC differences with CRT = 2 months is significant. Obviously, the cost functions and CRT should be in harmony to minimize the total costs.

**Table 9 – The sensitivity analysis downtime costs**

| Downtime costs per failure | Run-to-failure (z=0) | | Four annual inspections (z=4) | | Six annual inspections (z=6) | | Four annual inspections (z=4) | | Six annual inspections (z=6) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TRMC | Failures | TRMC | Failures | TRMC | Failures | TRMC | Failures | TRMC | Failures |
| € 500 | 100% | 84 | 99% | 56 | 99% | 42 | 73% | 28 | 60% | 0 |
| € 1.000 | 149% | | 132% | | 124% | | 90% | | 60% | |

## Sensitivity analysis on the CRT

Obviously, the CRT is an important variable in the model because it is the main driver for the likelihood of observation. When the CRT is zero, failures always come as a surprise, and cannot be prevented by inspections. Figure 33 shows the result of a simple sensitivity analysis for an imaginary component. The CRT in the left figure is 1 month, as opposed to 2 months in the right figure. As expected, the model is sensitive to fluctuations in the CRT, and the optimal TRMC (including downtime costs) vary accordingly. In this situation, the cost difference is 33%. Thus,

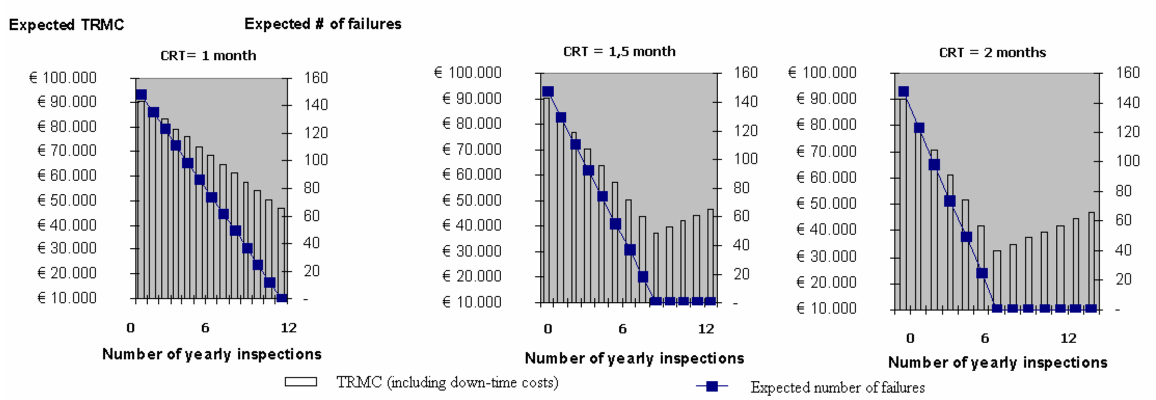



**Figure 33 – When the CRT is twice as large, the cost could decrease with approximately 33%, if the right number of yearly inspections is chosen.**

the CRT has a large influence on both the costs and the number of prevented failures. It is important for VI to obtain more information on this variable, if it wishes to make the inspection strategy more solid and profitable.

## 6.5 Applying the model in practice

### 6.5.1 Generalization of the model

The generalization (also referred to as the external validity) of a developed model determines to which extent the model can be used in different situation, besides the scope of the research problem. The developed model can be applied to simulate any VI section with serial components (such as the Belt Floorveyor or the Gappex). The components must also have a certain CRT to apply the model. Since many critical VI components are mechanical, it can be assumed that most components have a certain CRT. (When the CRT is zero, it could also be applied, but then observations are useless.In that case, statistic-based maintenance, for example with BPI, can provide new options)

This model is not limited to the products of VI. Basically, any serial system with mechanical components can be simulated with this model. An aspect that hampers the generalization of the model is that it requires scheduled downtime. The developed model builds upon the fact that VI customers operate 15 to 20 hours per day, and the number of inspections can increase to weekly or (even) daily inspections. When the customer runs 24/7, then this model cannot be applied. Optimizing maintenance policies (e.g. age-based) and clustering of maintenance activities becomes the next challenge.

### 6.5.2 Generalization of the reliability findings

The reliability assessment in Chapter 3 and Chapter 4 is built upon spare parts data of one specific customer. It is expected that the M(t) and the Weibull fitted parameters are indeed a proper indication of the degradation (due to wear) of the components under these conditions.

Nevertheless, although these sites are carefully chosen (for data availability and reliability reasons), there are three aspects that hamper the generalization of the reliability assessment.

- Firstly, the number of call-outs at the analyzed sites in this thesis is relatively high compared to other sites, due to the full-service contracts. The managers of the analyzed sites have no incentive to decrease call-outs, since VI solves their problems, irrespective of the reasons of the call-out.
- Secondly, the systems on these seventeen sites are used intensively (many hours per day and at a relatively high capacity).

- Thirdly, the operators that work with these systems are employed by a third party: these employees have no ties with the VI customer that 'could make them care about the system'.

### 6.5.3 Implementation of the model

This model can be very useful to advice customers on the intensity of preventive maintenance activities. Unfortunately, before it can be used, additional information is required. The Service Development and R&D departments should fill the gaps concerning of reliability distributions and CRT estimations, using the conveyor lists and the break-down of items (Bill-of-Materials).

One of the final questions concerns responsibility. Since the input data requires improvement, the department Service Development should remain responsible for finalizing the model for a specific section. The SPO would provide a good business case, since there are many Express Parcel sites that are serviced by annual inspections. Moreover, these sites depend on the availability of the SPO, so customers will be very interested in these developments. If this business case succeeds, the model should be applied to any VI-section with a serial structure. After that, the responsibility may be distributed among the service account managers that work with the model, because it will be made specifically for a certain customer (or site).

Finally, service account managers and sales engineers can apply this model to persuade their customers to adjust the inspection level. The intent of an analysis with this model should be to improve mutual profitability in business-to-business relationships. By increasing the frequency of inspections, it is likely that the system availability will increases simultaneously with customer satisfactions and turnover for VI.

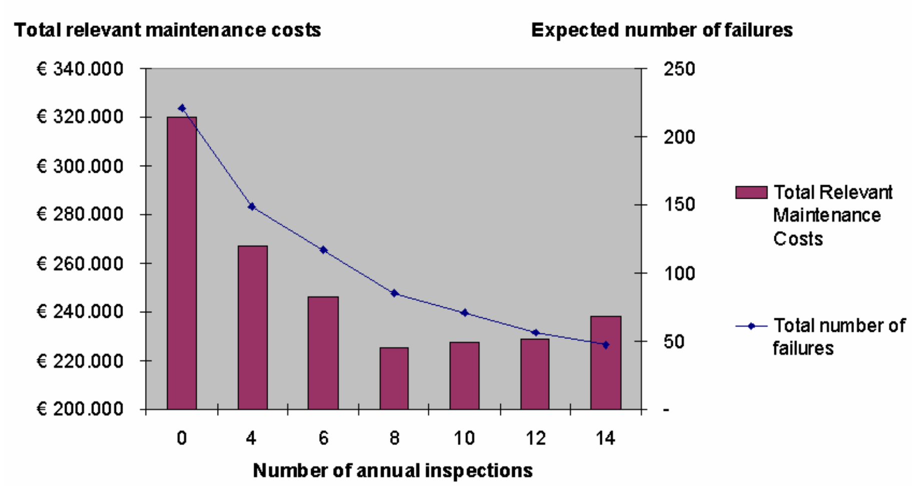



**Figure 34 – Illustration of findings of Section 6.1**

# 7 CONCLUSIONS AND RECOMMENDATIONS

**This final chapter presents the conclusions, managerial insights and recommendations, further research opportunities and the academic relevance.**

## 7.1 Conclusions

In this master thesis, a quantitative model has been developed, that calculates the expected total relevant maintenance costs (TRMC) and the expected number of failures for different inspection frequencies. The model is built in Excel, using straightforward, well-known parameters and an intuitive interface. The model can be used to simulate any VI section with serial components (such as the BF or the SPO). With this model, the main research question can be answered:

> How are the number of technical failures and total relevant maintenance costs of a VI-section influenced by different maintenance strategies?

To answer this research questions, the maintenance strategies called run-to-failure and inspection-based maintenance are analyzed with the developed model. Using cost parameters and reliability functions founded on historical data, four critical components of the SPO (i.e. diverts, crossings, shoes and merges) are entered into the model. For this system, the pro-active maintenance strategy consisting of eight annual visits outperforms the currently used strategy of four annual visits, by simultaneously minimizing costs and expected number of failures. Under these conditions, the expected number of failures decreased by 39%, and the average TRMC consequently decreased by 15%. Compared to run-to-failure, 28% of the costs are saved with this maintenance strategy. From this, it has been concluded that pro-active strategies with increased commitment in terms of resources and inspections can lead to increased reliability and performance. With more than ten annual inspections, the TRMC is beyond its lowest point, and starts increasing because additional investments in inspections do no results further decreased downtime and emergency costs.

It can be concluded that maintenance strategies determine a significant part of the TRMC and the expected number of failures. Moreover, besides the cost functions and inspection frequencies, there are two other important determinants, namely the component reliability and the CRT.

Sensitivity analyses have shown that maintenance decisions should be based on knowledge of the underlying deterioration processes. Wrong estimations of the component degradation can lead to costly decisions. The CRT also has a large influence on the optimal inspection frequency. Therefore, it is a prerequisite that VI obtains more knowledge on component degradation and the likelihood of observation (calculated using the CRT).

**Managerial insights on TCO**

The intent of TCO analysis is to improve mutual profitability in business-to-business relationships. An increasingly number of customers requires TCO estimations, and it is unlikely that this trend will change. VI subsequently needs to increase the company's knowledge on this subject. Maintenance costs and downtime costs are a major aspect of the TCO. However, it is not only a prediction of costs: implicitly, it is also a prediction for system availability, because availability and cost functions go hand-in-hand. TCO is merely a construct to support decision making, using total value received and availability as outputs, and system reliability and maintenance decisions as inputs. The model presented can specify the relevant maintenance and downtime cost. Nevertheless, reliability is the linking-pin in the trade-off between TRMC and system availability, and VI should therefore invest in reliability engineering before it can truly understand and predict TCO. This thesis has also shown that using averages can lead to costly results.

