Product Lifecycle Optimization using

Dynamic Degradation Models

PRODUCT LIFECYCLE OPTIMIZATION USING

DYNAMIC DEGRADATION MODELS

JOHANNES ADRIANUS VAN DEN BOGAARD

(M.Sc., Technische Universiteit Eindhoven)

A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHYLOSOPHY

DEPARTMENT OF MECHANICAL ENGINEERING

NATIONAL UNIVERSITY OF SINGAPORE

2005

PRODUCT LIFECYCLE OPTIMIZATION USING DYNAMIC DEGRADATION MODELS

Proefschrift

ter verkrijging van de graad van doctor aan de
Technische Universiteit Eindhoven, op gezag van de
Rector Magnificus, prof.dr.ir. C.J. van Duijn, voor een commissie
aangewezen door het College voor
Promoties in het openbaar te verdedigen
op woensdag 4 januari 2006 om 14.00 uur

door

Johannes Adrianus van den Bogaard

geboren te Helmond

Dit proefschrift is goedgekeurd door de promotoren:

prof.dr.ir. A.C. Brombacher
en
prof.dr. T.N. Goh

Copromotor:
dr.ir. J.L. Rouvroye

CIP-DATA LIBRARY TECHNISCHE UNIVERSITEIT EINDHOVEN

Bogaard, Johannes A. van den

Product Lifecycle Optimization using Dynamic Degradation Models. / By Johannes A. van den Bogaard. – Eindhoven : Technische Universiteit Eindhoven, 2006. – Proefschrift. -

ISBN 90-386-0605-2

NUR 964

Keywords: Reliability prediction / reliability optimization / degradation analysis / robust design / design of experiments / preventive maintenance / re-use

Printed by: University Printing Office, Eindhoven.

Acknowledgements

In Holland we have a well-known saying: "*een gewaarschuwd mens telt voor twee*". In short this means that a person that has been warned in advance counts for two, because he knows what to expect. I have been warned. Actually, I have been warned many times to the fact that doing a PhD is very demanding, but also a very rewarding period of time. So, when I started my PhD and Prof. Aarnout Brombacher and A/Prof. Loh Han Tong asked me to start a PhD jointly supervised by the Technische Universiteit Eindhoven (TU/e) and the National University of Singapore (NUS), I was very pleased. Now, at the end of my PhD, I can look back and say that doing a joint PhD has been a very demanding period, but the reward is more than I expected. First of all, I have been able to finish my thesis, which represents almost five years of work. Secondly, I got the chance to work in a multi-disciplinary, international environment together with great people, both from industry and from university. And finally, I hope to be rewarded with the scientific degree of Doctor of Philosophy. However, had it not been for the guidance and support from many, the effort might not have resulted in the great rewards. I would like to take this opportunity to express my appreciation to all of them. However, some of them deserve a special ‘Thank You’.

First, and foremost, I thank Prof. Aarnout Brombacher for his encouraging, enthusiastic, and patient support in the pursuit of this joint-PhD scheme. He not only contributed to the technical content of this research through intensive discussions, but he also offered me the opportunity to be part of a very big scientific and industrial project that enabled testing my theories in practice.

At NUS I want to thank Prof. Loh Han Tong for his support to start this PhD jointly with NUS. His hospitality at the Design Technology Institute (DTI) offered me the chance to collaborate with research engineers leading to fruitful discussions with different and challenging perspectives to my research topic. I also would like to thank Prof. Goh Thong Ngee at NUS and Prof. Henk Corporaal for their help with my thesis. Although their involvement in this project was in the later stage, it was very efficient and productive.

My special thanks go out to Dr. Jaya Schreeram (DTI) and Dr. Jan Rouvroye (TU/e) and Prof. Peter Sander for the time they spent having various discussions with me regarding my work and for their valuable suggestions rendered. Without your endless patience and support the end result would not have been the same. Jaya, thanks for teaching me how to do research.

I would like to convey my gratitude to my industry partners who have been involved directly and indirectly with this research project. Among them, I have to mention Guus Hulsken, Bert Peeters, Theo Theunissen (all Flextronics), Erik Nolting (OCÉ), and Henry Wynn, Alessandro DiBucchianico (Eurandom). It was Guus Hulsken who provided me with the opportunity to get more insight in reliability issues from an industry point of view. Also the numerous discussions we had together with all industrial partners have strengthened the practical applicability of ROMDA.

A number of master students contributed in the research reported in this thesis. I would like to thank all of them. They are Martijn van Hoorn, Ilse de Visser, Mark Damen, and Bart Lamers.

My colleagues in the subdepartment Quality and Reliability Engineering (QRE) at TU/e also gave me much support to work on my thesis. I would like to thank them all for helping me in one way or the other. They include Gembong Baskoro, Aarnout Brombacher, Hanneke Driessen, Roxana Ion, Lu Yuan, Valia Petkova, Jan Rouvroye, Peter Sander, Peter Sonnemans, and Ilse de Visser.

Finally, I have to thank Digipress for designing the cover of this thesis. I must thank my girlfriend Simone for her unfailing encouragement, love, support, and patience. I also owe a great deal of gratitude to my parents and my brother. They have supported me all the time, and their primary concern is always my well being. They always encouraged me to pursue higher education.

Johan van den Bogaard

2006

Table of contents

Summary

Companies have always been interested in optimizing product designs towards quality and reliability. Also maintenance is a major concern for manufacturers producing products where the economical lifetime exceeds the technical lifetime. Maintenance narrows the gap between the economical lifetime and technical lifetime. Especially preventive maintenance can be very attractive for companies. And recently, due to new environmental laws and legislations, which are known under the name "Waste Electrical and Electronic Equipment (WEEE)", companies have to reduce the environmental waste by recycling at least 75% of their complete product materials. A better way to comply with the environmental laws and legislations is by re-using products, systems, or sub-systems instead of recycling and reproducing products, systems, or sub-systems.

The main focus of this thesis is the development of one single method that provides the possibility to tackle the three requirements on product design process (optimization of design towards robust reliability, provide information for preventive maintenance and for re-use decisions) in an effective way without loss of quality of the solution.

In order to be able to develop such a method few steps have been taken. The first important step was to set boundaries for the research area. In summary the most important research boundaries are:

→ This research emphasized on gradual, or degraded, complete and partial extended failures of phase 2 and phase 4 of the roller-coaster curve.

→ This research took into account three causes of variability (unit-to-unit variability, variability due to operating and environmental conditions, and variability due to product degradation)

The next important step was to analyze existing methods that can provide a solution for the three design requirements. The review demonstrated that very useful concepts and ideas are presented in literature, but that not one single available method is able to provide a solution for the three design requirements simultaneously.

This lead to the urge to develop a new theoretical framework called ROMDA. This framework provides in twelve steps an approach for the method targeted in this research. A conceptually new contribution included in this framework is the time-dependent design of experiments.

Based on computer-based simulation experiments it was demonstrated that conceptually it is possible to provide a solution for the three design requirements using one single method. However, a critical analysis of the theoretical approach showed that the results of the theoretical framework could not be directly translated to a practically applicable method.

For this reason a step-by-step practical protocol is developed for ROMDA. This practical protocol takes into account the theoretical framework and all practical limitations of the theoretical approach.

The practical protocol of ROMDA is tested by means of three case studies performed at two different companies. In the first two case studies the purpose was to prove the applicability of the ROMDA practical protocol. The first case study was successful in this. However, the second case study was unsuccessful due to the fact that a wrong failure mechanism was identified as dominant. The consequences of focusing on less dominant failure mechanisms are a waste of money and time in terms of testing equipment and testing time. The third case study focused more on examining the possibility to reduce the risk of concentrating on wrong identification of the dominant failure mechanism. Suggestions have been given and initially tested. The suggested approach could indeed lead to less uncertainty, and therefore less risk, in focusing on non-dominant failure mechanisms.

The results of the computer-based simulation experiments combined with the results of the case studies lead to the conclusion that it is indeed possible to develop an effective single method (ROMDA) that can provide a solution for the three design requirements without loss of quality of the solution. ROMDA is described in both a theoretical framework and in a practical protocol in this thesis. Although the given protocol is already useful, further research is recommended to optimize the ROMDA method itself. Topics to be investigated include:

→ the influence of using other statistical distributions for the design parameters and the performance;

→ the need for and potential use of different reliability characteristics than those used in this research;

→ the potential of using more efficient and more accurate regression modeling techniques;

→ the use of Accelerated Degradation Testing (ADT) strategies instead of compressed-time testing strategies;

→ investigate possibilities to reduce the risk of focusing on non-dominant failure mechanisms.

Samenvatting

Bedrijven zijn van oudsher al geïnteresseerd in het optimaliseren van productontwerpen in termen van kwaliteit en betrouwbaarheid. Daarnaast gaat ook veel aandacht uit naar onderhoud bij producten waar de economische levensduur veel langer is dan de technische levensduur. Vooral preventief onderhoud van deze categorie producten kan voor bedrijven aantrekkelijk zijn. Ten derde is sinds kort grote druk op bedrijven komen te staan door nieuwe milieuwetten en regels. Deze milieuwetten en regels zijn bekend onder de naam "Waste Electrical and Electronic Equipment (WEEE)" and schrijven de betreffende bedrijven voor dat zij ten minste 75% van het complete product materiaal moeten recyclen. Hergebruik van systemen, sub-systemen of modules zou het aanzienlijk makkelijker maken aan de nieuwe milieuwetten en regels te kunnen voldoen.

In deze dissertatie wordt onderzocht of het mogelijk is een methode te ontwikkelen die voor alle drie de eisen aan het productontwerpproces (optimalisatie van het productontwerp in termen van kwaliteit en betrouwbaarheid, preventief onderhoud en hergebruik van delen van een product) een effectieve/efficiënte manier oplossing biedt zonder verlies van kwaliteit van de uitkomsten van de analyses.

Om deze onderzoeksvraag te beantwoorden zijn een aantal stappen genomen. Hierbij was de eerste stap het afbakenen van het onderzoeksgebied. De belangrijkste randvoorwaarden zijn:

→ Dit onderzoek richt zich op graduele, of degraderende, complete en partiële faalmechanismen uit de fase 2 en 4 van de badkuipcurve.

→ Dit onderzoek neemt drie oorzaken van variabiliteit mee, namelijk de product-tot-product variabiliteit, variabiliteit ten gevolge van gebruik en omgevingscondities, en variabiliteit ten gevolge van product degradatie.

De volgende belangrijke stap in dit onderzoek was een uitgebreide analyse te doen van bestaande methoden op (gedeeltelijke) bruikbaarheid voor de drie oplossingsmogelijkheden. Deze analyse leidt tot de conclusie dat er veel bruikbare concepten en ideeën beschreven staan in de literatuur, maar dat niet één enkele methode volledig geschikt is voor de beantwoording van de onderzoeksvraag.

De volgende stap in dit onderzoek was dan ook een nieuw theoretisch concept te ontwikkelen die de naam ROMDA heeft gekregen. Dit concept biedt in twaalf stappen een aanpak dat leidt tot een oplossing voor de drie eisen aan het ontwerpproces. Een conceptueel nieuwe bijdrage in het framewerk is het gebruik van tijdsafhankelijke 'design of experiments'.

Door middel van simulatie experimenten is aangetoond dat het theoretische concept achter ROMDA een oplossing kan bieden voor de drie eisen aan het ontwerpproces. Echter, een kritische analyse laat zien dat het theoretische concept niet direct praktisch toepasbaar is. Samengevat zijn de volgende belemmeringen voor praktische implementatie geïdentificeerd:

Om de verschillen tussen de theorie en de praktijk te overbruggen is een praktisch protocol voor ROMDA ontwikkeld. Dit praktisch protocol is gebaseerd op het theoretische concept van ROMDA, maar biedt stap-voor-stap oplossingen voor de praktische beperkingen van het theoretische concept.

Het praktische protocol van ROMDA is geverifieerd door middel van drie case studies die uitgevoerd zijn bij twee verschillende bedrijven. De eerste twee case studies hadden als doel aan te tonen dat het praktisch protocol van ROMDA werkt in de praktijk. Bij de eerste case studie bleek het practische protocol te werken, maar tijdens de tweede case studie is in de eerste fase van het protocol een verkeerde dominante faalmechanisme geïdentificeerd. De consequentie hiervan is dat alle andere stappen in het protocol op een minder dominante faalmechnisme gericht zijn, wat als inefficiënt en ineffectief in termen van geld en tijd beschouwd kan worden. Het doel van de derde case studie was te onderzoeken hoe het risico van een verkeerde geïdentificeerd dominant faalmechanisme gereduceerd kan worden in toekomstige cases. Suggesties zijn voorgesteld en initieel getest. De voorgestelde suggesties leiden inderdaad tot een afname van het risico om het onderzoek op verkeerde faalmechanisme te richten.

De resultaten van zowel de simulatie experimenten en de case studies leiden tot de conclusie dat het inderdaad mogelijk is een enkelvoudige methode (ROMDA) te ontwikkelen die op een efficiënte en effectieve manier voor alle drie gestelde eisen aan het ontwerpproces een oplossing kan bieden. Bovendien hebben deze oplossingen in ieder geval vergelijkbare oplossingskwaliteit.. Desalniettemin is vervolgonderzoek nodig om de ROMDA methode zelf te optimaliseren. ROMDA is in dit proefschrift beschreven zowel als theoretisch concept en als praktisch protocol. Hoewel het protocol al buikbaar is, is toch verder onderzoek nodig voor de optimalisatie van ROMDA. Onderzoeksonderwerpen daarbij zijn:

→ de invloed op de uitkomsten wanneer andere statistische verdelingen voor ontwerp parameters en prestatie karakteristiek gebruikt worden;

→ de behoefte aan en mogelijkheden van andere betrouwbaarheids-karakteristieken dan de in dit onderzoek gebruikte;

→ de mogelijkheden van accuratere en meer efficiënte modeleringsmethoden;

→ consequenties van het gebruik van Accelerated Degradation Testing ADT test strategieën in plaats van de Compressed-Time test methoden;

→ de mogelijkheden voor het voorkomen van verkeerde conclusies in met name de eerste fase van het ROMDA protocol waar de dominante faalmechanismen worden bepaald.