**Applying this model to improve customer satisfaction**

This model can be very useful to advice customers on the intensity of preventive maintenance activities, because these decrease failures and downtime costs, whilst increasing turnover and profits for VI. Analyses of current activities show that increasing preventive maintenance will lead to better performance. With this model, VI can persuade customers to increase the inspection level. Chapter 6 describes how this might work in practice.

## 7.2 Recommendations and future research possibilities for VI

**Recommendations concerning data gathering and analysis**

Currently, data is recorded for administrative reasons, rather than for finding reliability measures or improving ways of operations. If VI desires to truly expand the knowledge on component degradation, it is crucial to collect a large database on time-to-failures of its components, because in-field data is an important source of information.

As discussed in the introduction, the gathering of in-field data has recently begun. This project is essential for the automated collection of data, because it makes extraction of information more convenient and less time-consuming. Within a few months, VI can start transforming the field data into knowledge on reliability. This thesis describes how time-to-failure data can be transformed into degradation knowledge effectively. The literature review has high-lighted that the use of solely the mean may lead to poor results, which is confirmed in this research. An appropriate starting point for any reliability analysis is the Weibull distribution. All-in-all, this also means that VI is close to being able to optimize the frequency of inspections, but gathering more information is essential.

**New research possibilities for VI**:

In addition to preceding suggestions concerning data gathering and analyses, the following two research possibilities have a large potential for VI:

- Corrective costs are incredibly larger than preventive costs, due to downtime and labor costs, as opposed to relatively low component costs. It is therefore very useful to perform additional preventive actions, whenever a mechanic is on-site for the call-out. This is called opportunity based maintenance. For full-service contracts or on-site teams, this can be very beneficial because it can prevent expensive emergency call-outs. In this case, it is in VI's interest to actively perform preventive and opportunity based maintenance.
- Continuous monitoring can be an effective tool to increase the likelihood of observation prior to failure. When the demand for high availability get more important in the tendering phase, it may be very interesting to quantify this. Especially when it comes to capital goods, the investment in monitoring equipment can negligible compared to the overall cost. The returns in higher availability, on the other hand, can be rather interesting for the customer. This model also has the potential to assess continuous monitoring options.
- VI should invest in the development of usage-profiles. These usage-profiles should capture the combination of situational factors, for example speed and capacity. Provide the R&D department more time and resources to test the different circumstances, and advising customers on usage, reliability and availability can professionalize.

## 7.3 Academic relevance and recommendations for further research

Dekker (1996) explains the difficulties in the field of maintenance modeling that create a gap between theory and practice. He argues that maintenance models are too difficult to understand and interpret, because many papers have been written for mathematical purposes only. This thesis tries to bridge this gap, and shows the practical relevance of theories, by firstly looking at the situation and consecutively developing a model. Where many maintenance models are very complex, this model is generic and uncomplicated. In this sense, this thesis is a good example that applies academic theories into practice. The chosen parameters are straightforward, and the (more difficult, statistical part) is 'hidden' in a database, to decrease potential barriers for practitioners.

**Academic relevance**

The functionality of the model, developed in this thesis, is innovative by applying the conditional residual time (CRT) as a means to calculate the probability that a damaged component is observed and renewed prior to failure. A major advantage of this approach is that the CRT is a straightforward and useful method to assess the effectiveness of inspections, simplifying maintenance modeling. The case of VI is an interesting illustration that the CRT has great potential to simulate the efficiencies of inspections.

Furthermore, this thesis displays an interesting case where the inclusion of downtime costs, as part of the TCO, leads to optimal results for both customer and producer. TCO should lead to improved mutual profitability. Basically, this shows that sellers should be aware of the fact that their customers paid the price for downtime, and customers should be aware that their suppliers can decrease these downtime costs with additional investments.

A Scarce data is a problem of many academics, and this thesis is innovative by aggregating the data of different sites (see Chapter 4). Potentially, this method can be applied at several companies with comparable systems in the field. Undoubtedly, it is not the finest way to obtain knowledge on the degradation of components, but if your options are little, this method does provide you with reliable insight into what happens with the systems.

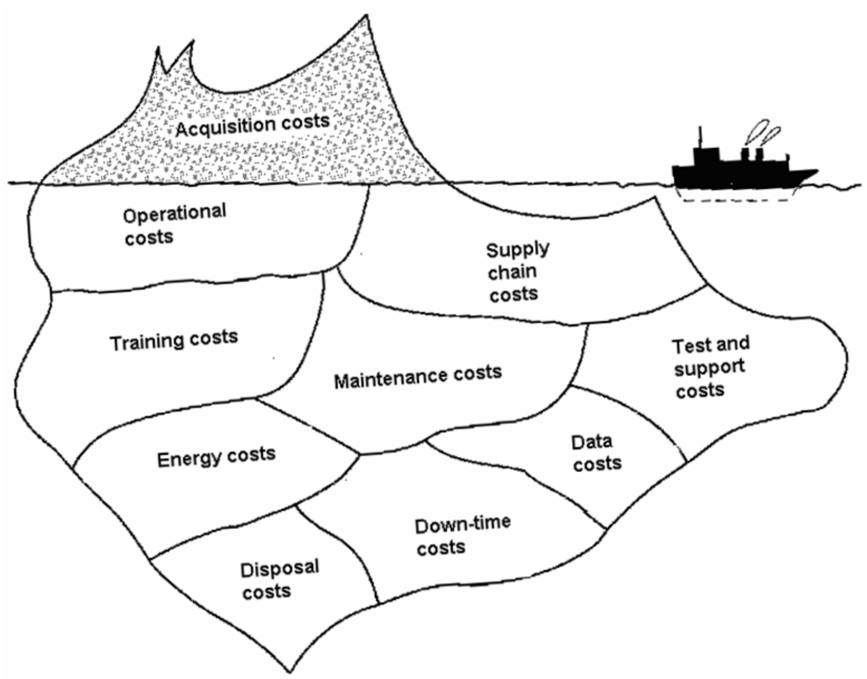
**Academic challenges with the model**

The situation of a serial VI system with plenty of scheduled downtime is rather straightforward. At least two extensions for the developed model are very interesting to improve its general applicability. Firstly, the model should be extended for situations where preventive maintenance consumes production time. In this case, clustering of maintenance activities play an important role, which should be based on the age policies. Secondly, this model can be extended to incorporate parallel, redundant systems.

# REFERENCES


- Barringer, H.P., Weber, D.P., (1996) 'Life Cycle Cost Tutorial', *Fifth International conference of process plant reliability.*
- Bertrand, J.W.M. and Fransoo, J.C., (2002) 'Operations Management Research Methodologies Using Quantitative Modeling', *The International Journal of Operations & Production Management* 22(2), pp. 41-264
- Bevilacqua, M., Braglia, M., (2000) 'The analytic hierarchy process applied to maintenance strategy selection' *Reliability Engineering and System Safety*, p.70-83.
- Blanchard, B.S., Fabrycky, W.J., (1998) '*Systems engineering and Analysis',* New Jersey, USA , Prentice Hall.
- Christer, A.H., (1999) 'A review of Delay Time Analaysis for Modelling Plant Maintenance', *Journal of the Operational Research Society*, Vol 50, p 1120-1137
- Dekker, R., (1996) 'Applications of maintenance optimization models: a review and analysis', *Reliability Engineering and System Safety*, p. 229-240.
- Dekker, R., Wildeman, R.E., Van Der Duyn Schouten, F.A., (1997) 'A review of multi-component maintenance models with economic dependence', *Mathematical Methods of Operations Research*, Vol 45, no 3, p. 411-435
- Dohi, T., Kaio, N., Osaki, S., (2002) 'Renewal Processes and Their Computational Aspects'. In Stochastic Models in Reliability and Maintenance, Shunji Osaki (Eds), Springer-Verlag Heidelberg, NY
- Franssen, R., (2006) '*Life Cycle Cost Analysis, For Baggage Handling Systems of VanderLande Industries'* (Master-Thesis project), Eindhoven University of Technology
- Garg, A., Deshmukh, S.G., (2006) 'Maintenance Management – literature review and directions', *Journal of Quality in Maintenance Engineering, Vol. 12, No 3, p. 205 – 238.*
- Kelly, A. (1997) '*Maintenance Strategy'*, BCM Butterworth Heinemann, Oxford, UK.
- Kelly, A. and Harris, M.J., (1978) *'Management of Industrial Maintenance',* Butterworh, London, UK
- Kumar, U.D., Crocker, J., Chitra, T. and Saranga H., (2006) '*Reliability and Six sigma',* Springer, NY, USA
- Kranenburg, A., (2006) '*Spare parts Inventory Control under system Availability Constraints'*, PhD thesis TU/e, Beta
- Levitt, J., (1997) '*The handbook of Maintenance Management'*, Industrial Press, NY, USA
- Lewis, E.E., (1996) '*Introduction to Reliability Engineering',* John Wiley & Sons, USA

- Mann, L., Saxena, A. and Knapp, G.M., (1995) `Statistical-based or condition-based preventive maintenance', *Journal of Quality in Maintenance Engineering,* Vol 1, No. 1, pp 46-59
- Mitroff I.I., Betz F., Pondy L.R., Sagasti F., (1974) '*On managing science in the systems age: two schemas for the study of science as a whole systems phenomenon'*, Interfaces 4 (3), p. 46-58
- Murthy, D.N.P., Atrens, A., Eccleston, J.A., (2002*) 'Strategic Maintenance Management', Journal of Quality in Maintenance*, Vol. 8, No 4, p. 287 – 305.
- Nakagawa, T., (2002) 'Imperfect preventive maintenance models' In *Stochastic Models in reliability and Maintenance Editor*; Shunji Osaki, Springer-Verlag Heidelberg, NY
- Nakagawa, T., (2006) *'Shock and damage models in reliability theory'*, Springer, NY
- Öner, K.B., Franssen, R., Kiesmuller, G.P., Van Houtum, G.J., (2007) *"Life Cycle Costs Measurement of Complex Systems Manufactured by an Engineering-to-Order Company", FAIM2007 Philadelphia, USA.*
- Semi-Standard E10-0304E. *Specification for definition and measurement of equipment reliability, availability and maintainability* (2004)
- Smeitink, E., and Dekker, R., (1990) A Simple Approximation to the Renewal Function, *IEEE Transactions on Reliabilty, Vol 39, No.1*
- Stoneham, D., (1998) "Maintenance Handbook and Technology", *Elsevier Advanced Technology Press*, Oxford, UK.
- Swanson, L., (2001) 'Linking Maintenance strategies to performance', *International Journal of Productions Economics*, Vol 70, p. 237-24
- Van Aken, J. E., Berends, H. en Van Der Bij, H., (2007) '*Problem Solving in Organizations'*, Cambridge: Cambridge University Press
- Van Putten, R., (1999), '*LCC and availability for materials handling systems'* (Master-thesis project), University of Twente
- Vlasblom, R., (2009) 'Steering *LCC in the early design phase'* (Master-thesis project), Technical University of Eindhoven
- Waeyenberg, G., and Pintelon, L., (2002) 'A framework for maintenance concept development', *International Journal of Production Economics*, p. 299-313
- Wang, H. and Pham, H., (2006) *'Reliability and Optimal Maintenance',* Springer Series in Reliability, Springer-Verlag, London, UK
- Yang, G., (2007) *'Life Cycle Reliability Engineering'*, John Wiley & Sons, New Jersey, USA




By Walter Stein

July 6, 2009

# APPENDIX 1: OVERVIEW RESEARCH DESIGN

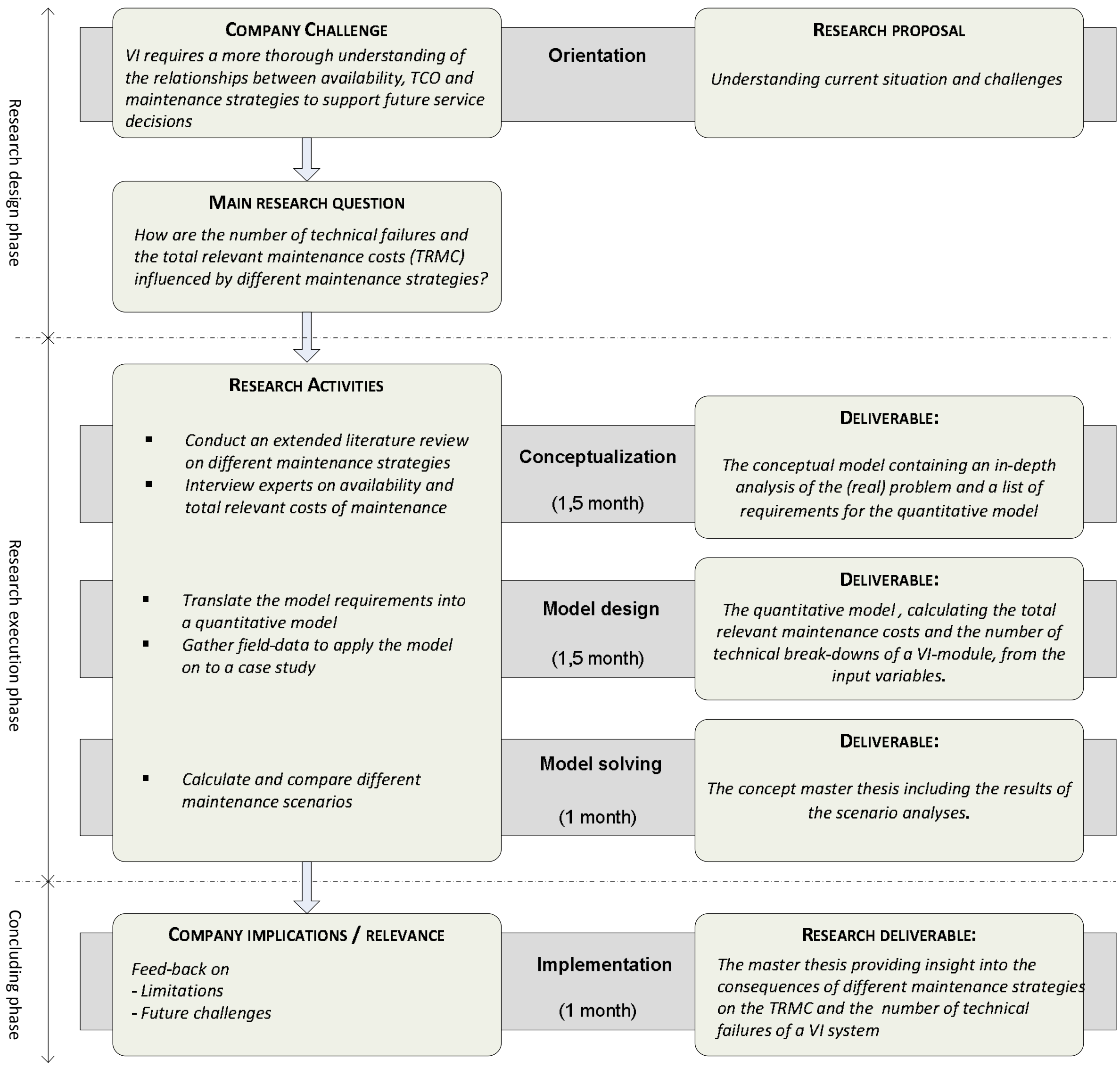
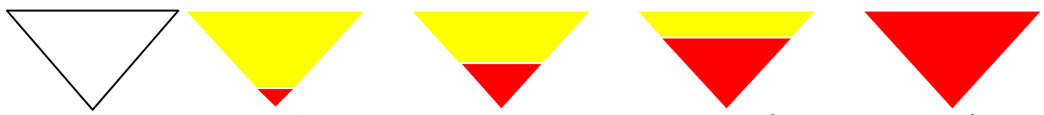



**Figure 35 – Overview research design**

## APPENDIX 2: THE SERVICE OFFERINGS OF VI

Currently, more than 500 customers enjoy the services provided by VI. In most cases, customers sign a service contract. Obviously, all these customers have different requirements. These requirements depend on several factors, such as size of the Installed Base, number of production hours per year or downtime costs. To be able to adjust the offered service contract to customer requirements, VI provides five different levels of service and support: ranging from None to Total (see Figure 36). *None* means that the customer did not sign a contract. Obviously, VI will still be willing to sell spares or provide support; however, nothing is agreed upon. *Total* means that VI will place a VI service team on-site, that provides all the required services.



| None | Basic | Support | Support Plus | Total |
|---|---|---|---|---|
| | During VI office hours | Around the clock 365 days per year | Around the clock 365 days per year | Around the clock 365 days per year |
| Possibility to order spare-parts | **Services included:**<br>Hotline 8/5<br><br>Remote support 8/5<br><br>Mobilisation priority 8/5 | **Services included:**<br>Hotline up to 24/7<br><br>Remote support up to 24/7<br>Mobilisation priority up to 24/7<br>Inspections | **Services included:**<br>Hotline up to 24/7<br><br>Remote support up to 24/7<br>Mobilisation priority up to 24/7<br>Inspections including maintenance | **Services included:**<br>Full service by Vanderlande Industries service organisation on the Customers premises, possibly in shifts |

**Figure 36 – VI customizes the service offerings from standard service packages (source: VI)**

The service contract is build up from these standard elements. It can be easily adjusted, because within each element there are different options and possible agreements. Within the service contract, all agreements, from inspection interval to (for example) hotline support cost, are specified. A detailed description of these activities is given below:

- <u>Hotline</u>

Hotline support for operational problems or bottlenecks is provided through an international helpdesk. The customers have again a number of options (minimal versus normal support; modem support or controls helpdesk, etc). The customer centre is the primary contact for the customers, to report problems or system breakdowns or for ordering spare parts. Each call will be logged, and if needed, passed on to the appropriate engineer.

- <u>Remote support</u>

For installed control systems (such as Warehouse Management or Warehouse Control Systems), VI provides remote support by means of a VPN connection. This allows the Service Department to connect remotely to review the functioning of the system controls, check the status, give advice how to solve a problem and, if possible, solve the problem itself.

- <u>Mobilization priority</u>

VI has a team of Service Engineers that is dedicated to quick-response. This is necessary because a large number of customers require this; and therefore a response time is agreed upon to pick up the phone, and if required, arrive at site. This can for example be 1 hour repair, plus 2 hours travelling. These response times are defined when a service contract is set up.

- System inspection

The inspections provide an overview of the system status, and identify areas of concern. During a system inspection, service engineers review the current condition of the system. Many VI systems have mechanical components where the condition can be seen, smelled or heard, so this is a local inspection which may lead to a *Condition Based Maintenance* activity.
After the system inspection is performed, a report is generated and supplied to the Customer highlighting the areas of concern, or where improvement work is required.

- System maintenance

During the system maintenance, the service engineers perform the scheduled (preventive) maintenance activities on the equipment. These may have resulted from the inspections, or upon customer request, or upon contract agreements.

- Full maintenance via on-site teams

The most intense kind of service currently offered is the Full Maintenance, where management and (maintenance) staff are provided to maintain the entire system or even the total facility. The main advantages of On-site teams are that the VI-team gets to perfectly understand the customer's environment and practices, whereas the customer can concentrate on his core-business. The team will be in the best position to recommend system modifications and method changes that improve the overall system efficiency. VI has On-site teams in the Airports of London, Oslo, Bahrain and Amsterdam.