List of tables

List of figures

List of symbols

R	Reliability
t	Time
λ	Failure rate
D(.)	Degradation Function
N(.)	Normal Distribution
σ	Standard Deviation
ε	Residual Deviation
μ	Statistical Mean
DP	Design Parameter
PC	Performance Characteristic
T	Temperature (K)
E_a	Activation Energy (eV)
k	Boltzmann's constant (V/K)
τ	Target Mean Value
MTTF	Mean Time To Failure
VTTF	Variance Time To Failure
SDTTF	Standard Deviation of Time To Failure

Nomenclatures

ADT	Accelerated Degradation Test
AFT	Accelerated Failure Test
ALT	Accelerated Life Test
AST	Accelerated Stress Test
ANOVA	Analysis of Variance
CCD	Central Composite Design
CDF	Cumulative Distribution Function
CM	Corrective Maintenance
DF	Degree of Freedom
DOE	Design of Experiments
DP	Design Parameter
EET	Ecology, Economy, and Technology
ESS	Environmental Stress Screening
FL	Failure limit
FMEA	Failure Mode and Effects Analysis
FTA	Fault Tree Analysis
HCF	High Capacity Feeder
KPI	Key Performance Indicator
LSE	Least Square Estimation
LSL	Lower Specification Limit
MLE	Maximum Likelihood Estimation
MSA	Measurement System Analysis

MSI	Manual Sheet Input
MTTF	Mean Time To Failure
PDF	Probability Distribution Function
PC	Performance Characteristic
PCP	Product Creation Process
PM	Preventive Maintenance
PWBA	Printed Wire Board Assembly
RA	Region of Acceptance
ROMDA	Concept for Reliability Optimization using Degradation Analysis
RT	Region of Tolerance
RPN	Risk Priority Number
SDTTF	Standard Deviation of Time To Failure
SL	Specification Limit
SPC	Statistical Process Control
SSE	Sum of Squares Error
TSM	Technical Service Manual
TTF	Time-to-failure
USL	Upper Specification Limit
VTTF	Variance of Time To Failure
WEEE	Waste Electrical and Electronic Equipment

1 Introduction

1.1 Introduction

Companies have always been interested in optimizing product designs towards quality and reliability, as literature clearly shows in numerous books (Blischke and Murthy (2000) [BLI00], Phadke (1989) [PHA89], Nelson (1982) [NEL82]) and many conferences (Annual Reliability and Maintainability Symposium (RAMS)) and scientific journals (Quality and Reliability Engineering International (QREI), Reliability Engineering and System Safety (RESS), IEEE Transactions on Reliability).

Also maintenance is a major concern for manufacturers producing products where the economical lifetime[1] exceeds the technical lifetime[2]. Maintenance narrows the gap between the economical lifetime and technical lifetime. A wealth of literature on maintenance related topics can be found (Ebeling (1997) [EBE97], Pecht (1995) [PEC95], Knezevic (1997) [KNE97], Osaki (2002) [OSA02])). Especially preventive maintenance can be very attractive for companies, as explained in the following literature (Gertsbakh (2000) [GER00], Canfield (1986) [CAN86], Legat (1996) [LEG96]).

---

[1] Economic lifetime is defined in this thesis as the average time where it is justified to replace a product for economic reasons [BRO04]

[2] Technical lifetime is defined in this thesis as the average time that a product requires to reach end-of-life due to technical failures [BRO04]

And recently, due to new environmental laws and legislations, which are known under the name "Waste Electrical and Electronic Equipment (WEEE)" enacted by the directive of the European Parliament and of the council on waste electrical and electronic equipment, companies have to reduce the environmental waste by recycling at least 75%[3] of their complete product materials. A better way to comply with the environmental laws and legislations is by re-using products, systems, or sub-systems instead of recycling and reproducing products, systems, or sub-systems (Hulsken, et al. (2003) [HUL03], Lambert (1999) [LAM99]).

Optimization of product designs towards reliability, providing information necessary for optimal preventive maintenance decisions, and providing information enabling optimal re-use decisions are three design requirements for companies that are currently tackled separately. However, the three design requirements are closely related in terms of information needed to provide a solution for them separately. For all three design requirements the designer is required to know the time-dependent functional behavior of the products in relation to its specification limits, as will be explained in more detail in chapter two. And in order to optimize a design with respect to reliability, it is necessary for the designer to know how the behavior, or performance, over time with respect to the specification limits of the products can be influenced by design changes. The main goal of this thesis is to investigate the possibility to tackle the three above-mentioned design requirements within one method.

In order to put the contents of this thesis in perspective, section 1.2. first provides a short description of the research framework. The next section elaborates on

[3] Article 7a of the Official Journal of the European Union enacted by the directive of the European Parliament and of the council on waste electrical and electronic equipment (WEEE), 2003

the problem definition, the research objective of this thesis and the research questions that need to be answered in order to reach the research objective. Section 1.4 gives a brief overview of the research methodologies that have been used with the intention to answer the research questions. Finally, section 1.5 provides an overview of the structure of the rest of the thesis.

1.2 Research framework

The research of this thesis focuses on the possibility to tackle the next three design requirements:

→ Optimization of product design towards robust reliability

→ Provide information enabling decisions on re-use of systems or sub-systems

→ Provide information necessary for optimal preventive maintenance decisions

The combination of optimization of a product design towards reliability on one hand, and provide information for optimal preventive maintenance decisions and provide information enabling optimal re-use decisions on the other hand, leads to the necessity to consider after sales activities in the design phase. Optimization of a product design can be done in many ways. Chapter two provides the definition of optimization towards reliability in this research.

Three areas of interest in the field of quality and reliability are currently being tackled separately, in different stages of the product lifecycle. It could be beneficial to investigate if these three areas of interest have something in common that could lead to a more efficient and effective new approach leading to useful solutions. The main goal of the research described in this thesis is defined as to investigate the possibility to tackle the three design requirements using one method. A natural question would be why to tackle the three design requirements using one method. Intuitively, one can imagine that providing a solution for multiple goals at once might just be more efficient than solving them separately. As an example, imagine the following:

→ Currently to optimize a product design towards reliability method A is used.

→ Currently to make preventive maintenance decisions method B is used.

→ Currently to make re-use decisions method C is used.

Imagine a new method, method D, provides the possibility to solve for the three design requirements using only method D. Then the following pre-conditions illustrated by the next equations need to be satisfied in order to make method D beneficial compared to performing method A, B, and C separately. These equations are illustrative examples, but will not be treated as mathematical quantities.

$$EFFORT\ (D) < EFFORT\ (A + B + C)$$

And

$$QUALITY\ SOLUTION\ (D) \geq QUALITY\ SOLUTION\ (A) + QUALITY\ SOLUTION\ (B) + QUALITY\ SOLUTION\ (C)$$

Effort in this context means the effort it takes to perform a method in terms of time and costs. So, in other words, performing method D should be less time-consuming and more cost-effective than performing methods A, B, and C separately. And this should be done in such a way that at least the same quality of solution can be guaranteed using method D in comparison to using method A, B, and C separately. “Quality Solution” means the quality of the solution for the specific goals. Method A refers to optimization of a product design and, therefore, method A provides an optimum performance of the product in terms of reliability. Method D should at least provide the same optimum with respect to reliability behavior of the design as method A does. The same line of reasoning can be followed for methods B and C compared to method D.

The relevance for both the industry and science of the research described in this thesis is clearly illustrated by big research projects like the “Signature Analysis” project that is partly funded by the Ecology, Economy, and Technology (EET) programme of the Dutch Ministry of Economic Affairs (EET Grant EETK 20037) and partly funded by Flextronics. In this project the possibilities of finding signals, or signatures, of products that could be used for estimating the functional behavior of products over time is being researched. With these signals, or signatures, it would become possible to gather enough information to make preventive maintenance and/or re-use decisions. And ideally, this information should already be obtained in the design phase making optimization of product designs towards reliability possible. The Signature Analysis project is a joint project between industry, Flextronics and OCE BV, and scientific research institutions, like TU/e, Eurandom, and Design Technology Institute (DTI).

The next section focuses on the problem definition that is researched in this thesis. The problem definition is then translated to a research objective that can be achieved by answering the presented research questions.

1.3 Problem definition, research question, and research objectives

Problem definition

Currently, companies tackle the three design requirements separately in different stages of the product lifecycle. In other words, they optimize the product designs in the design phase. And later in the product lifecycle, they concentrate on methods and tools to make preventive maintenance and re-use decisions of systems, or modules, possible. Intuitively, one could say this approach is ineffective and inefficient in terms of time and costs, as discussed section 1.2. Therefore, the problem definition for this thesis is:

> *The three design requirements (optimization of product design towards robust reliability, provide information enabling re-use of systems or sub-systems, and provide information necessary for optimal preventive maintenance decisions) need to be tackled more effectively and efficiently.*

Research objective

An intuitively more effective and efficient approach to solve for the three design requirements is to tackle the three design requirements using one method. At the cost of some extra time and money in the initial phases this method is expected to provide enough information to optimize the product design and simultaneously provide enough information to make preventive maintenance and re-use decisions.

The problem definition stated above leads to the following research objective:

Develop a method that is applicable by designers that offers the possibility to tackle the three design requirements using one method such that it is more effective than tackling the three design requirements separately, without loss of quality of the solutions.

Research questions

The research objective defined above describes a challenging objective including many facets that need to be considered. The research objective can be translated into a main research question:

Is it possible to develop a method that provides the possibility to tackle the three design requirements in an effective way without loss of quality of the solution?

In order to make it possible to answer this main research question sub-research questions are defined to structure the research to smaller objectives. The first sub-research question that needs to be answered in order to answer the main research question is:

Is it possible to specify the link between the information required to solve for the design requirements separately?

In order to be more effective using one method than using separate methods to solve for the three design requirements it is necessary that some link exists between the design requirements. Obviously, as already insinuated in section 1.1 and 1.2, it can be expected that a link exists in terms of information that is needed to solve for the design requirements. The purpose of this sub-research question is to define the exact link between the required information. With the answer to this question it becomes possible to examine methods in literature that could be useful in developing a new method.

When the necessary information is known and this information can somehow be linked, the next essential thing to know in order to answer the main research question is whether any methods in literature provide a way of linking this information and, therefore, provide a method to tackle all three design requirements in one effort. This leads to the following sub-question:

Are methods available in literature that take into account the required information for the three design requirements?

If the answer to this sub-research question is yes, then the main research question can be answered positively, because it would mean that a useful method already exists in literature. If the answer is no, the next question is which methods, concepts, or ideas of available methods in literature can provide a basis for a new method that can take the necessary information for the three design requirements into account. And what adjustments to these methods, concepts, or ideas are necessary for such a new method to fulfill the requirements? This leads to the following sub-question:

Which methods, concepts, or ideas available in literature could serve as a basis for a new method and what adjustments are necessary *taking into account the required information for the three design requirements?*

Literature provides a wealth of methods and tools in the area of quality and reliability. All these methods have their own strengths and weaknesses. Therefore, it is considered logical and important to first survey these available methods and analyze their strengths and weaknesses. The next thing would be to combine all strengths of useful methods and therefore reduce the weaknesses of a new method that enables the designers to tackle the three design requirements. It is highly likely that combining methods is not enough to meet the research objective. It is more likely that adjustments are necessary. When a new method is developed, the question arises if the newly developed method really works as desired. This then has to be proven by scientific research. So, the next sub-question is:

Can it be proven that the newly developed method can indeed tackle all three design requirements using just one method in a more effective and efficient way?

When this question can also be answered positively, then the main research question can also be answered positively.

With the purpose of providing answers to all the above-presented research questions, a certain sequence of steps is taken and certain research methodologies have been used. The next section provides a description of a research design of the complete research project and the research methodologies that have been used for this research.

1.4 Research methodology

This section gives an overview of the research methodology that is used. The overview starts by defining the form of the research. The next part presents the research design. This part also discusses the research methods that have been used in the research in order to provide answers for the research questions.

Primitive forms of research

De Leeuw (1996) [LEE96] describes two primitive forms of research, the *empirical cycle* (De Groot, 1994 [GRO94]; De Leeuw, 1996 [LEE96]) and the *regulative cycle* (Van Strien, 1986 [STR86]).

In the empirical cycle the researcher starts collecting facts from a knowledge reservoir to create a theoretical framework for his research. With this knowledge the researcher constructs hypotheses and derives predictions from these hypotheses. The predictions are then tested in an empirical environment by conducting a case study or an experiment. Finally the researcher evaluates the new empirical material and reports his findings that can be added to the knowledge reservoir.

The regulative cycle uses a different approach when it comes to practice and the knowledge reservoir. First the researcher starts with exploring the problem in an organization. When the problem is known the knowledge reservoir is consulted to define a solution for the problems of the organization. The regulative cycle results in a solution, based on scientific knowledge, which is implemented in the organization.

A regulative cycle results in a solution for one single company. The main objective of this research is to develop a theory that can be applied in a broad domain, and therefore this research follows the empirical cycle.

The next section sketches the outline of the research design and describes the consequences for the research methodology of this choice.

Research design

The main determinant for the research domain is the result, which is the end of the empirical cycle. The result of this research is a theory that is tested by empirical observations. There are several methodological approaches to test a theory, such as an experiment, a survey or a case study [VER99]. In this research two research methodologies have been selected. Firstly, a computer simulation experiment has been selected. The reasons behind this choice are:

→ The most important advantage of computer simulation is that various alterations to the model (the intervention) can be made relatively easily and cheaply.

→ The effects to occur due to intervention using computer simulation take a very limited time-span.

→ Intermediate results that are unavailable in case studies can be observed in computer simulation experiments.

So, basically computer simulation experiments can give a good insight in a model in a very short time-span.

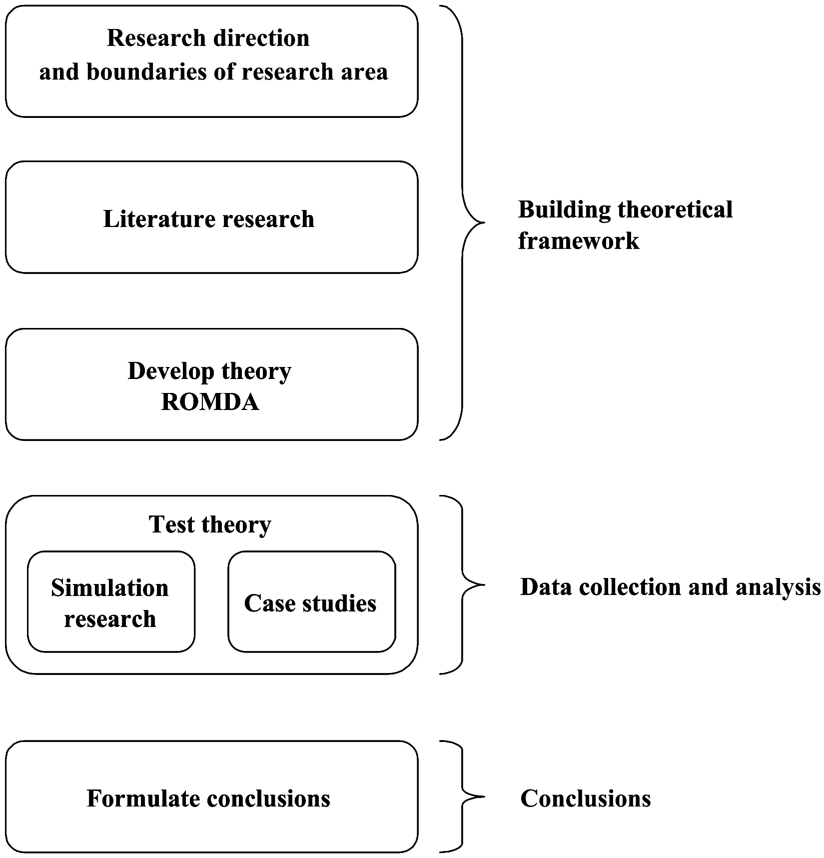


Figure 1.1: Outline of research.