In addition to these building blocks of the services contract, VI also offers the following packages:

- Spare parts

In addition to the different Service packages, VI can supply the necessary spare parts. This happens initially in the form of a customized spare parts package and during the operational lifetime of the system the spare parts are replenished upon customer order. This customer order is not necessarily the same as customer usage, which hampers spare parts analysis. The customer has a can choose between buying the parts and storing the parts at their own site, or the customer can use the consignment option. With this option, the VI remains the owner of the spares (and bears the risks), and the customer pays a (annual) fee for the possibility to buy the parts. Within the consignment contract it is specified where the stock is located. Parts can be stocked at the customer site and at a VI warehouse. The parts can also be shared by multiple VI-customers at a VI warehouse.

- Revision, Modification and Retrofit (RMR)

RMR refers to system upgrades to ensure the long-term performance of a system or to adjust the system to future requirements.

- Revision: Restoring the system to its original status by means of large-scale predictive maintenance.
- Modification: Adjusting the system to current and future requirements (extension of functionality).
- Retrofit: Restoring the system to a maintainable status by updating products and software that are currently available in the market.

Revision and retrofit can be seen as major preventive maintenance actions.

- Training

Many customers have their own technical service department, and therefore VI has developed a whole range of training possibilities. For example, before the system is commissioned, VI provides fundamental maintenance training in Veghel. Here, the customer's technicians are instructed on the essential basic maintenance activities (on equipment, tools, wires, etc), or on emergency situations. Another example is on-site training for new technicians, or after a system update. An additional advantage of training is that the technicians learn the VI-terminology. This is very efficient when a customer calls the second or third line support.

- Business Process Intelligence (BPI) tool

BPI is a VI-tool that can be installed at a customer site, which gathers, archives and analyses relevant business data. It is not solely used for service, but also for reporting and diagnosis of current operations. The BPI-tool has a large potential: the customer can control its processes better, and VI can increase the service performance. Therefore the number of installations is likely to increase over the next years.

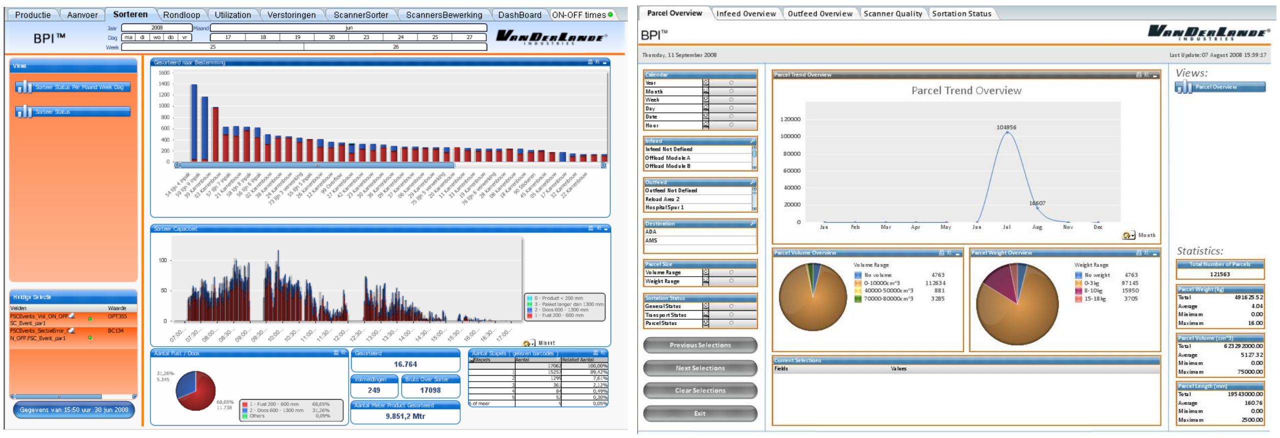



**Figure 37 – Impression of the BPI tool**

- Maintenance Management Systems (MMS) and the Mobile Inspector (MI)

In order to streamline the maintenance processes, VI offers their customers to implement a (computerized) Maintenance Management System (MMS). The purpose of an MMS is to support effective and efficient maintenance management and reduce lifetime costs. The MMS can also create the reports on the performance. Which system VI implements, depends on the size of the total system, and customer requirements. The possible software packages are Maximo, Ultimo or Q3.

Furthermore, field service engineers are equipped with a PDA with *Mobile Inspector* (MI) software, built by VI. During preventive maintenance, the engineers can use the predefined checklists to record the maintenance actions taken and the current service status of the system. After the inspection or action, it replicates the data input into to the service back-office. Unfortunately, corrective actions are not (or at least seldomly) recorded, and the MI does not have standardized drop-down menus to brief on the problem.

# APPENDIX 3: RELATED PROJECTS EXECUTED WITHIN VI

VI started several projects to increase their knowledge on system degradation and life-cycle, in order to make forecasts on TCO and availability.

*On data gathering*
VI currently measures the life-cycle characteristics (e.g. output, number of runs) at a small number of customers with so-called PosiSorter systems via the BPI-tool. Ruud van Heesch, an employee of Service Development, is working on the translation from maintenance activities and lifetime measurements, towards lifetime estimates of the critical components of the PosiSorter. Therefore he gathers this information, and transforms and translates these measurements into lifetime knowledge. However, gathering information of maintenance activities appears to be difficult. Moreover, since the number of failures is relatively low, and the influencing factors of both the system and the environment have a large potential impact on the degradation, this knowledge will probably not be available for the next few years.

*On maintenance and availability*
Many initiatives have come from VI employees (often on customer requests) on this subject. A promising initiative came from René Potters, an R&D employee. He recently has developed a useful maintenance sheet for the divert/merge section of the Tubtrax system (a transportation system), based on reliability and time estimates, that calculates maintenance costs and system availability. However, it is not based on grounded maintenance literature, and the interaction between preventive and corrective maintenance is imprecise.

*On availability*
Availability is an often used key performance indicator (KPI) to assess the installed system and to report to a customer. An early graduation project on availability gave insight into this area (Van Putten, 1999). Another example of a graduation project on availability is Van Helden (2004). It can be concluded that the ETO nature of the VI-systems, rerouting, miss-sorts and different utilization hamper availability calculations. Sometimes it is also difficult to make the distinction between operational and technical failures.

*On TCO*
TCO is a concept that receives more attention lately. In some occasions, customers ask VI to make estimations on the cost of ownership, as part of the order tendering. To learn more of the different cost drivers, Franssen (2006) devoted his graduation project on this subject, and identified the main cost buckets of the life-cycle costs (LCC) of a BHS of VI. He created a tool that estimates the TCO of a baggage handling system in the design phase. An important finding was that it appeared that maintenance and downtime costs together accounted for almost 70% of the total LCC of a baggage handling system.

*On steering the TCO in the design phase*
Rutger Vlasblom executed a graduation project within the Pricing department on the trade-off between availability and TCO. His focus is on the design phase, namely the MTBF of eleven baggage handling sections. He created a tool that calculates the system availability and TCO, based on MTBF measures at Schiphol Airport, and will execute sensitivity analyses to assess the effect of differences in the MTBF.

# APPENDIX 4: THE POSISORTER

**Figure 38 – The PosiSorter at DHL Drachten**

The PosiSorter (SPO) is a horizontal, high speed sorting conveyor with extruded aluminum carriers, which can carry a wide range of products. The carriers are connected to the conveyor with two chains, driven by one heavy motor. Divert shoes are mounted upon the aluminum carriers. At the sort destination the shoes are diverted over 20 or 30 degrees, causing them to slide across the carriers and gently push the product positively into the output spurs. The number of shoes diverted depends on the length of each product. Available for single sided sorting and dual sided sorting. The dual sided sorting model has a pre-sort to direct the shoes to the side of the sorter corresponding with the output spur. Typical applications are Express Parcel sorting systems, receiving and shipping systems of Distribution centers.

The most frequently failing mechanical parts include divert shoes, divert switches, merges, crossings and carriers. Parts that fail less frequently include valves, timing belts, photo switches, approximation switches, bearings and brushes. Parts that hardly even fail are the sprockets, chains and the motors, since these are heavily over-dimensioned in order to prevent failures via design (and thus via an additional design-investment).
In terms of data collection, the main disadvantage of the SPO is that it is usually not maintained by an on-site VI team. The maintenance can be executed by VI engineers, local partners, the technical department of the customer, or a combination. This will require that someone has to keep track of all maintenance activities at a certain site. This data would be more reliable with an on-site VI team. A second problem is that customers of SPO's often do not keep track of the operational failures. Therefore, it would be difficult to calculate the total system availability.

There are some additional advantages. Firstly, the SPO is often sold with a full-service contract; which means that VI executes all (at least most) preventive and corrective activities. This increases the reliability of the data.
Another advantage is that the operations of the customer within express parcel are similar: namely the sortation of parcels. This implies that the systems are (1) often very dusty due to wear of the cardboard packages, (2) used twice a day at high capacity for a certain number of hours,

but in between there is planned downtime (thus preventive maintenance actions do not interfere with production).
Final advantage of the SPO is that VI is the only supplier of the critical (spare) parts. This increases the probability that spare parts of the critical components are ordered at VI, thus internal administration can be used from the ERP system. Obviously, there is the possibility that customers repair the parts. This happens for example at UPS (therefore this customer, with over 100 SPO's, cannot be used in this research). However, in combination with a full-service contract, it is very unlikely that customer repair the broken parts.

This combined make the SPO a good case for this thesis.

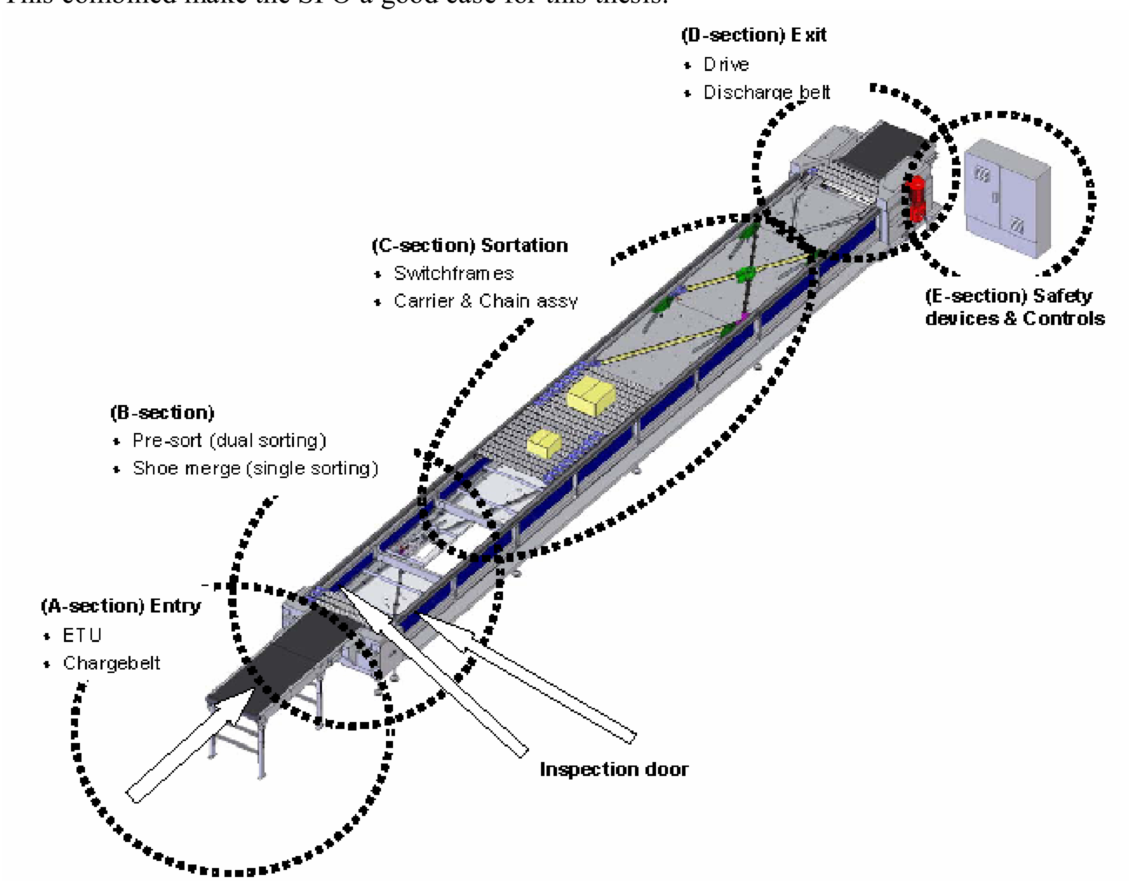



**Figure 39 – The parts of a PosiSorter**

## APPENDIX 5: CRASH VERSUS WEAR

A second difficulty with the spare parts data was to distinguish between crash and wear. Crashes lead to large orders of spare parts, whereas this research focuses on normal wear of parts. Crashes cannot be examined in (this) research, so the data needs to be filtered on crashes. There is no clear distinction between crashes and wear (and tear), and often not possible to point-out one cause directly. This distinction is difficult and debatable. To make the distinction even more complicated; it may have been that additional shoes have been ordered, on the same work-order, but (for example) to place them on stock.

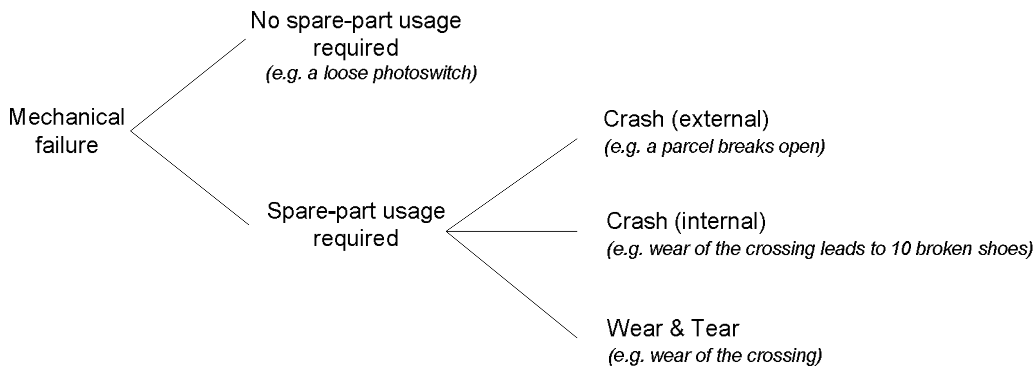



**Figure 40 – This taxonomy shows the potential causes of spare part usage**

First of all, all orders that were attributed to a crash, by the engineer-on-site, are deleted. For example, in some work-orders the reason for a call-out due to ‘opened parcel’, ‘heavy parcel’, or ‘extraneous objects’, or even ‘fork lifts’. So, all spare parts orders with an odd explanation are also deleted. Finally, all work-orders that included carriers are ordered are deleted from the file, since it is very likely that this has been a crash as well.
Unfortunately, this cannot be done by looking descriptions solely. Work-orders are filled up for administrational reasons, and not to serve maintenance analyses, which makes appropriate descriptions (for example ‘reason of replacement’ on the work-orders) often incomplete or inaccurate. Therefore, the distinction between crash and wear had to been made on other grounds. But, this led to definition problem. When is a replacement due to wear? What is a crash? The opinions on this matter vary within VI. For example, the shoes are designed to break whenever the pressure on a shoe gets too high. It is the so-called weakest link and breaks during normal operation. Therefore, small ordered quantities of shoes are considered normal failures, and used in this analysis. However, when the number of ordered components increases, and other critical components are ordered in the same work-order (for example, when 20 shoes and 1 crossing are ordered) it is more likely that the sorter has had a crash. When there has been doubt, the orders have also been deleted.

# APPENDIX 6: SPSS RESULTS

This appendix presents the tables that belong to the analyses of the impact of influencing factors on the spare part demand. Only the models that accurately represent the situation are shown.

## Divert switches demand

**ANOVA[c,d]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 4780,610 | 5 | 956,122 | 3,137 | ,049[a] |
| | Residual | 3657,390 | 12 | 304,783 | | |
| | Total | 8438,000[b] | 17 | | | |

a. Predictors: Length, Number of packages sorted, Maintenance partner, Average speed of the PosiSorter (m/min) , Count of Shutes

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: Divert switch spares

d. Linear Regression through the Origin

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Zero-order | Partial | Part |
| 1 | Maintenance partner | -4,905 | 3,959 | -,643 | -1,239 | ,239 | ,423 | -,337 | -,235 |
| | Number of packages sorted | 1,312E-7 | ,000 | ,715 | 2,073 | ,060 | ,686 | ,513 | ,394 |
| | Average speed of the PosiSorter (m/min) | 10,513 | 11,206 | ,647 | ,938 | ,367 | ,589 | ,261 | ,178 |
| | Count of Shutes | ,061 | ,506 | ,130 | ,121 | ,906 | ,575 | ,035 | ,023 |
| | Length | -1,955 | 6,450 | -,184 | -,303 | ,767 | ,587 | -,087 | -,058 |

a. Dependent Variable: Divert switch spares

b. Linear Regression through the Origin

## On the aggregated demand

**Model Summary**

| Model | R | R Square[b] | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | ,882[a] | ,779 | ,711 | 33,758 | ,779 | 11,442 | 4 | 13 | ,000 |

a. Predictors: Maintenance partner, Hours run (31 march 2009), Length, Capacity

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

**ANOVA[c,d]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 52155,401 | 4 | 13038,850 | 11,442 | ,000[a] |
| | Residual | 14814,599 | 13 | 1139,585 | | |
| | Total | 66970,000[b] | 17 | | | |

a. Predictors: Maintenance partner, Hours run (31 march 2009), Length, Capacity

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: Total number of spares used

d. Linear Regression through the Origin

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Zero-order | Partial | Part |
| 1 | Hours run (31 march 2009) | ,002 | ,001 | ,818 | 3,716 | ,003 | ,800 | ,718 | ,485 |
| | Capacity | 36,955 | 13,962 | 1,269 | 2,647 | ,020 | ,705 | ,592 | ,345 |
| | Length | -22,213 | 12,539 | -,743 | -1,772 | ,100 | ,627 | -,441 | -,231 |
| | Maintenance partner | -12,511 | 5,679 | -,582 | -2,203 | ,046 | ,523 | -,521 | -,287 |

a. Dependent Variable: Total number of spares used

b. Linear Regression through the Origin

## Shoe demand

**Model Summary[c,d]**

| Model | R | R Square[b] | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | ,883[a] | ,780 | ,712 | 13,672 | ,780 | 11,495 | 4 | 13 | ,000 |

a. Predictors: Length, Hours run (31 march 2009), Maintenance partner, Average speed of the PosiSorter (m/min)

b. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

c. Dependent Variable: Shoe spares

d. Linear Regression through the Origin

**ANOVA[c,d]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 8594,978 | 4 | 2148,745 | 11,495 | ,000[a] |
| | Residual | 2430,022 | 13 | 186,925 | | |
| | Total | 11025,000[b] | 17 | | | |

a. Predictors: Length, Hours run (31 march 2009), Maintenance partner, Average speed of the PosiSorter (m/min)