The second research methodology that has been used in this research is the case study. The reasons for this choice are:

→ The case study offers the possibility to gain an overall picture of the research object.

→ The degree of pre-structuring is far less than using a survey or an experiment. As a result, the case study is far more flexible in comparison with the other strategies.

→ It is not only of interest to know if the newly developed method really works, but also the conditions in which the method works are of interest. Hence, more in-depth research is required.

→ In this research the case study is used to test, or validate, the theory or method that has been developed.

An outline of the research design is presented in figure 1.1.

The research design consists of 5 steps. The goal of the first step is to define the research direction and the boundaries of the research area. Chapter one and chapter two present the results of this step. Chapter one defines the research objectives and chapter two basically defines the direction of the research and the boundaries of the research area. The next step in the research design is a literature research. The literature research has two purposes. First of all, it is researched if literature provides methods that solve, or partly solve, the research questions that have been defined in chapter one. The second purpose of the literature research is to examine possible useful ideas or concepts that could be used in the theory development step, which is step three in the research design. The fourth step concerns the collection of empirical data. For collecting the empirical data the computer simulation experiment and the case study approach is used, as mentioned in the introduction of this section. The last step in the research design is the evaluation of the findings and finally the drawing of conclusions. The conclusions are formulated by reviewing all the facts that follow from the research methods. Generalization of the results to other domains is discussed. This discussion leads to recommendations for further research.

1.5 Structure of thesis

The remainder of this dissertation consists of 7 chapters that can roughly be divided in three parts, as was shown in figure 1.1. In part one (covered by chapter 2, 3, 4, and 6) the theoretical framework is built. In part two (covered by chapter 5 and 7) simulation experiments and the collection of empirical data using case studies is described; it describes the results of the simulations experiments and the three case studies. In part three (covered by chapter 8) the data from the case studies is analyzed resulting in conclusions of this research.

2 Research topic

Chapter one stressed that quality and reliability related topics in the form of the three design requirements are relevant topics for research. This chapter focuses on the type of products and failure mechanisms that are taken into account in the theory development in chapter 4. In order to develop quality and reliability related methods meeting the earlier stated requirements, it is considered essential to start by giving the most important definitions used in the area of quality and reliability. The next section translates the research objective and research questions to a more technical perspective within the quality and reliability area. For this purpose a well-known book written by Spence and Soin [SPE88] will be used. This section implicitly explains some of the boundaries that apply for this research. The next section presents more boundaries of research in terms of a classification of failure mechanisms using two classification systems, namely one developed by Blache and Shrivastava (1996) [BLA94] and the roller-coaster curve developed by Wong (1988) [WON88]. The rest of this chapter is more focussed on solution directions. First the focus will be on the connection of necessary information between the three design requirements. The connection between these information needs is then discussed. The necessary information and the connection between the necessary information lead to a solution direction. Finally, this theoretical solution direction is discussed in the last section.

2.1 Definitions

When a system, product or component ceases to perform its intended function we speak of a failure. Kumar and Crocker (2000) [KUM00] use the following definition of the **failure** of a system:

Any event or collection of events that causes the system to lose its functionability

where **functionability** is defined as [KUM00]:

The inherent characteristic of a product related to its ability to perform a specified function according to the specified requirements under the specified operating conditions

The definition of failure in combination with the definition of functionability is closely related to the definition of quality. A commonly used definition of **quality** is [GAR88]:

Quality [means] conformance to requirements

According to Lewis [LEW96] the definition of quality leads to two related considerations:

1. Quality is associated with the ability to design products that incorporate characteristics and features that are highly optimized to meet customer’s needs and desires.
2. Quality is associated with the reduction of variability in these performance characteristics and features.

The first consideration speaks for itself. Products generally are designed to meet customer’s needs and desires in an optimal way considering all constraints that are applicable for designing products.

The second consideration underlines the influence of variability on the performance characteristics. Two possible causes for variability are:

→ Unit-to-unit variability

→ Variability due to operating and environmental conditions

Generally, the product variabilities arising from lack of precision or deficiencies in manufacturing processes may lead to failures or infant mortality [LEW96]. But also variability due to operating and environmental conditions may lead to failures. A product is designed for a certain task, but customers could use the product for different, and often unexpected, purposes. An example of variability in operating conditions could be the differences between heavy users and light users. Heavy users could be car drivers driving 60.000 kilometers a year, while light users drive 5.000 kilometers a year. It is easy to imagine the influence of variability due to environmental conditions on the performance characteristics of products. Copier machines are used in offices, but also on the manufacturing floor in the Netherlands, but also in Ethiopia, where the weather is clearly less humid and dustier compared to the weather in the Netherlands.

Quality is often confused with reliability. Although these terms are strongly related, they both describe a different concept. In this thesis, **reliability** will be defined as [LEW96]:

Reliability is the probability that a system will perform its intended function for a specified period of time under a given set of conditions.

Improving product reliability is an important part of the larger overall picture of improving product quality, which leads to the idea that "reliability is quality over time," as Condra [CON01] emphasized.

Reliability can quantitatively be defined in terms of the Probability Density Function (PDF) and the Cumulative Density Function (CDF) for the time-to-failure.

The CDF, F(t), is defined as the probability that an item operating at time t=0 under stated conditions fails at or before time t. The following must hold true for the probability of survival, reliability R(t) and the probability of failure F(t):

$$R(t) + F(t) = 1 \tag{2.1}$$

The PDF for the time-to-failure, f(t), describes the probability that an item, functioning at time t=0, will fail in an interval *dt* at some point in time. Mathematically this is the first derivative of F(t), so:

$$f(t) = {}^{dF(t)}\!\big/_{dt} \qquad \text{or,} \tag{2.2}$$

$$f(t) = -\frac{d}{dt}R(t) \tag{2.3}$$

Using this last equation 2.3 another frequently used reliability parameter, the failure rate, can be defined as:

$$\lambda(t) = \frac{f(t)}{R(t)} = -\frac{1}{R(t)}\frac{d}{dt}R(t) \tag{2.4}$$

The failure rate λ(t) goes under a variety of other names like [JEN82]:

→ Hazard rate

→ Instantaneous hazard rate

→ Instantaneous failure rate

→ Age-specific failure rate

→ Mortality rate

In this thesis only the terms failure rate and hazard rate will be used.

Another commonly used term in this thesis and in the field of quality and reliability is robust design. A **robust design** may be defined as one for which the performance characteristics are very insensitive to variations in the manufacturing process, variability in environmental operating conditions, and deterioration with age [LEW96]. A more detailed description of robust design methods and approaches will be discussed in chapter 3.

This section gives the definitions of the most basic and often used definitions in the field of quality and reliability. Other terms or definitions will be given when the text requires these definitions.

2.2 Translation of research objective to theoretical framework

Chapter one describes the research objective of this research. The research objective is translated into research questions. This section provides a more in-depth discussion on the technical meaning of the research objective. For the purpose of explaining the technical meaning of the research objective some concepts of the book "*Tolerance Design of Electronic Circuits*" by Spence and Soin 1997 [SPE97] are used.

The authors explain that as a consequence of the tolerances associated with all manufacturing components sometimes the specifications laid down by the customer will be violated. As a result the manufacturing yield[4] is less than 100%, which is undesirable, or even unacceptable.

In order to understand the theory presented by Spence and Soin, some definitions are provided next.

The first definition that is important for the discussion of the theory is the term **tolerance region**. **Tolerance region** (R_T) is defined as [SPE97]:

> *A rectangular region defined by the nominal values and tolerances of the parameters in the* ***parameter space.***

When really considering the probability density distributions of the parameters in the parameter space a rectangle is not the best representation. Better would be an elliptical shape, but for explanation purposes a rectangle is used in the figures.

---

[4] Manufacturing yield can be defined as the fraction of manufactured systems that satisfies the specifications [SPE97].

The **parameter space** has as many dimensions as there are parameters in the system and in which, as a consequence, a single point represents a single system.

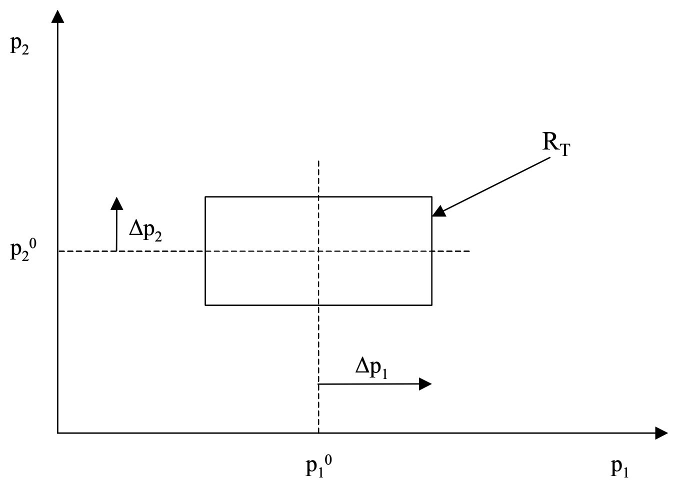


Figure 2.1: Tolerance region (RT) in parameter space [SPE97].

Most systems contain more than just two parameters, so that parameter space has many dimensions. Visualization then becomes very difficult, or maybe even impossible. Because of this in the illustrations only 2 parameter systems will be used. However, the line of reasoning is identical for the multi-parameter situation.

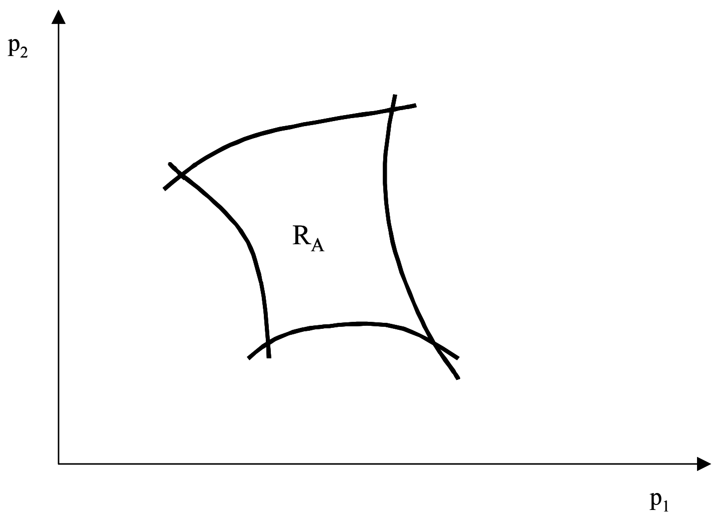


Figure 2.2: Region of acceptability in parameter space.

Customers, although usually implicitly, provide specifications on system performance by means of upper and/or lower bounds of acceptability on system performance. However, the **performance space** (sometimes called 'output space') is not the same as the **parameter space** (sometimes called the 'input space') within which we have, readily available, a simple description (R_T) of the bounds within which the manufactured systems lie. The specifications in the performance space have to be projected into the parameter space for the purpose of comparing the tolerance region (R_T), in which all manufactured products are located, and the **region of acceptability** (R_A), in which all acceptable products are located.

When both the tolerance region R_T and the region of acceptability R_A are displayed in the parameter space, useful insight can be gained into the unwanted effects of component tolerances. This is illustrated by figure 2.3. The dots in figure 2.3 represent the manufactured systems.

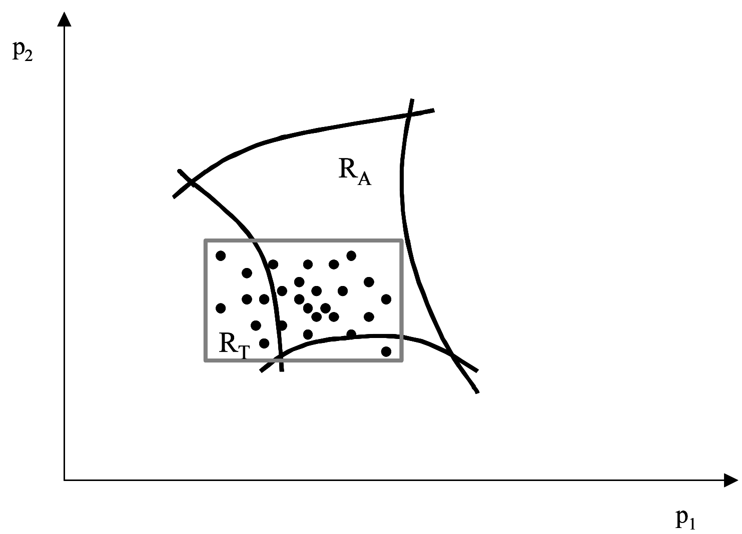


Figure 2.3: Some manufactured systems fail the specifications.

Figure 2.3 clearly shows that the manufacturing yield is less than 100%.

The purpose of tolerance design is to improve the design in terms of the manufacturing yield. A simple means of increasing the manufacturing yield is to adjust the *nominal* values of the parameters, while leaving their tolerances fixed, so that R_T is more centrally located within R_A. Such an adjustment of the parameter values to increase the manufacturing yield is called **design centring**, as Spence and Soin [SPE97] explain.

Having centred the design, and achieved a greater yield, it is appropriate to direct attention to parameter tolerances. However, it should be noted that tightening the tolerances will lead to 100% yield, but the costs to the customer will be higher since the cost of a component is typically an inverse function of its tolerance [SPE97].

In very introductory words tolerance design is explained in this section. Generally speaking, tolerance design is very appealing for optimization purposes of the product design once a design concept has been chosen. A clear link between the parameters and their tolerances and the performance of the systems make design optimization possible. But note that tolerance design is only directed to time-independent performance of the systems. The purpose of the optimization in tolerance design is to optimize the performance of the system at time t=0 (manufacturing yield). And, when looking at the objective of this research project, time is a very important factor.

Translating the objective of this research using the concepts of tolerance design would mean that the tolerance region would move over time as a result of degradation of the manufactured systems over time. And therefore, the optimization objective is not to optimize the design in terms of yield at time t=0 only, but also in terms of performance over time. Figure 2.4 gives an example of how the time-dependent performance of the systems could influence the tolerance region of the systems.

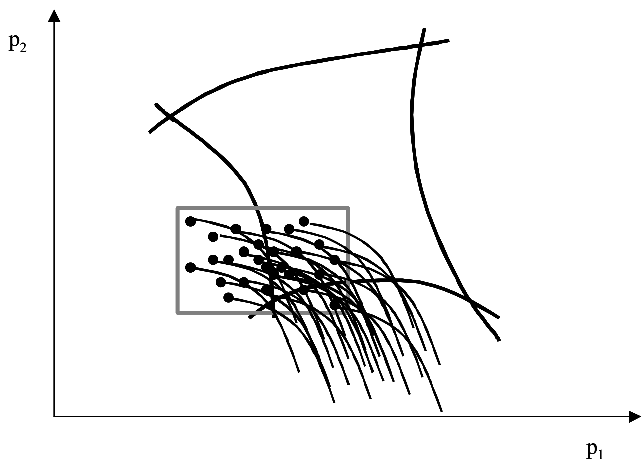


Figure 2.4: Systems degrading over time in the parameter space.

In figure 2.4 the value of parameter p_1 increases over time and the value of parameter p_2 decreases over time. Using the tolerance design optimization methodology, where the nominal values of the parameters are adjusted, the tolerance region would be centered giving the highest manufacturing yield. However, as can be seen in example figure 2.5a, many systems start failing after some time, where time could either be calendar time or in terms of usage (e.g. number of cycles). In this figure the more realistic elliptical curves have been used.

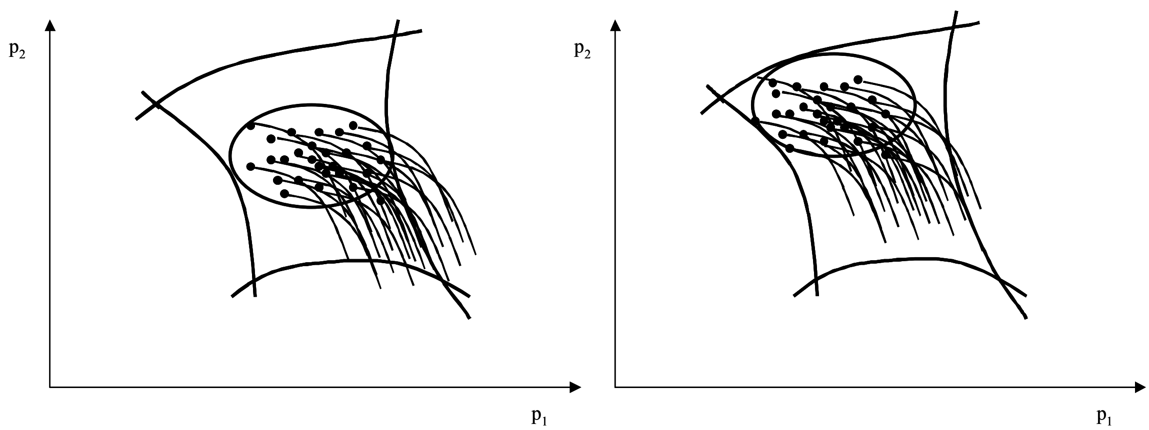


Figure 2.5:

a) *Optimized design using design centering.*

b) *Optimized design taking into account degradation over time.*

When the direction of the degradation of the systems in terms of the parameters is known, it would be better to optimize the design in such a way that not only the yield is maximum at time $t = 0$, but stays maximum over time. Therefore, the design shown in figure 2.5b would perform better over time than the design shown in figure 2.5a.

In conclusion, the first design requirement of the research objective is not directly satisfied by tolerance design, because tolerance design does not take into account the effects of degradation over time. However, the ideas behind tolerance design are still very appealing due to the fact that the effects of parameters and their tolerances are included in the optimization of the performance of a population of systems or products.

The above stated conclusion is clear in relation with the description of tolerance design. However, it should be emphasized that the interesting part of the explanation lies in the fact that it focuses on degradation of design parameters instead of degradation of only the performance characteristic. This approach can provide major advantages in finding a solution for the research objective of this thesis. In order to explain this, a line of reasoning will be given focusing on the separate design requirements.

Optimization of product design towards robust reliability

Design optimization towards robust reliability can be done in many ways. Chapter 3 provides an extensive description on the many possible methods that could be used. A very appealing method for design optimization toward robust reliability was presented by Tseng et al [TSE94]. They link design to reliability using Design of Experiments in combination with degradation tests. The authors optimize the design in terms of initial design parameter value settings. This will be explained in more detail in chapter 3. But one of the disadvantages of the method is that they do not take the degradation of the design parameters into account, and only focus on the degradation profiles of the performance characteristic. But, as explained previously in this section, it would be very beneficial to combine the ideas behind tolerance design with degradation analysis giving better optimization opportunities. But to do so, the degradation profiles of the design parameters have to be taken into account.

One of the requirements for a new method to meet the objective stated in chapter one is that the solution quality of the new method should at least be equal to currently used methods. Without the use of the time-dependence of the physical design parameters, which is suggested here, but just the initial values in relation with reliability characteristics, at least equal solution quality can be guaranteed using the new method compared to methods like the ones introduced by Tseng et al [TSE94].

Although the main focus of this research is not to develop a better optimization method, but to combine three design requirements, it is clear that this might be possible with an approach using the extra information of the degrading design parameters.

Provide information necessary for optimal preventive maintenance decisions

When decisions on preventive maintenance have to be made on a complete population of a product, it suffices for a service engineer to know when the products start to fail. Statistical failure data would be enough detail. This is cost effective when the products, parts or modules are cheap or easy (and therefore cheap) to replace. However, in complex, or expensive product, parts or modules, it is highly possible that a technically well-functioning product is discarded when only statistical failure data is used. Then it could be beneficial to use degradation data on individual product level that is being monitored during operations. In other words, the service engineers need to know the status, or condition, of the product at all time to be able to make optimal preventive maintenance decisions. A large variety of literature on condition monitoring related methods is available. This will be discussed in chapter 3. A problem that often makes condition monitoring on the performance of a product difficult is the fact that performance characteristics are often very hard to measure, or to monitor online.

Consider for example of the braking system of a car. The real performance characteristic of a brake is the braking power. However, measuring braking power is very difficult and can only be done in a service garage with special, and expensive equipment. It would be much easier if certain physical properties, or parameters, could be monitored that offer the possibility to say something about the condition of the braking system. Examples of easier measurable physical parameters could be the brake disk thickness, the margin between the piston and the brake, and so on. When the relationship between these physical parameters and the performance characteristic of the brake system is known, then it would be possible, by measuring the physical parameters, to say something about the status of performance of the system. But to do so, information is needed on the time-dependent behaviour of these physical parameters. This links back to the description, and advantages, of tolerance design in relation with the time-dependent parameter behaviour as presented in this section.

Provide information enabling decisions on re-use of systems or sub-systems

A similar line of reasoning as given for the design requirement on preventive maintenance can be used for the third design requirement. Statistical failure data only provides the possibility to make re-use decisions on complete product population level. As explained before, this might be a big disadvantage for expensive, or measurably difficult products.

Therefore, having information on the condition of a product makes re-use decisions on individual product level possible. Also here it might be very difficult to measure the performance characteristic of a product. When the relationship between the performance of the product and its physical parameters is known over time, it would suffice to just measure the physical parameters to judge the condition of the product and, therefore, enabling service engineers to make a good decision on re-use possibilities. These are most often easier to measure than the performance characteristic of the product, which eventually results in faster and cheaper tests.

The brief discussion on the three design requirements in relation with the description of tolerance design shows the advantages that could be gained by also using the time-dependent parameter information. For this reason these arguments will be taken into account in chapter four, where the newly developed method is presented.

2.3 Failure Classification

2.3.1 Failure classification from Blache and Shrivastava, 1994

A product is considered to be reliable, according to the definition, when it performs its intended function under operating conditions for a specified period of time. When this is not the case, the product fails. This section provides an explanation of classes of failures that this research focuses on by using two well-known failure classification systems from literature, respectively the classification system of Blache and Shrivastava [BLA94] and the Roller-coaster curve developed by Wong [WON88]. The next section explains the link between the classes of failures and the three design requirements considered in this research. Then a translation to necessary information for the three design requirements is made keeping in mind the failure classes.

Blache and Shrivastava [BLA94] classified different failure modes by studying the performance function of the item. Figure 2.6 shows the suggested classification scheme for failure modes. A brief description of the different failure modes is as follows [BLA94]:

1. *Intermittent failures:* Failures that last only for a short time. A good example of this is software failure that occurs only under certain conditions that occur intermittently.
2. *Extended failures:* Failures that continue until some corrective action rectifies the failure. They can be divided into the following two categories:
    a. *Complete failures,* which result in total loss of function
        i. *Sudden failures:* Failures that occur without any warning
        ii. *Gradual failures:* Failures that occur with signals to warn for the occurrence of a failure
    b. *Partial failures,* which result in partial loss of function
        i. *Sudden failures:* Failures that occur without any warning
        ii. *Degraded failures:* Failures that occur with signals to warn of the occurrence of a failure

A complete and sudden failure is called a *catastrophic failure* and a gradual and partial failure is designated a *degraded failure*.

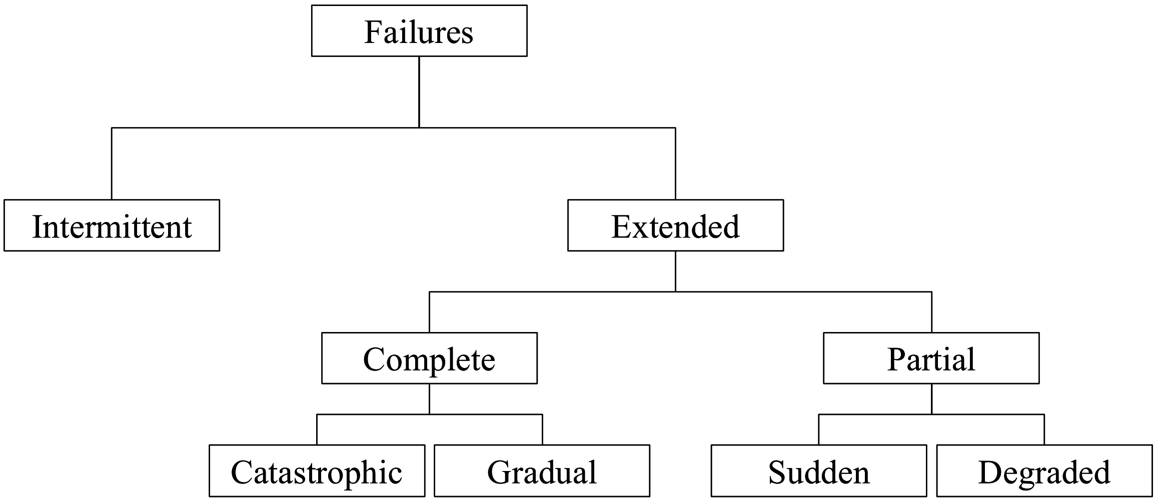


Figure 2.6: Failure classification (from Blache and Shrivastava, 1994 [BLA94]).

The classification of failures given by Blache and Shrivastava [BLA94] provides a good classification of possible failure modes. But their failure modes classification does not really relate failures to time. For this reason also the roller-coaster curve classification system is used and presented next.

2.3.2 Rollercoaster curve

A traditionally classification of failure modes over time is represented by the bathtub curve. The bathtub curve is used to describe the failure rate for many engineering components. Not only the failure rates of electrical components, but also mechanical and electromechanical components can use the bathtub curve as failure classification model. The bathtub curve may be divided into three phases [LEW96]:

1. Infant mortality (infancy) period
2. Useful life period
3. Wear-out period.

A general shape of the bathtub curve is shown in figure 2.7.

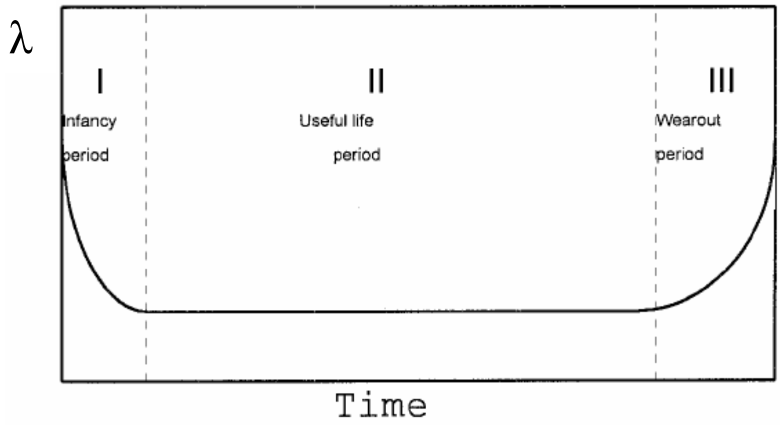


Figure 2.7: Bathtub curve with a time-dependent failure rate [LEW96].

During the early life of a component, the infant mortality period, there are early failures caused by initial weakness or defects in material, poor quality control, inadequate manufacturing methods, poor processes, human error, substandard materials and workmanship and inadequate debugging. Early failures show up early in the life of a component and are characterised by a high failure rate in the beginning, which keeps decreasing as time elapses. Other terms for this decreasing failure rate period are burn-in period, break-in period, early failure period, wear-in period and debugging period. Burn-in tests or some other screening processes usually detect the failures occurring during this period [JEN82].

During the second part of the bathtub curve the failure rate is approximately constant. This period of life is known as the useful life during which only random failures occur. There are various reasons for the occurrence of failures in this period: power surges, temperature fluctuations, human errors, overloading, earthquakes etc. Screening techniques or maintenance practices cannot eliminate these failures. But by making the product designs more robust with respect to the environments, the effects could be reduced.