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: Shoe spares

d. Linear Regression through the Origin

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Zero-order | Partial | Part |
| 1 | Maintenance partner | -4,631 | 2,409 | -,531 | -1,923 | ,077 | ,564 | -,471 | -,250 |
| | Hours run (31 march 2009) | ,001 | ,000 | ,815 | 3,702 | ,003 | ,748 | ,716 | ,482 |
| | Average speed of the PosiSorter (m/min) | 26,246 | 7,292 | 1,414 | 3,599 | ,003 | ,712 | ,706 | ,469 |
| | Length | -11,138 | 4,307 | -,919 | -2,586 | ,023 | ,585 | -,583 | -,337 |

a. Dependent Variable: Shoe spares

b. Linear Regression through the Origin

## <u>Crossing demand</u>

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Zero-order | Partial | Part |
| 1 | Hours run (31 march 2009) | ,000 | ,000 | ,710 | 4,037 | ,001 | ,710 | ,710 | ,710 |

a. Dependent Variable: Crossing spares

b. Linear Regression through the Origin

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Correlations | | |
|---|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Zero-order | Partial | Part |
| 1 | Hours run (31 march 2009) | ,001 | ,000 | ,833 | 2,035 | ,065 | ,710 | ,506 | ,388 |
| | Number of Crossings | ,466 | ,788 | ,603 | ,591 | ,566 | ,552 | ,168 | ,113 |
| | Maintenance partner | -1,825 | 2,058 | -,362 | -,887 | ,393 | ,404 | -,248 | -,169 |
| | Average speed of the PosiSorter (m/min) | -,244 | 7,734 | -,023 | -,032 | ,975 | ,440 | -,009 | -,006 |
| | Length | -3,144 | 4,291 | -,449 | -,733 | ,478 | ,457 | -,207 | -,140 |

a. Dependent Variable: Crossing spares

b. Linear Regression through the Origin

**Correlations**

| | | | Planned maintenance visit | Call-out visit | Total number of spares used | Age (in days) | Number of packages sorted | Hours run (31 march 2009) | Average speed of the PosiSorter (m/min) | Capacity | Length of the PosiSorter (m) | Countofsections |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | Planned maintenance visit | Pearson Correlation | 1,000 | -,233 | ,320 | -,109 | ,030 | -,081 | ,600* | ,753** | ,500 | ,334 |
| | | Sig. (2-tailed) | | ,422 | ,264 | ,712 | ,918 | ,782 | ,023 | ,002 | ,069 | ,244 |
| | Call-out visit | Pearson Correlation | -,233 | 1,000 | ,846** | ,633* | ,601* | ,628* | -,361 | -,069 | -,020 | ,206 |
| | | Sig. (2-tailed) | ,422 | | ,000 | ,015 | ,023 | ,016 | ,205 | ,816 | ,947 | ,479 |
| | Total number of spares used | Pearson Correlation | ,320 | ,846** | 1,000 | ,558* | ,602* | ,567* | -,023 | ,346 | ,255 | ,384 |
| | | Sig. (2-tailed) | ,264 | ,000 | | ,038 | ,023 | ,034 | ,938 | ,226 | ,380 | ,176 |
| Age (in days, hours run of packages sorted) | Age (in days) | Pearson Correlation | -,109 | ,633* | ,558* | 1,000 | ,983** | ,992** | -,303 | ,043 | -,043 | ,324 |
| | | Sig. (2-tailed) | ,712 | ,015 | ,038 | | ,000 | ,000 | ,293 | ,883 | ,883 | ,259 |
| | Number of packages sorted | Pearson Correlation | ,030 | ,601* | ,602* | ,983** | 1,000 | ,985** | -,194 | ,190 | ,074 | ,406 |
| | | Sig. (2-tailed) | ,918 | ,023 | ,023 | ,000 | | ,000 | ,505 | ,515 | ,803 | ,150 |
| | Hours run (31 march 2009) | Pearson Correlation | -,081 | ,628* | ,567* | ,992** | ,985** | 1,000 | -,300 | ,031 | -,043 | ,315 |
| | | Sig. (2-tailed) | ,782 | ,016 | ,034 | ,000 | ,000 | | ,297 | ,917 | ,883 | ,273 |
| Independent variables | Average speed of the PosiSorter (m/min) | Pearson Correlation | ,600* | -,361 | -,023 | -,303 | -,194 | -,300 | 1,000 | ,650* | ,245 | ,043 |
| | | Sig. (2-tailed) | ,023 | ,205 | ,938 | ,293 | ,505 | ,297 | | ,012 | ,398 | ,883 |
| | Capacity | Pearson Correlation | ,753** | -,069 | ,346 | ,043 | ,190 | ,031 | ,650* | 1,000 | ,691** | ,542* |
| | | Sig. (2-tailed) | ,002 | ,816 | ,226 | ,883 | ,515 | ,917 | ,012 | | ,006 | ,045 |
| | Length of the PosiSorter (m) | Pearson Correlation | ,500* | -,020 | ,255 | -,043 | ,074 | -,043 | ,245 | ,691** | 1,000 | ,869** |
| | | Sig. (2-tailed) | ,069 | ,947 | ,380 | ,883 | ,803 | ,883 | ,398 | ,006 | | ,000 |
| | Countofsections | Pearson Correlation | ,334 | ,206 | ,384 | ,324 | ,406 | ,315 | ,043 | ,542* | ,869** | 1,000 |
| | | Sig. (2-tailed) | ,244 | ,479 | ,176 | ,259 | ,150 | ,273 | ,883 | ,045 | ,000 | |

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.07 level (2-tailed).

**Figure 41 – The correlation table**

## APPENDIX 7: THE RENEWAL FUNCTION

The expected number of renewals per position is required to calculate the maintenance costs in the model. The renewal process is used to approximate the expected number of failures on a certain position in the system. Let N(t) be the number of renewals during the time (0,t). The inter-arrival times of the failures $X_1$, $X_2$...$X_i$ are identically and independently distributed non-negative random variables (the renewal process is generalization of Poisson processes). M(t) is the expectation of the number of renewals per position of component $x_i$.

$$\mathrm{M(t)} = \mathrm{E[N(t)]} = \sum_{n=1}^{\infty} n \cdot P\{N(t) = n\} \tag{22}$$

The probability of N(t)=n needs to be rewritten before it can be entered into Excel. The expected number of renewals up to time t is $\mathrm{N(t)} = \max\{\mathrm{n}: \mathrm{S_n} \le \mathrm{t}\}$. This equals $P\{N(t) \ge n\} = P\{S_n \le t\}$. The latter formula is used to rewrite the probability of N(t)=n:

$$\mathrm{P\{N(t) = n\} = P\{N(t) \ge n) - P\{N(t) \ge n+1)} \tag{23}$$

$$\mathrm{P\{N(t) = n\} = P\{S_n \le t) - P\{S_{n+1} \le t)} \tag{24}$$

The step is to define $F^{(n)}(t)$, as the n-fold convolution of F(t), presenting the probability that the $n^{th}$ renewal occurs by time t;

$$\mathrm{P\{S_n(t) \le t\} = F^{(n)}(t)} \tag{25}$$

If (5) is entered into (4), then

$$\mathrm{P\{N(t) = n\} = F^{(n)}(t) - F^{(n+1)}(t)} \tag{26}$$

where $F^{(n)}(t)$ is recursively defined as

$$\mathrm{F^{(n)}(t)} = \int_0^t F^{(n-1)}(x)dF(x) \cdot \tag{27}$$

According to Kumar et al. (2006), the formula for expected number of renewals (2) can be simplified to

$$\mathrm{M(t)} = \sum_{n=1}^{\infty} n \cdot \left\{\mathrm{F^{(n)}(t) - F^{(n+1)}(t)}\right\} \tag{28}$$

$$\mathrm{M(t)} = \sum_{n=1}^{\infty} \mathrm{F^{(n)}(t)} \tag{29}$$

Therefore, numerical approximations need to be used to find the renewal function (Smeitink and Dekker, 1990). Many authors approximate this renewal function, but difficulties with these approximations are wide-spread; some are difficult to implement, others are difficult to calculate or require too much calculation for large numbers of t. An overview can be found in Dohi et al. (2002). Another option is to make the continuous function discrete, to ease computational efforts. Osaki et al. (2002) provide a discrete analogy of this function; the so-called renewal probability mass function:

$$\mathrm{M(d)} \;\; = F(d) + F * M(d) = \sum_{i=1}^{d} m(j) \tag{30}$$

where, m(j) (j = 0,1,2… and m(0) = 0) is the probability that the failure occurs at time d. This is calculated by:

$$\mathrm{m(d)} \;\; = f(d) + \sum_{j=1}^{d} m(d-j)f(j) = f(d) + \sum_{j=1}^{d} f(d-j)m(j) \tag{31}$$

This function is programmed in the presented model.

# APPENDIX 8: WEIBULL PLOTTING AND FITTING

This appendix illustrates how the discrete approximation of the pdf can be entered into Weibull ++ to estimate the parameters of a distribution.
The averages of the age categories are used as State End Time. On the right the different analysis options are given. In this case, it is chosen to use the two-parameter Weibull. This leads to the following results:

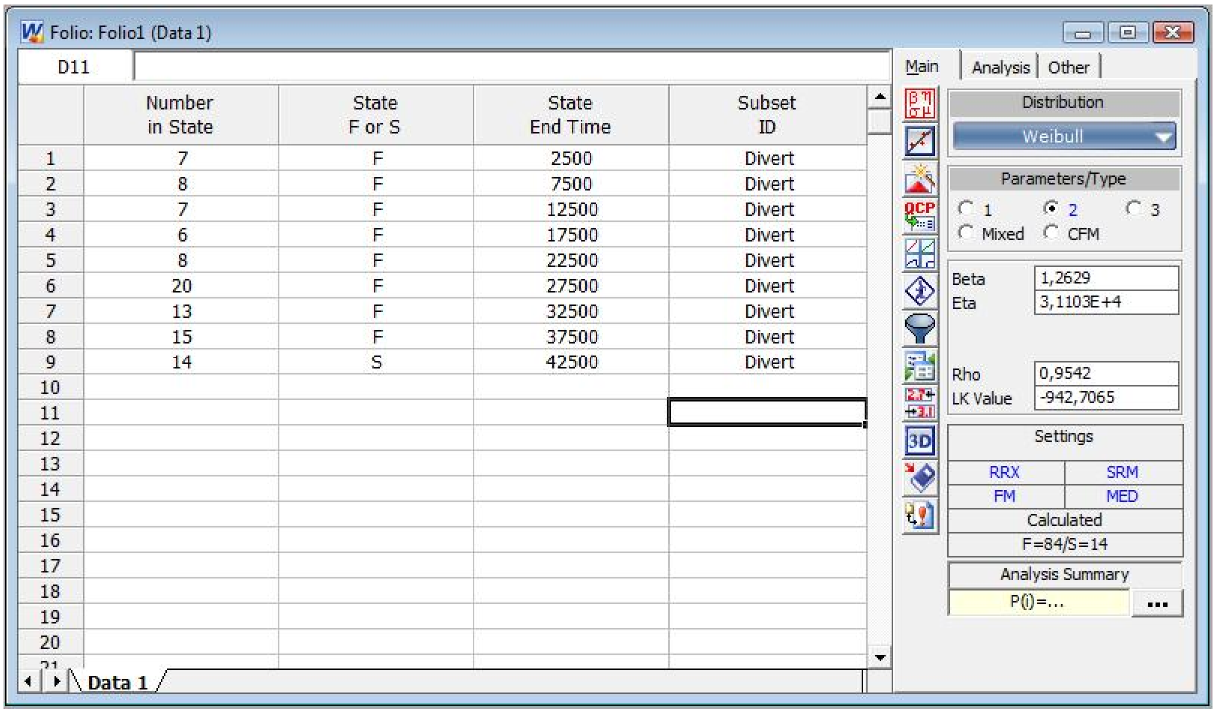
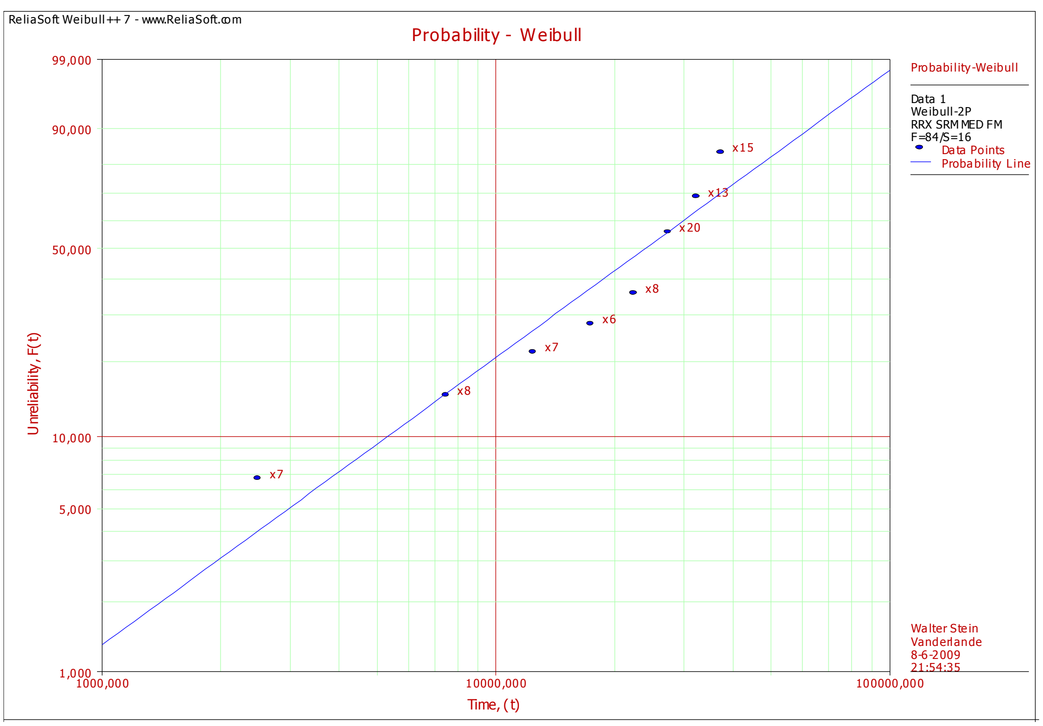



Figure 42 – This is the input window of Weibull++



A Weibull distribution is plotted on specially constructed plotting paper with two logarithmic scales; the Y-axis indicates the unreliability function $F(t_i)$ and the X-axis indicating obtained TTF in terms of $t_i$.

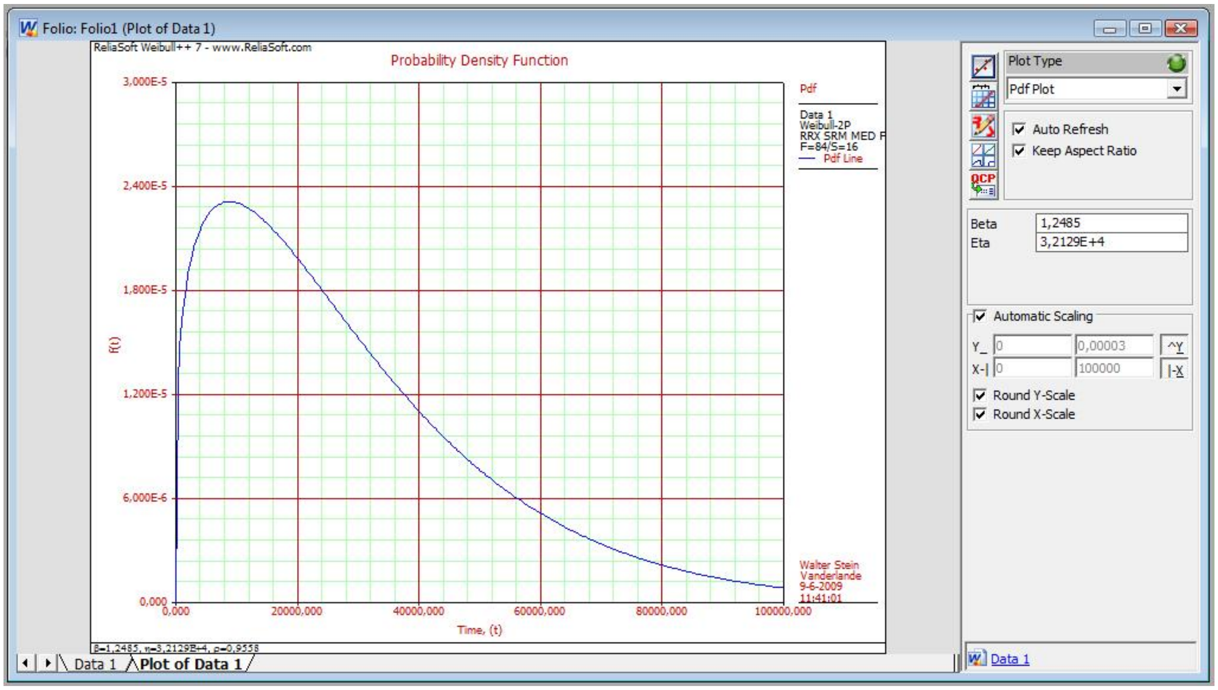



**Figure 43 – The generated results of the fitting exercise by Weibull++.**

It can be seen that plotted line nicely approaches the data points, with this input data this leads to β=1.25 and η=32,130.

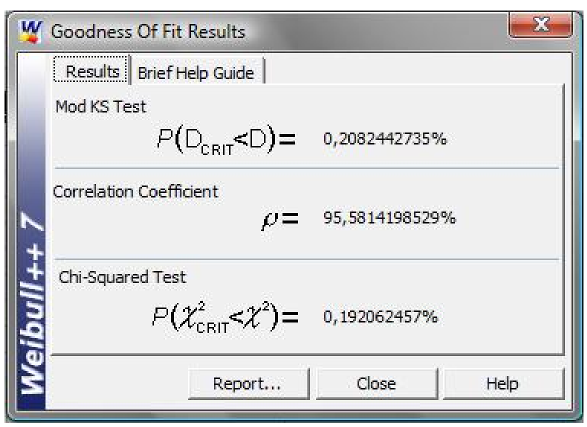



**Figure 44 – The goodness-of-fit tests are automatically generated**

Even though, the line may seem quite straight and the correlation coefficient is rather high, the Kolmogorov-Smirnov test (Mod KS test) is not significant.

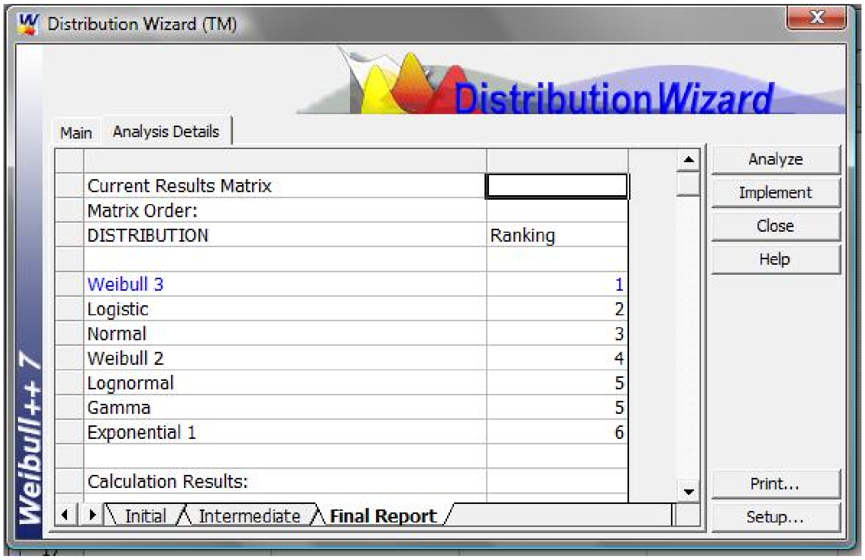



**Figure 45 – The Distribution Wizard of Weibull++ indicates that other distributions may lead to better results**

The engineer has a few options. The first option is to fit the data onto another distribution, such as the Weibull three-parameter or the logistic distribution. During a solid reliability analysis this would probably be the best option, especially when dedicated software programs are used. However, for an initial reliability analysis the Weibull distribution seems to be an appropriate start, as argued in chapter two. Moreover, it can be easily implemented in Excel, so it fits the purpose of this research.