After the useful life the wear-out period starts, when the failure rate increases. The causes for these 'wear-out' failures include wear due to aging, fatigue cracking, corrosion and creep, short designed-in life of the component under consideration, poor maintenance, wear due to friction and incorrect overhaul practices.

The onset of rapidly increasing failure rates normally forms the basis for determining when components should be replaced and for specifying the system's design life. Design with more durable components and materials, inspection and preventive maintenance are a few of the approaches to produce products with a longer useful life.

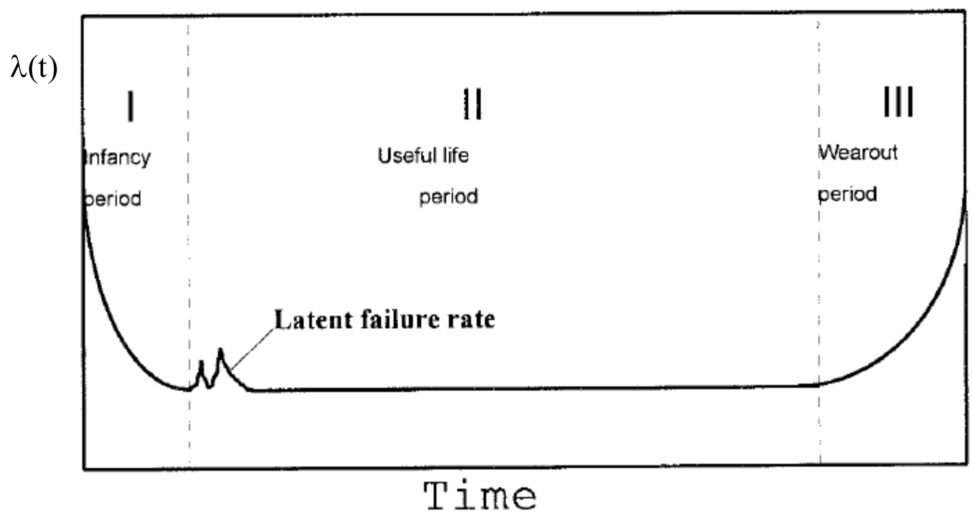


Figure 2.8: Bathtub curve with latent failures [JEN82].

The phases of the bathtub curve were observed in many components and products. This is why the bathtub curve is considered typical for many products. Several years ago, researchers in the electronic industry have identified another typical failure pattern called latent failures (also known as freak failures). When the stresses, which are acting on the components, exceed the design strength, there is often a "jump" in the failure rate curve as illustrated in figure 2.8.

No one can predict when latent failures will occur and they are basically unavoidable [JEN82]. They can be reduced by redesigning for extreme conditions, i.e. over designing, built in redundancy, or by using the Environmental Stress Screening (ESS) test [WON90] before the product is delivered to the customer. During these tests the component is exposed to excessive stress environments, such as vibration and thermal cycling over a certain period of time.

Researchers have shown that in several branches of electronics industry the bathtub characteristic for failure rate is an exception rather than a rule [BRO00]; especially the constant failure rate bottom of the bathtub curve, which has been used for many years for predicting systems reliability. In situations where product reliability is primarily determined by the reliability of components, this constant component failure rate model or the exponential law dominated the field. But usually this is not adequate and therefore a roller-coaster failure rate curve has been proposed by Wong in his paper *Off The Bathtub onto The Roller-Coaster Curve* [WON88] to replace the constant failure rate to describe product reliability in the field. Wong shows, based on screening data and operational data, that indeed one can expect "electronic" systems to have generally decreasing hazard rate curves with failure humps on them. The recognition of a hump of failures on the hazard rate curve dates at least back to 1968 when Peck [PEC68] called the hump on the hazard rate curve as freak failures that should be eliminated via stress screening. Also data from the 1961 paper by Milligan [MIL61] shows a hump in the failure rate curve, after superimposing the pertinent data points. Many other reports ([JEN82], [EDG79], [BRA79], [KZA79], [GEN87], [MEY87]) show this hump or a few humps in the hazard rate curve.

The data presented in a paper entitled *Reliability Assessment of Spacecraft Electronics* written by Hecht and Fiorentio [HEC87] shows, for both the overall system hazard rate and the parts quality failures hazard rate curves, strong roller-coaster characteristics as was pointed out by Wong [WON88]

A representation of a roller-coaster curve is illustrated in figure 2.9.

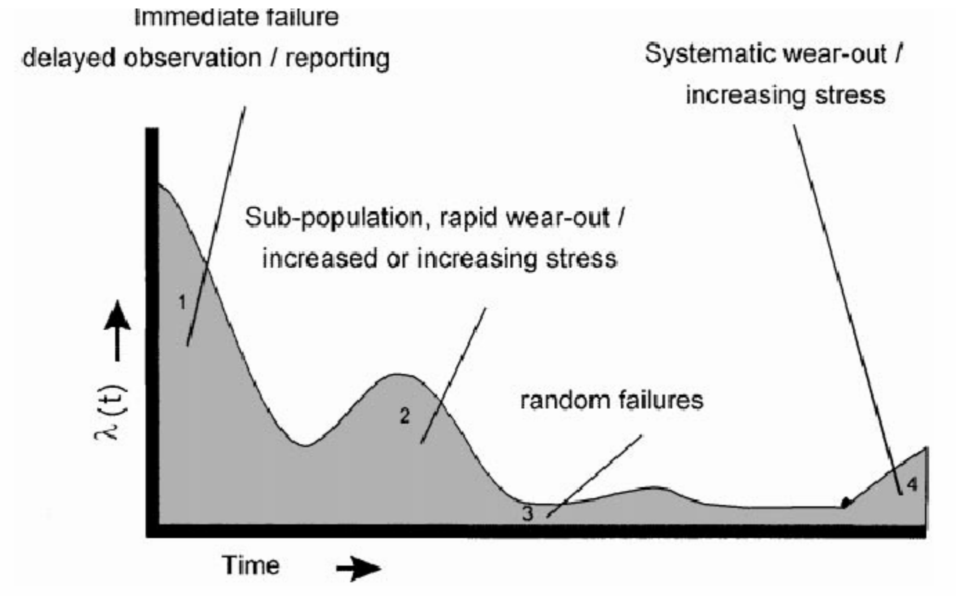


Figure 2.9: Rollercoaster curve [WON88].

Early failures or Hidden 0-hour failures:

Failures that occur at or shortly after t=0. These products arrive out of specification at the customer. They have either slipped through final tests, have been damaged during transport or are used in an unanticipated manner. Although these failures should all be observed at t=0, complex functionality or delay in customer reporting can cause delay in reporting these failures. One of the major reasons for this kind of failures is not a technically defective product, but a mismatch between technical product specification and the customer specification. Failures in this phase are by definition time-independent.

Early wear-out:

Only sub-populations of products show these kind of early wear-out failures. The reason for this different reliability behaviour in comparison to the main population is the difference between either the strength of products, especially, or between how customers will use the same products. Examples are products that are produced with internal flaws. When stresses are acting on these products, these flaws can cause a far faster wear-out than the main population. These sub-populations can appear as one or more “humps” on the roller coaster curve. These early wear-out failures are difficult to detect during production because on the product level these sub-populations initially show no different behavior with respect to the main population. Failures in this phase of the Roller-coaster curve are time-dependent and are dynamical of nature.

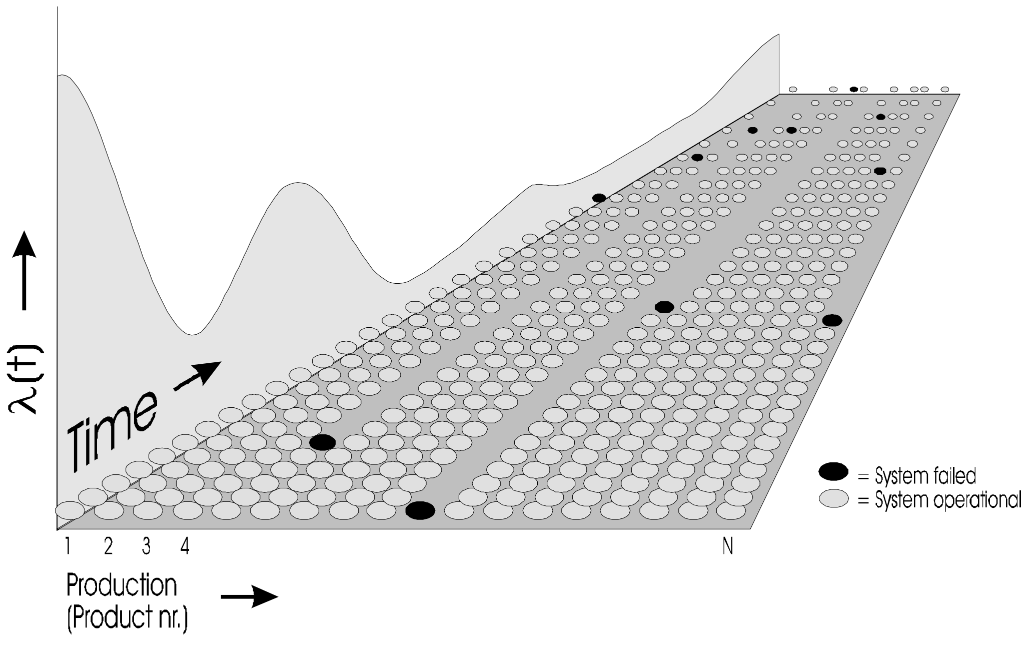


Figure 2.10: Translation from failed products to the four-phase rollercoaster curve [BRO92].

Stable system with only random failures:

Entering this phase of the Roller-coaster curve all sub-populations, containing early wear-out failures, have been removed. At this point in time there will be a rather homogenous population. Only external events with a strong “random” character, such as lightning, power shocks and mechanical shocks, can cause a product to fail at this time. Although many of these events occur with a low probability, these rare events can always happen. If the likelihood of occurrence for these events is constant in time and the product population is homogenous, this will result in a constant failure rate, as can be seen in figure 2.9.

Systematic wear out:

Basically this phase of the curve shows much similarity with the second phase (early wear-out) of the failure rate curve. Only this phase considers all of the remaining population. As the population of remaining products is arrived at this interval in time most products, especially mechanical products, but also electronic products, begin to show some form of degradation. Well-known degradation effects are corrosion of metals and increased brittleness of plastics. Although the level of degradation will be different for every product in a large population, at one moment in time all products have failed. At the moment in time where these failures start to dominate the failure rate curve, it will lead to an increasing failure rate and the systematic wear-out has begun.

It is important to recognize that there is a difference between failures that occur in phases 3 and 4 and failures that occur in phases 1 and 2. The phase 1 and phase 2 failures only occur in distinct sub-populations of products or product users, while phases 3 and 4 are relevant for the entire remaining population of products.

2.3.3 Variability in relation to failure

As mentioned before, variability, or component tolerances, are important factors influencing the performance of products. This section goes more into detail about the link between variability and product failure.

In section 2.1 two causes of variability were summed that lead to unreliable or lower quality products. These two causes are [LEW96]:

→ Unit-to-unit variability

→ Variability due to operating and environmental conditions

One cause of variability can be added [LEW96]:

→ Variability due to product deterioration/degradation

Figure 2.11 shows three possible effects of component tolerances on the performance of products and their relation to the roller-coaster curve for all phases. The two vertical lines per distribution indicate the specification limits in the performance space.

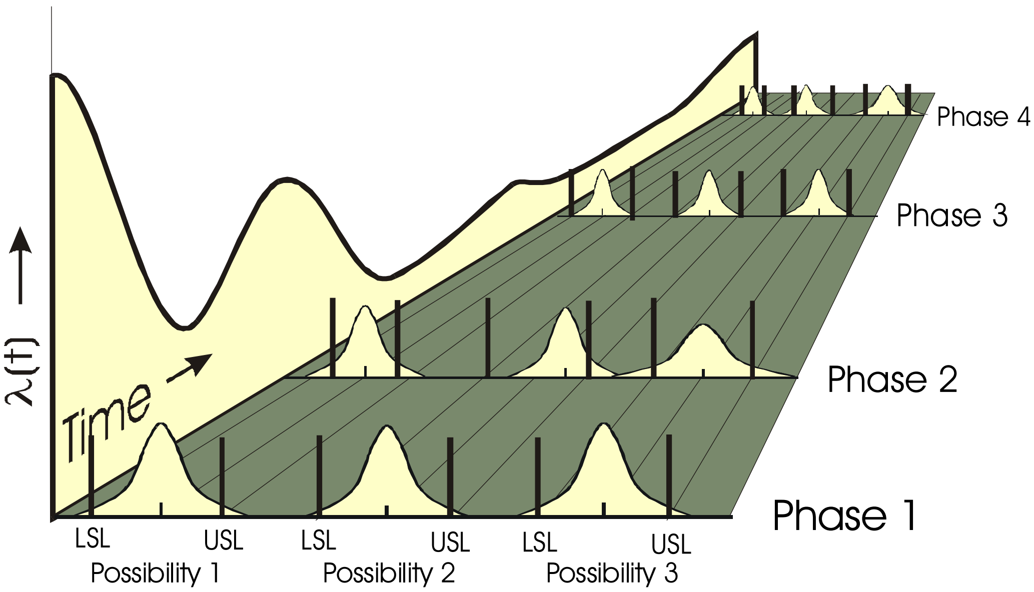


Figure 2.11: Possible effects of variability in relation with the Roller-coaster.

In phase 1 some of the products are out of specification and they fail directly. In phase 2 it is possible that the curve becomes wider. A cause might be degradation. Another possibility is that the curve shifts and this might be caused by drift of the mean of the performance characteristic. A third possibility might be that customer use is different then expected that translates itself in a shift of limits. Same effects as described for phase 2 count for phase 4, but then for the complete population, while phase 2 failures count for sub-populations.

2.3.4 Failure modes considered in this thesis

The classification of failure modes given by Blache and Shrivastava [BLA94] and the failure classification represented by the roller-coaster curve provide a good insight on the classes of failures this thesis will focus on. The emphasis of this thesis will be on gradual, or degraded, complete and partial extended failures of phase 2 and phase 4 of the roller-coaster curve. Phase 1 failures are very relevant for quality related failures, as Lu [LU02] explains in her thesis. Also phase 3 failures are important for reliability analysis, but these types of failures are impossible to predict on single product level due to the random character of their causes. Intermittent failures are more software related and different approaches are necessary to improve the reliability of products in relation to intermittent failures. The same accounts for sudden extended failures. Sudden failures are impossible to predict by laws of physics combined with statistical analysis.

2.4 Necessary information for the three design requirements

The research objective that was defined in chapter one is to develop a method that can tackle the three design requirements in one method.

The previous section provided two failure classification systems that were used to explain on what failure classes this research focuses. These failure classes can be directly linked to the three design requirements. The emphasis of this thesis will be on gradual, or degraded, complete and partial extended failures of phase 2 and phase 4 failures of the roller-coaster curve. So, basically, the emphasis is on degradation related failures of products. In order to optimize a product design towards reliability it is necessary that the behaviour of the product can be predicted over time. Predicting the reliability of a product over time is possible with degradation related failures. This has already been explained in section 2.2. And for both the second and third design requirement, it is necessary to know the status of the products at all times during their life and predict the remaining life of the products. This is possible with degradation related failures.

It is clear that degradation information is very useful in order to meet the three design requirements. But more information is necessary for the purpose of developing a new method that can tackle the three design requirements. Table 2.1 gives an overview of the information that is needed in order to tackle the three design requirements separately.

Information is needed about the performance of the complete population of products. In other words, the statistical properties of the products, or the variations in the properties of the products, are needed in order to meet all three design requirements. Also the time-dependent performance, or degradation behavior, should be known for all three design requirements. The time-dependent behavior of the products should somehow be measured or indicated. Therefore, time-dependent indicators are necessary. To make a design of a product more reliable, information about the dominant time-dependent design parameters is needed together with the performance characteristic that is an indicator for the performance, or quality, of the product over life. This was already explained in section 2.2. For re-use, a time-dependent indicator is sufficient. This could be the time-dependent performance characteristic, or all dominant time-dependent design parameters. Sometimes it is hard to directly monitor the time-dependent performance characteristic, but if the functional relationship between the Performance Characteristic (PC) and the Design Parameters (DP's) is known, only one of these two has to be monitored to know the behavior of the product over time. It could be very useful for both re-use and preventive maintenance to have information about the functional relationship between the dominant time-dependent DP's and the time-dependent PC, but it is not necessary for the above-mentioned reason. However, for optimizing the reliability of a product design over life, this information is essential. And, in order to know when a product is at the end of its technical life, information about the failure limits in the performance space is necessary. This accounts for all three design requirements.

Table 2.1: Overview of information needed for simultaneously solve for the three design requirements.

	1. Design	2. Re-use	3. Prev. Maint.
Needed information	Statistical properties products	Statistical properties products	Statistical properties products
	Time-dependent behavior	Time-dependent behavior	Time-dependent behavior
	Time-dependent Design Parameters (DP)	Time-dependent indicators	Time-dependent indicators
	Time-dependent Performance Characteristics (PC)		
	Functional relationship between PC and DP's		
	Failure limits (FL) / Specification limits	Failure limits (FL) / Specification limits	Failure limits (FL) / Specification limits

Obviously, all three design requirements need almost similar information in order to tackle them. Optimizing a product design towards reliability requires some more information, because the link of the performance characteristic to the design parameters is needed, although this information might also be very valuable for making re-use and preventive maintenance decisions, as explained in section 2.2. But in general, the needed information is almost similar and could be combined in one method. In essence, just a bit more than necessary has to be done for the second and third design requirement, but then all three design requirements can be tackled using only one method. In chapter one the first sub-research question was:

Is it possible to specify the link between the information required to solve for the design requirements separately?

This question can now be answered positively. A clear link exists between the necessary information for the separate design requirements and can be specified (table 2.1). And therefore, it is possible to consider the three design requirements within one method.

This section discusses the importance of degradation information for the development of a new method. Also the importance of variability, or component tolerances, was explained. The next section provides a more in-depth discussion on degradation information and information about the statistical properties of products in relation to quality and reliability. This information is a necessity in order to understand the information and judge if literature already provides methods that link the needed information.

2.5 Direction of research: Degradation and Variation

Failure of products is often the result of the effect of deterioration. The degradation process leading to a failure is a complicated process. Figure 2.12 shows examples of three general shapes for degradation curves in arbitrary units of degradation and time: linear, convex, concave [MEE98a]. Dasgupta and Pecht (1991) [DAS91] divided failure mechanisms into two broad categories:

1. overstress failures
2. wear-out failures

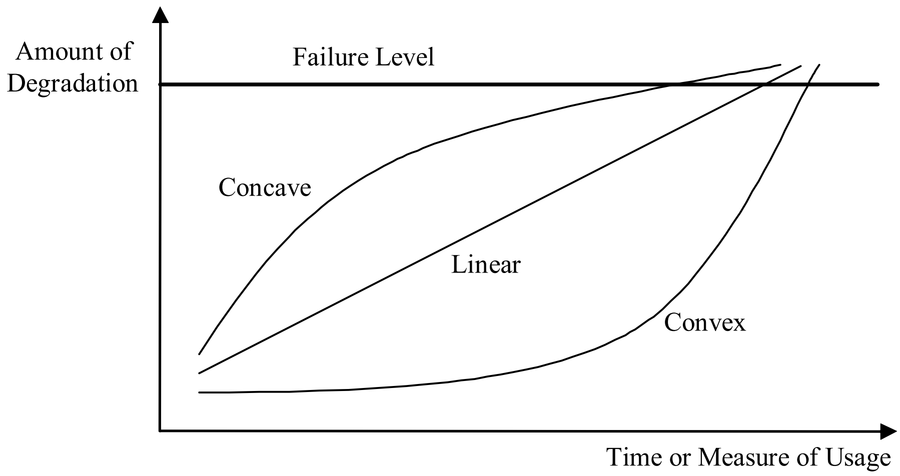


Figure 2.12: Possible shapes for univariate degradation curves (from Meeker and Escobar [MEE98a]).

Overstress failures are those due to brittle fracture, ductile fracture, yield, buckling, large elastic deformation, and interfacial de-adhesion. Wear-out failures are those due to wear, corrosion, dendritic growth, inter-diffusion, fatigue crack propagation, diffusion, radiation, fatigue crack initiation, and creep.

The rate at which the deterioration occurs is a function of time and/or usage intensity. If all manufactured units were identical, operated under exactly the same conditions and in exactly the same environment, and if every unit failed as it reached a particular "critical" level of degradation, then, all units would fail at exactly the same time. The usage intensity, or operating conditions, can vary from user to user, and is called variation of degradation due to operating conditions. The variation in the degradation process not only depends on variation of degradation due to operating conditions, but also on variability in environmental conditions, manufacturing variability, and material variability. These factors combine to cause variability in the degradation curves and in the failure times. Meeker and Escobar (1998) [MEE98a] categorize all these types of variability as follows:

1. **Unit-to-Unit Variability**

    a. ***Initial conditions.*** Individual units will vary with respect to the amount of material available to wear, initial level of degradation, amount of harmful degradation-causing material, and so on.

    b. ***Material properties.*** Variability due to variations in quality of material used.

    c. ***Component geometry or dimensions.*** Unit-to-unit variability in component geometry or dimensions can cause additional unit-to-unit variability.

    d. ***Within-unit variability.*** Often there will be spatial variability in material properties within a unit (e.g. defects).

2. **Variability due to Operating and Environmental Conditions**

    User profiles, or stress functions, are generally complicated functions over time. Driving a car illustrates both causes of variability. The degradation processes in a car differ for both a gentle driver in a nice environment and a rough driver in a harsh environment like Alaska.

    Figure 2.13, taken from a book by Bogdanoff and Kozin (1985) [BOG85], gives an impression of a possible degradation curve, by the example of growth of fatigue cracks, taking into account all sources of variation. The degradation curves are based on the Paris-rule model (e.g. Dowling, 1993) [DOW93].

This example shows that failure of products can often be traced back to an underlying degradation process, taking into account all sources of variability influencing the degradation process. Therefore, to design high-reliability products, it is necessary to consider all sources of variability influencing the deterioration, and therefore the failure, of products. Design parameters need to be chosen in such a way that they are insensitive for, or robust against, all sources of variability that are considered uncontrollable factors influencing the reliability of products.

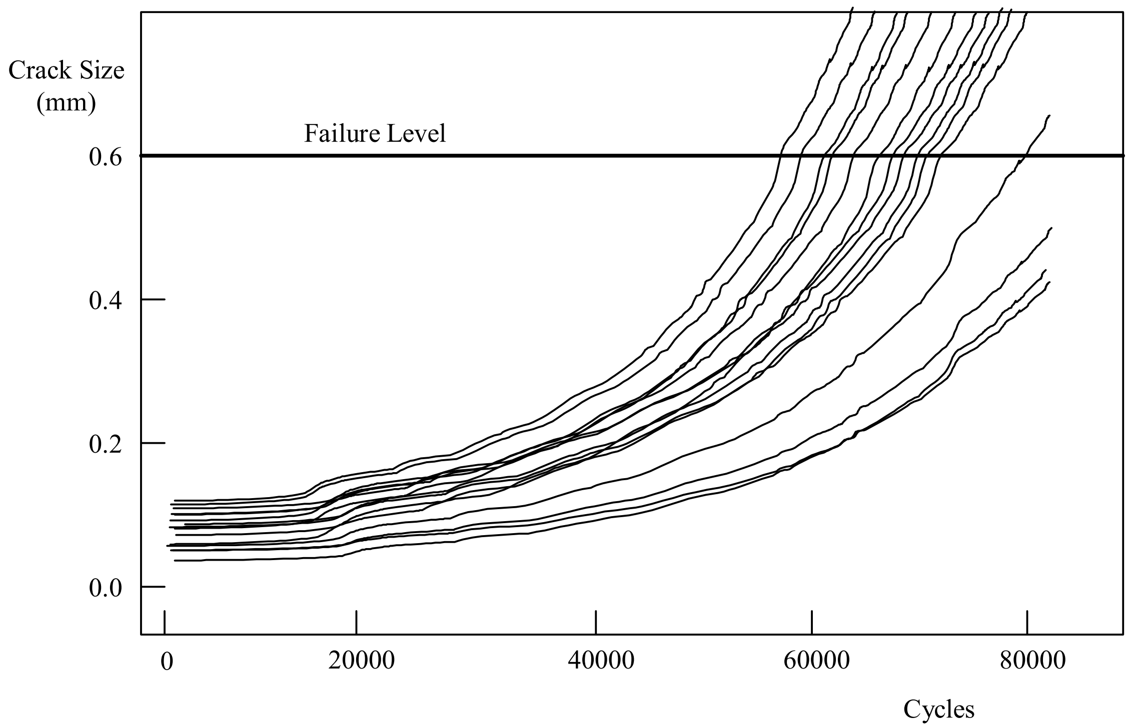


Figure 2.13: Plot of Paris model for growth of fatigue cracks with unit-to-unit variability in the initial crack size and material parameters C and m, and with a stochastic process model for the changes in stress over the life of the unit [BOG85].

2.6 Motivation for direction of research

Traditional statistical approaches to reliability analysis of physical and other electro-mechanical products are based on life tests that record only time-to-failure of a sample. Such analyses have been extensively studied and developed over the past few decades, and countless number of articles have been published in addition to the many books authored in the area, e.g., [LAW82], [NEL82], [KAP77], [LEW87], [ELS96]. However, to remain profitable in today's intense global competition, some life tests result in few or no failures in a short life testing time. In such cases, it is difficult to assess reliability with traditional reliability studies that record only failure time. To study this type of reliability problems, accelerated life tests that record failure and censoring times subjected to elevated stress are widely used. However, for products that are already highly reliable, the fact that few or even no failures are likely to occur during a reasonable testing period makes it difficult with traditional failure-time data to identify the important factors that in fact affect reliability out of potentially, important ones [CHI01]. If a product has characteristics such that degradation over time can be related to its failure time, then collecting degradation data can provide important information about a product reliability.

A recent approach is to observe degradation measurements of product performance during the experiment. Product performance is usually measured in terms of physical properties. These physical properties are called 'degradation indicators' that depend on degradation mechanisms. In a degradation test, one has to pre-specify a level of degradation, obtain measurements of degradation at different times, and define that failure occurs when the amount of degradation for a test unit exceeds the threshold level. Thus, these degradation measurements may provide some useful information to assess reliability. In most reliability tests, degradation data have some important practical advantages. Wu and Tsai [WU00a] summarize the following from literature (e.g. [NEL90] and [MEE93]) as important practical advantages:

→ Degradation data can be analyzed earlier, before a failure actually occurs. For highly reliable products, it is possible that the traditional life test will provide few or no failures. On the other hand, a degradation test can provide some information about unfailed units.

→ Degradation data may yield more accurate life estimates than the accelerated life test with few or no failures. A degradation test can get information at lower levels of stress, which reduces the extrapolation error of estimating product life under normal conditions.

→ Degradation data can provide better information of degradation processes, which help us to find the appropriate mechanistic model for degradation and accelerated stresses.

In the paper "Statistical Tools for the Rapid Development & Evaluation of High-Reliability Products" Meeker and Hamada [MEE95a] add some important limitations in the amount of available information using time-to-failure data:

→ Standard deviations of important reliability characteristics, like estimates of percentiles of the life distribution, are larger than they would be with degradation data [LU95].

→ Verification of acceleration-model assumptions is much more difficult.

→ It is difficult or impossible to estimate important reliability characteristics like degradation rate.

All the reasons summed above give a strong motivation for the recent shift in reliability research direction from failure-data oriented to degradation-data oriented.

The reliability modelling, prediction, and improvement method that is presented in this thesis not only follows the recent trend regarding degradation analysis, but the method also follows another recent trend, which is the area of robust reliability. Robust design is an experimental strategy to make a quality characteristic insensitive (robust) to various noise factors. Taguchi classifies noise factors into:

→ Manufacturing variation

→ Various environmental and use conditions

Product-design factors affect the elements of the degradation-caused failure model. In this thesis, improving reliability in a robust manner is defined as to find combinations of product-design factors that decrease the standard deviation of the failure distribution and that:

1. Decrease the mean of the degradation rate distribution.
2. Increase the mean of the failure distribution. This does not apply if the critical failure limit is user-defined (soft failures).
3. Decrease the mean of the initial degradation-level distributions.

Figure 2.14 graphically shows the above mentioned improvement properties.

The overall objective of the optimization step is to decrease the standard deviations of both distribution 2 and distribution 3, and of the degradation rate distribution. Then, the first optimization objective is to decrease the rate of the degradation. This is not shown in figure 2.14. The second optimization objective is to increase the mean of the failure distribution represented by distribution 2. And the third optimization objective is to minimize the mean of the initial degradation distribution at $t = 0$, which is indicated with distribution 3 in figure 2.14.