Another look into the data used shows that the number of early failures is rather high. Therefore, it was chosen to see check the data for robustness. For example, what happens to the results when the early failures are deleted from the sample? These results are shown in the figure below.

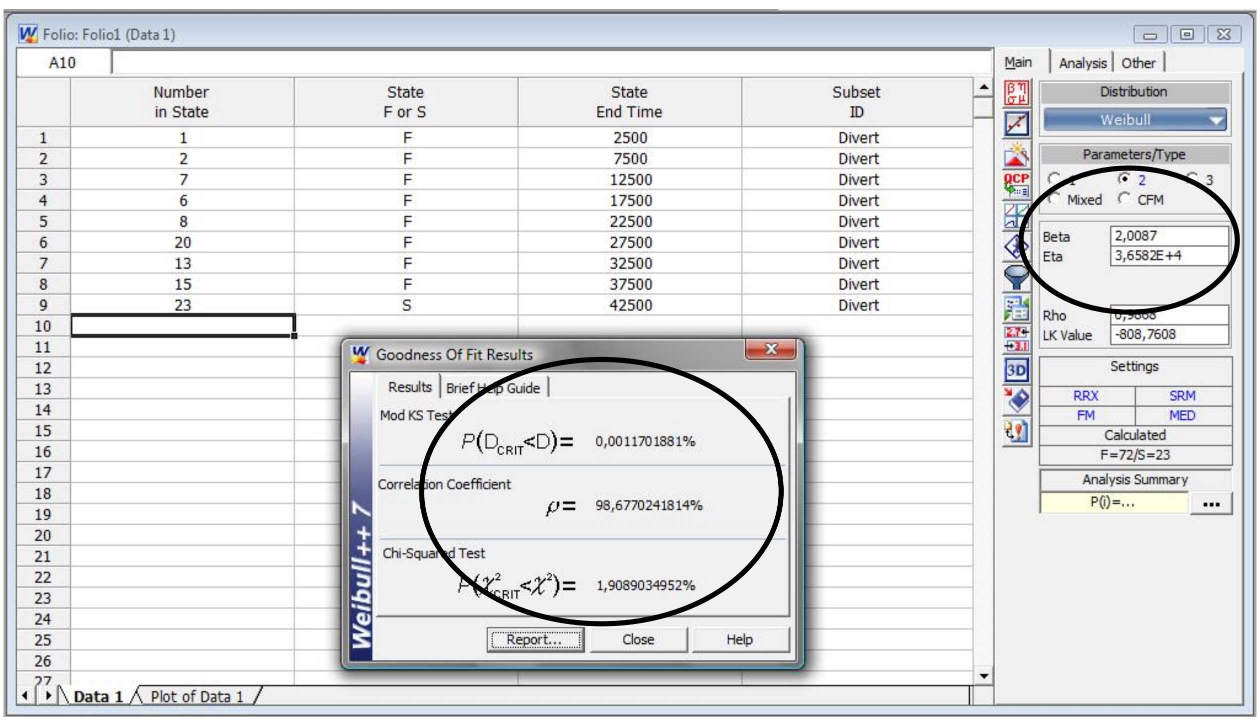



**Figure 46 – The input and the goodness-of-fit windows when the early-failures are deleted**

It can be seen that the results have improved drastically. The goodness-of-fit test is now significant ($p<0,01$) with $\beta=2.00$ and $\eta= 36,580$ (data is found in the circles). The correlation coefficient also increased, and in this case (see below) the line goes nicely through the dots.

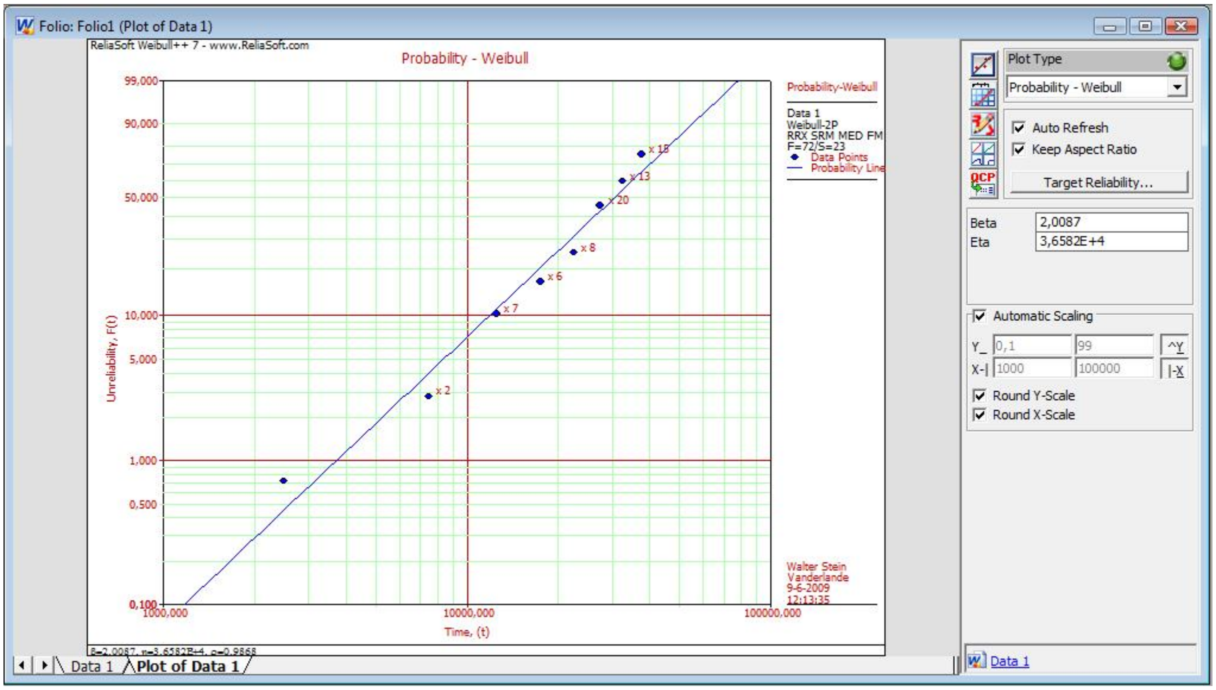
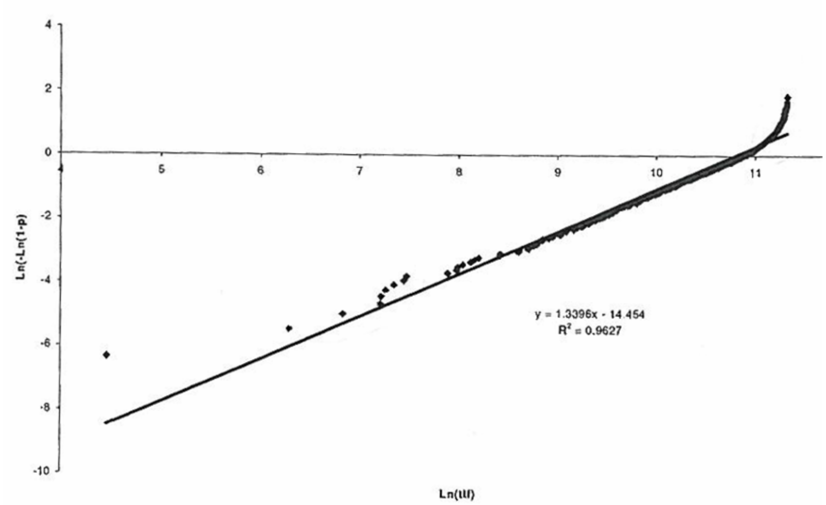



**Figure 47 – The renewed chart, where the early failures are deleted**

This raises the question whether it is allowed to do this? An example of Kumar et al. (2006) suggests that it is possible to have different failures modes presents in only sample (see the figure below). The first failing parts might be the early failures. The second shape are close to the linear line, and a lower shape ($\beta<1.34$). Finally, the steep increase (at the right top) shows failures that are better modeled by a higher shape ($\beta>1.34$). This may indicate that the sample in non-homogenous, or the system may not have obtained a steady-state, or many wear has not been the primary causes of the failures. It can be concluded that there can be several reasons why the early failures bias the results. Therefore, it is chosen to delete the early failures, and increase the survivors.



A more in-depth analysis is of the failure behavior lies beyond the scope of this master thesis, but hopefully it became apparent that there are multiple options to empirically analyze the historical field data. For now, it is presumed that the results above are an appropriate indication of the failure distribution of the crossing, but it is obvious that this will require further research within VI.

It is crucial to have sufficient and accurate life-to-failure data in order to make accurate estimates about the expected longevity of their products. And VI must realize that when the knowledge on lifetime increases, their analyses to spare parts, maintenance, and warranties will also improve.

## APPENDIX 9: COST FUNCTIONS

The following averages are assumed for the cost functions during maintenance handlings:

| | |
|---|---|
| Employee costs | = € 80 per hour |
| Downtime costs | = € 500 per hour |
| Inspection costs four components | = 4 hours with 2 employees |
| Replacement time | |
| Prev | = 0.25 hour |
| Corr | = 1 hour |
| Traveling time | = 2 x 1 hour |
| Emergency fee | = 50% |

This leads to the following cost functions:

Downtime costs = {average downtime} x {average downtime costs}
= {2 hours} x € 500
= € 1.000 per failure

Inspection costs = {average traveling plus inspection time} x {2 engineers} x {employee costs per hour}
= {2 hours traveling plus 4 hours inspection} x 2 x € 80
= € 960 per inspection

Prev. action costs = {average time per replacement} x {cost per hour}
= {0.25 hour} x € 80 x 2
= € 40 per preventive action

Corr. action costs = {average time per call-out} x {cost per hour} x 50% emergency costs
= {2 hours traveling plus 1 hour working} x € 80 x 150%
= € 360 per preventive action (or call-out)

# APPENDIX 10: IMPRESSION OF THE MODEL