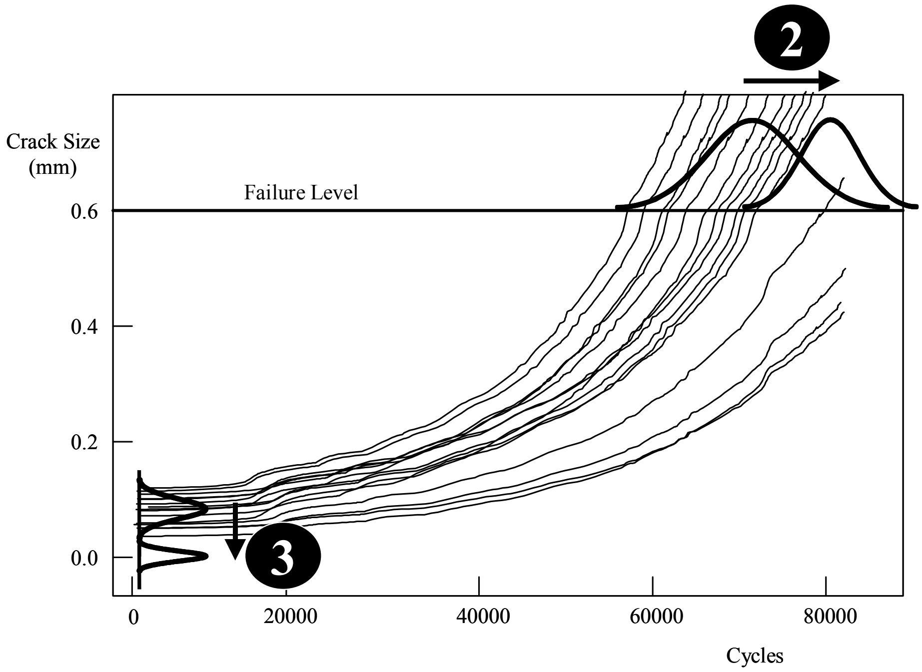


Figure 2.14: Graphical representation of reliability optimization.

The next chapter discusses the existence of methods in literature that provide a way of tackling all three design requirements simultaneously. The information provided in this chapter will be used to come to criteria that make the literature evaluation possible.

3 Literature review

3.1 Introduction

Extensive literature is available on quality and reliability related topics. This chapter analyses the available literature in relation with the problem definition that was presented in chapter one. The problem definition has been analysed in more detail in chapter two and it could be concluded that a large similarity exists between the necessary information to solve for the three design requirements. This chapter judges the strengths and weaknesses of available methods and tools in literature by judging how good the available methods and tools meet the requirements of handling the necessary information that is presented in chapter two. To do so, a translation is made from information necessary (table 2.1) to solve for the three design requirements to criteria that a method has to meet in order to be able to solve for the three design requirements.

The next section of this chapter classifies the available literature for the purpose of clarity. Many methods and tools in literature are closely related to each other. It would be impossible to give a description of all methods and tools and consequently analyse the strengths and weaknesses of all these methods and tools. In order to make an analysis of methods in literature possible, a classification of available methods is made. This classification is arbitrary, but covers the main classes of quality and reliability related methods in literature.

This chapter continues with a short description of all the classes of quality and reliability related methods and tools. After the description of all classes an analysis is presented on the strengths and weaknesses of the classes of methods in relation with the criteria that a method has to meet in order to solve for the three design requirements. Even within a certain class of methods it is hard to judge the strengths and weaknesses due to the great variety of methods within a certain class. In order to make this analysis still possible, a list of literature references of books and papers that fall in that particular class of methods is firstly given. Then one well-known book for that particular class of methods will be used to analyse the strengths and weaknesses.

Finally, this chapter finishes with a summary of the conclusions for all classes of methods and tools in literature. The results of this chapter make it possible to answer the second and third research questions. These questions are:

> *Are methods available in literature that connect, or take into account, the necessary information for the three design requirements?*

> And:

> *Which methods, concepts, or ideas available in literature could serve as a basis for a new method and what adjustments are necessary to these methods in literature to connect, or take into account, the necessary information for the three design requirements?*

> The answers to these questions serve as a starting point for chapter four.

3.2 Criteria for Reliability Prediction and Improvement

Already for centuries reliability plays an important role in industry and scientific research. In all these years many books and papers have been published with many different approaches to reliability related issues. However, not all methods and tools are relevant for all classes of reliability related problems. In order to distinguish and judge the usability of all reliability related methods and tools available in literature, this section presents a set of criteria that help to classify the usability of methods and tools.

Figure 2.11 of section 2.4.3 shows the roller-coaster curve and the possible causes that explain the roller-coaster curve. Figure 2.13 of section 2.6, which is similar to figure 3.1 below, gives an example of how products could behave over time in the performance space and how this translates to failures over time. With the use of this figure the criteria for reliability prediction and improvement purposes will be defined and explained.

One of the first things that obviously influence the quality, and therefore the reliability, of a product is the unit-to-unit variation. Weak products are already closer to the failure level and they might even degrade faster than very good products (figure 3.1). Unit-to-unit variation should therefore be taken into account when judging the suitability of certain quality and reliability related methods and tools to meet the three design requirements as presented in chapter one. This, therefore, is criterion 1.

Another obvious criterion that enables an engineer to judge if preventive maintenance of a product or module is necessary, or if re-use of that particular product or module is possible, is that at least the performance of the product population over time should be known. A suitable method should be able to model and analyze the performance of the product population over time. Also for the purpose of optimizing the design towards reliability information about the performance over time is very useful, as section 2.4 and 2.6 of chapter two explained. So, the second criterion is the ability to model and analyze the product time-dependent performance.

The second criterion is, however, quite stringent for preventive maintenance and re-use purposes. In chapter two it was explained that for preventive maintenance and re-use only time-dependent indicators are necessary to know. Only for optimizing the design of a product is it necessary to have more detailed knowledge on how design parameters in relation with the performance characteristic of that product influence the reliability of the product. Therefore, an extra criterion is formulated for the purpose of preventive maintenance and re-use, namely the ability of a method to analyze the status of the product. Two types of data could be used for this purpose, namely statistical failure data and degradation data.

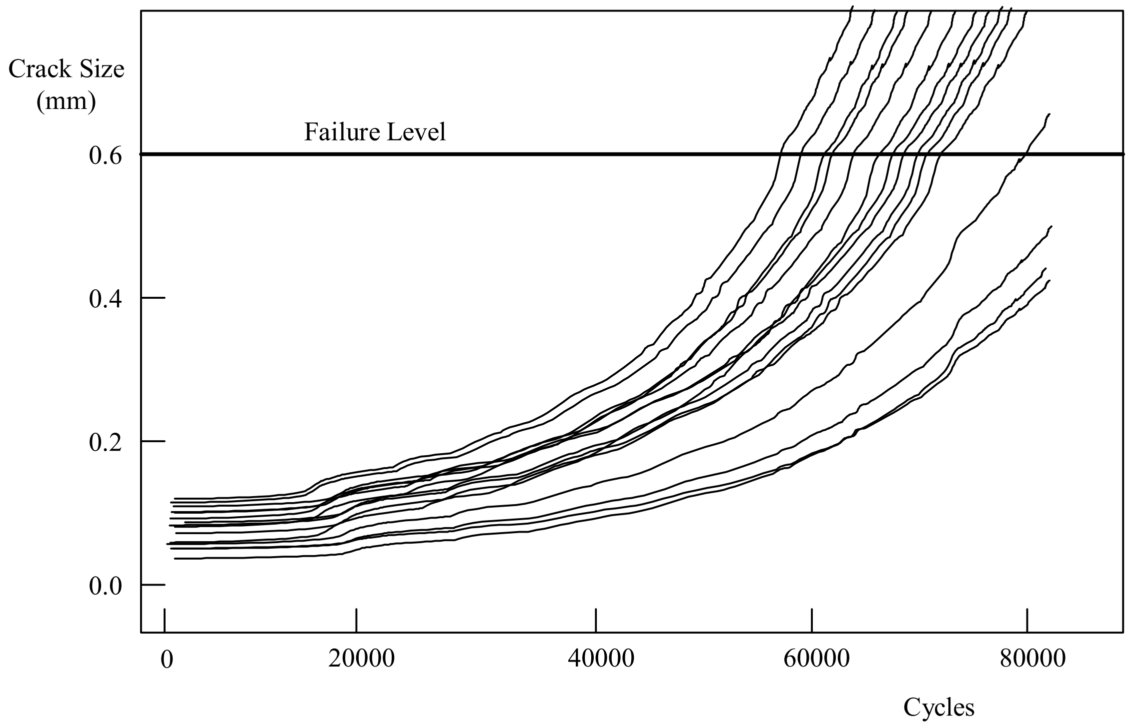


Figure 3.1: Plot of Paris model for growth of fatigue cracks with unit-to-unit variability [BOG85].

The product time-dependent performance information should be gathered through testing or maybe even from the field[5]. It is easy to imagine that it is not always possible to get all the data that is needed about the performance of the product population over time. Data could be missing. Therefore, it might be necessary that the performance of the products over the remaining lifetime (not captured in the gathered data) has to be predicted. For example, imagine that data is only available until 60.000 cycles in figure 3.1. In order to know how failures over time of the complete population looks like, a suitable method should be able to predict how the unfailed product population performs until failure. Therefore, predictability of product performance over time is considered as the fourth criterion.

[5] In this context with field is meant the use of the products by the users.

The next step in judging the reliability of a product population is to translate the time-dependent performance of the product population into failure times. This step is necessary for improving the design of the products. One of the objectives of improving the reliability of a product population is increasing the mean of the time-to-failure and decreasing the variance of the time-to-failure of the product population, as explained in chapter two. The fifth criterion will consequently be the ability of a method or tool to translate and analyze the product population performance over time to statistical failure data.

And finally, as one of the three design requirements is optimizing the design of the products, this should therefore be included in the criteria judging the suitability of reliability related methods and tools. Optimization of a product design can be done in many ways, but in this thesis the definition of optimization described in chapter two is used, and will be used throughout this thesis. In summary the following six criteria are defined:

1. Ability to address unit-to-unit variability
2. Ability to model and analyze product time-dependent behavior
3. Ability to analyze the product status
4. Ability to predict product behavior over time
5. Ability to analyze statistical failure data
6. Ability to optimize the product design in terms of reliability

The next section presents a classification of available quality and reliability related methods and tools in literature.

3.3 Classification of quality and reliability related methods and tools

A rich variety of methods and tools on quality and reliability related issues are available in literature. It is almost impossible to judge all available methods separately. For this reason a classification of quality and reliability related methods and tools is proposed. The proposed classification is not complete such that many methods cannot always be classified in one class of methods, but overlap a few classes. However, it provides a good overview of what strengths and weaknesses certain classes of methods have in relation to the criteria that are proposed in the previous section.

The next classes of quality and reliability related methods and tools are recognized from literature:

1. Statistical Failure Analysis related methods
2. Stress-Strength related reliability methods
3. Reliability by DOE related methods
4. Reliability by Accelerated Testing related methods
5. Reliability by Degradation Analysis related methods
6. Robust Design related methods
7. Preventive Maintenance/Condition Monitoring related methods

Although the selection of classes of methods is arbitrary, these methods all have clear distinctive goals or approaches. This is explained in section 3.4.

In order to explain how these classes of methods are analyzed in relation with the criteria given in section 3.2, the next section provides a description of all classes of methods and tools and their weaknesses and strengths. An overview of the conclusions will be presented in a table. Table 3.1 will be used for this purpose.

Table 3.1: Overview table of reliability related methods and criteria for reliability prediction and improvement.

	Criteria for Reliability Prediction and Improvement							
	Ability to	addres unit-to-unit variability	model and analyse product time-dependent behaviour to degradation data	analyse product status	predict product behaviour over time	analyse statistical failure data	design reliability optimisation	
							deterministic	robust
Reliability Related Methods	1. Statistical Failure Analysis							
	2. Stress-Strength Reliability Analysis							
	3. Reliability by DOE							
	4. Reliability by Accelerated Testing							
	5. Reliability by Degradation Analysis							
	6. Robust Design							
	7. Maintenance/-Condition Monito-ring							

Judging all the classes of methods to the criteria is not a “good or bad” process. Some classes of methods are better on certain criteria than others and some methods completely ignore a certain criterion. For this reason the “goodness”, or suitability to take into account a certain criterion, will be valued by either a “o”, a “+” or a “++”, where “o” means the class of methods does not take that criterion into account at all, where “+” means the methods in that class take a certain criterion into account, but not in an optimal way, and where “++” means that methods in that class take a certain criterion very good into account.

3.4 Detailed description of all classes of quality and reliability related methods and tools

This section provides a description of the different classes of quality and reliability related methods and tools. This section follows the same sequence of classes as presented in section 3.3. In the description of the different classes of methods all criteria for goodness-of-use will be included in relation with the methods. Also the shortcomings will be discussed in relation with the contents of the methods. It is assumed that the reader is familiar with basic knowledge of quality and reliability related material that is presented in e.g. the book *Introduction to Reliability Engineering* written by Lewis [LEW96]. However, appendix 1 presents some important preliminaries crucial to the treatment of lifetime and reliability related data.

3.4.1 Statistical Failure Analysis related methods

This class of reliability methods restricts the reliability analysis and prediction more or less to the analysis of lifetime data, or failure data. The book '*Mathematical Theory of Reliability*' written by Barlow and Proschan [BAR65] is generally considered as one of the first more quantitative (or mathematical) and formal approach to this class of reliability methods. Since the appearance of this classic book, as Blischke and Murthy state in their book '*Reliability – Modelling, Prediction, and Optimization*' [BLI00], the theory of statistical failure analysis has grown at a very rapid rate, as can been seen by the large number of books and journal articles that have appeared on the subject.

Literature related to statistical methods used in the analysis of lifetime data lies scattered in a large number of books (e.g. Mann, Schafer, and Singpurwalla [MAN74], Kapur, and Lamberson [KAP77], Lawless [LAW82], Nelson [NEL82], and many more) and a large number of professional journals: *IEEE Transactions on Reliability, Biometrika, Annals of Mathematical Statistics, Journal of the American Statistical Association, Technometrics*, among others. For the analysis of this class of reliability methods the book '*Methods for Statistical Analysis of Reliability and Life Data*' of Mann, Schafer, and Singpurwalla [MAN74] is used as a reference book. Although this is an old book, it is still complete and focuses solely on statistical failure analysis related methods.

Statistical failure analysis related methods are concentrated on the analysis of lifetime data. In other words, these methods model failure data of products over time by using distribution functions, like Exponential distributions, Weibull distributions, Normal distributions, and other statistical distributions.

A failure time distribution, therefore, represents an attempt to describe mathematically the length of life of a component, system, or a product. There are many physical causes that individually or collectively may be responsible for the failure of a product at any particular instant. This class of reliability methods assumes that it is not possible to isolate these physical causes. This is why all possible modes of failure are included in a failure time distribution. The modes of possible failure will affect the analytic form of the failure distribution. The art in this type of methods is the choice of the failure distribution representing the lifetime data. The basic problems addressed in statistical failure analysis related methods are those of specifying models to represent distributions of lifetimes and to making statistical inferences on the basis of these models. In some situations specific parametric models can be employed to represent lifetime distributions, and inferences based on these. In others, use of a parametric family of models may not be feasible, and nonparametric methods can be used.

Numerous parametric models are used in the analysis of lifetime data in problems related to the modeling of aging or failure processes. Among these models, a few particular distributions occupy a central role because of their demonstrated usefulness in a wide range of situations. In this category are the exponential, weibull, gamma, and lognormal distributions. To cover all the distributions currently in existence would require an entire book. For a detailed description of these and other statistical models the reader is referred to extensive literature that is available (Wolstenholme (1999) [WOL99], Crowder, Komber, Smith, and Sweeting (1991) [CRO91], Leemis (1995) [LEE95], Rao (1992) [RAO92]).

Extensive motivation for the various statistical models will not be provided in this thesis. The extensive literature on lifetime models provides the theoretical motivation for the choice of particular models. Some theoretical motivation for particular models can be found in the series by Johnson and Kotz (1970) [JOH70], which extensively catalogs mathematical and statistical properties of most of the distributions and provides additional references concerning their areas of application. Some other references among numerous others are: Meeker and Escobar (1998) [MEE98a], Chick and Mendel (1996) [CHI96], Wu and Tsai (2000) [WU00a], and many more.

The second class consists of nonparametric procedures that do not depend on the assumption of a specific family of distributions.

In the case of a parametric approach, once a model is specified with its parameters and data have been collected, one is in the position to evaluate the model's goodness-of-fit, that is, how well the model fits the observed pattern of data. A procedure called *Parameter Estimation* assesses the goodness-of-fit by finding parameter values of a model that best fits the data.

There are two generally used methods for parameter estimation. They are least-squares estimation (LSE) and maximum likelihood estimation (MLE). A short elaboration on these two estimation methods is given in this section, because in the rest of the thesis these two estimation methods are used.

The principle of maximum likelihood estimation, originally developed by Fisher [FIS12], states that the desired probability distribution be the one that makes the observed data most likely, which is obtained by seeking the value of the parameter vector that maximizes the likelihood function. A likelihood function would look like

$$L(w;y) = f(y|w) \tag{3.1}$$

$L(w;y)$ represents the likelihood of the parameter w given the observed data y, and as such is a function of w. The MLE estimate is obtained by maximizing the likelihood function. In practice, the maximum likelihood estimate is obtained by maximizing the log-likelihood function *ln L(w)*, instead of the likelihood function. This is because *L(w)* is usually a product of terms, while *lnL(w)* is a summation of terms. In general, it is easier to maximize a summation than a product of terms.

In MLE the parameter values that are "most likely" to have produced the data are sought. In LSE, on the other hand, parameter values are sought that provide the "most accurate" description of the data, measured in terms of how closely the model fits the data under the square-loss function. Formally, in LSE, the *sum of squares error* (SSE) between observations and predictions is minimized:

$$SSE(w) = \sum_{i=1}^{m} \left(y_i - prd_i(w)\right)^2 \tag{3.2}$$

where $prd_i(w)$ denotes the model prediction for the i-th observation. Note that SSE(w) is a function of the parameter vector $w = (w_1,...,w_k)$.

It should however be noted that, although least squares methods provide simple and fairly effective ways of obtaining estimates, they are not a substitute for efficient methods of estimation, such as maximum likelihood, when precision is important [LAW82]. Therefore, MLE should be preferred to LSE. There is a situation, however, in which the two methods intersect. This is when observations are independent of one another and are normally distributed with a constant variance. In this case, maximization of the log-likelihood is equivalent to minimization of SSE, and therefore, the same parameter values are obtained under either MLE or LSE [MYU03]. Ogasawara [OGA03] shows in his paper '*Correlations among Maximum Likelihood and Weighted/Unweighted Least Squares Estimators in Factor Analysis*' a comparison of the performance of MLE methods with LSE based methods.

For in-depth, technically more rigorous treatment of the topic, extensive literature is available (e.g., Bickel & Doksum (1977) [BIC77], Casella & Berger (2002) [CAS02], Spanos (1999) [SPA99]).

Conformance with criteria

This section gives a short elaboration on how all criteria have been judged. Naturally, the process of judging is arbitrary. For this reason one book has been used as the reference book. Other closely related methods described in other books could give a somewhat different outcome.

The first criterion is the ability of a method to address unit-to-unit variability. Statistical failure analysis methods do not explicitly take unit-to-unit variation into account. Implicitly, unit-to-unit variation can be observed as a result in the failure data, but the causes of variation are not known. For this reason, this method scores a "o/+".

Criterion 2 addresses the fact that a method should be able to model and analyze time-dependent degradation data. This method does not take time-dependent degradation data into account, and therefore is given the score “o”.

The third criterion is less stringent than the second criterion. It is possible to make preventive maintenance decisions on the basis of statistical failure data, by knowing when the majority of the products starts to fail. A service department can decide with information about percentage of failed products when, in time of usage, preventive maintenance has to be carried out. However, this decision always concerns the complete population of that particular product, and can never be taken on individual products. This can be a big disadvantage when the repairable, or replaceable, parts or actions are very expensive. When the product was a strong product, it could function for another year. But this part of the technical lifetime is then thrown away. Therefore, this class of methods is honored with the score “+”.

The fourth criterion is about predicting the rest of the life of a product when data is not available until failure of all products. A lot of attention has been given to this problem in statistical failure analysis related methods. A data set missing parts of the data is called censored data and many methods are proposed to solve for this problem. However, as Meeker, Escobar, and Lu (1998) [MEE98b] explain, there is more justification and credibility for extrapolation using degradation data. Therefore, the score for this criterion is “+/++”.

The fifth criterion is about analyzing statistical failure data, which is exactly the purpose of this class of methods. So, the score is “++”.

And finally, one of the criteria for the judgment of the usability of reliability prediction and improvement methods that was proposed in this chapter was the ability of a method to optimize a product design. In the book of Mann, Schafer, and

Singpurwalla (1974) [MAN74] there is nothing about optimization of a product's design by using statistical failure data. So, the score for this criterion is "o". Note that some other books provide a discussion on this topic. However, optimization purely on statistical failure data always remains a weak point, since no knowledge is available on design parameter level.

3.4.2 Stress-Strength related reliability methods

Many authors have extensively described Stress-Strength related reliability methods (Jensen (1995) [JEN95], Bhattacharyya and Johnson (1974) [BHA74], Lewis (1994) [LEW94], Brombacher (1992) [BRO92b]). For the description of stress-strength related reliability methods this section uses the book '*Electronic Component Reliability: Fundamentals, Modelling, Evaluation, and Assurance*' written by Jensen [JEN95]. Jensen calls this class of methods load-strength methods. Closely related methods use more or less the same fundamentals and ideas, but for clarity reasons this book is used as reference for this class of methods.

The load-strength concept is based on the energy storage in a component to explain failures in a component. The concept divides components into "perfect" and "practical" objects. A "perfect" component is defined as a component that is finite and everywhere homogeneous. Perfect components store energy when a load (e.g. mechanical, thermal or power load) is applied. The nature of the stored energy can be for example electrical, heat or mechanical energy, but may be transformed during the storage. The energy storage process is basically linear, but there are limits to the amount of energy that can be stored. When this limit is reached, the component will fail. The strength of a component is thus defined as the value of the applied external load that causes the component to fail. When the energy stored in a component remains below this value, then a load may be applied to a component for a infinite time or number of cycles without changes in the component. In principle perfect components can have infinite lives.

In practical situations however, components are not perfect. A “practical” component can now be defined as a component where local departures from perfection are present. These local departures, called flaws or defects, reduce the strength of components below the theoretical value obtainable in “perfect” components. The terms flaw or defects not only describe situations, such as cracked or pitted material, but also for example contamination of foreign material or the existence of dislocations in the crystal structure. These flaws can arise due to imperfect material handling, processing or component manufacturing.

Practical components contain a variety of flaws and the strength will be distributed around a mean value. Not only the strength of practical components must be expected to show a distribution around a mean value, but also loads often have a range of values and can thus be describe by a statistical distribution. By combining these two distributions it becomes possible to determine the failure probability. An example of a distribution of load and strength is given in figure 3.2.

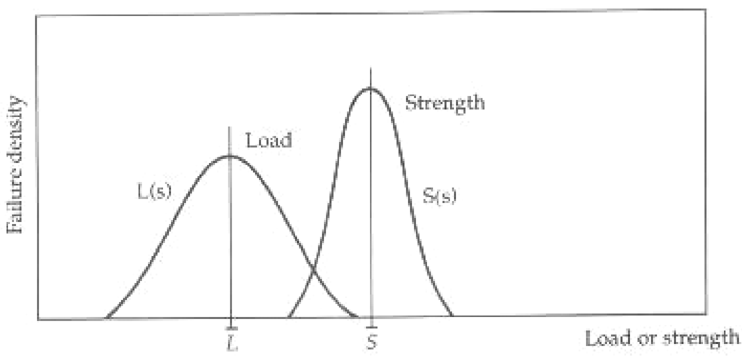


Figure 3.2: Distribution of Load and Strength [LEW96].

This set of distributions will evidently cause some failures. One can imagine that there will be situations where the load on a particular component will be greater than the strength of that component and failure will occur.

The reliability of a batch of components with strength distribution S(s) that are subjected to a load with distribution L(s) can mathematically be described by:

$$R = \int_0^{\infty} \left[S(s) \int_0^{s} L(s) ds \right] ds \qquad (3.3)$$

Also failures that arise from the creation of weak sub-populations of components through errors in processing or poor workmanship can be modeled in the strength distribution of components. A distribution of this weak sub-population with a smaller strength will appear in front of the distribution of the main population. An example of such a bimodal distribution is given in figure 3.3.

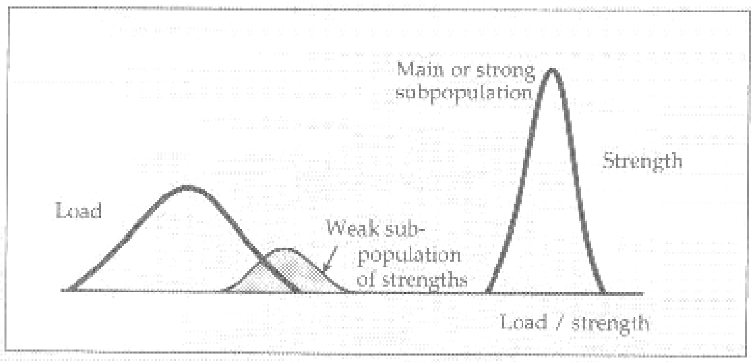


Figure 3.3: A weak sub-population of component strengths [LEW96].

Using this load-strength concept makes it possible to develop models for component reliability.

The description given in this section covers the basic ideas behind stress-strength methods. For a more detailed description the reader is referred to the book of Jensen [JEN95].

Conformance with criteria

Stress-strength related methods take unit-to-unit variation on performance level into account. But a translation back to the parameter space, or production process, causing this unit-to-unit variation is less evident. The score, however, is "+/++" for the reason that this method does take this property into account from time t = 0.

This class of methods also analyses time-dependent behavior, but then from a different perspective than all other methods. It analyses and predicts the decrease of the strength of the population of products. Again, this is not done to the level of design parameters. This is why the score is "+".

The third criterion is about analyzing the status of a product. Jensen [JEN95] does not really go into this topic. Strength is somewhat hard to always define for every product. But when this is possible, one could imagine that the status could somehow be analyzed. If it would serve the purpose of preventive maintenance or re-use of parts of a product it might be hard to estimate. Therefore, this method is given the score "+" on this criterion.

Also the fourth criterion is less explicitly explained. It is more explained as a concept of thought, than as a real proof. However, when using the same assumption as with the third criterion, one could imagine that it would be possible to predict missing failure data. However, since this is not really explicitly described or proven, it is rewarded with a score "+".

The fifth criterion is about analyzing statistical failure data. Again, since the stress-strength method is more or less a concept of thought, although case studies definitely exist (especially in the field of structural reliability (Christensen and Murotsu [CHR96])), it is difficult to really judge the strength of the method on this criterion. It is possible to calculate the probability of failure when the strength and stress distributions are known. But working backwards, by analyzing failure data and translating this back to stress and strength distributions seems difficult. The score given for this criterion is “0/+”.

In the stress-strength related methods the load is explicitly taken into account. In principle, this information could be very valuable for making a design robust against the load that is applied on the products. The information is valuable, but how to really optimize a design is not explicitly explained in the book of Jensen. This is why the score is “o/+”.

3.4.3 Reliability by DOE related methods

A wealth of literature exists on Design Of Experiments (DOE) related methods. Well-known authors on this topic are: Montgomery and Runger (1999) [MON99], Cox and Reid (2000) [COX00], Bhote and Bhote (2000) [BHO00], Condra (2001) [CON01]. This section does not only use the book of one author as reference book, because DOE related methods are all more or less similar in the description of the method.

Statistically designed experiments have been used extensively for the purpose of estimating or demonstrating existing reliability. Until a few years ago, designed experiments appear to seldomly used to improve reliability of products by identifying the important parameters (factors) affecting reliability out of many potentially important ones. These important factors can be identified empirically through experimentation, which involves making deliberate changes in the factor values (levels) and observing the resulting reliability. Besides identifying the important factors, levels for these factors that yield reliability gains can be recommended. Statistically designed experiments, like Design of Experiments (DOE), provide a systematic and efficient plan of experimentation to achieve the goal of studying several factors simultaneously. Designed experiments, which have successfully been used to improve quality characteristics, can also be used to improve reliability, according to Condra [CON01].

DOE can be described as a group of techniques for organizing and evaluating tests so that it provides the most valuable data and makes efficient use of assets [FRI97]. DOE's must be designed effectively and efficiently. An effectively designed experiment is, according to Frigon and Mathews [FRI97], an experiment that is feasible and enables to draw inferences to the population of interest. An efficient experiment is, according to Frigon and Mathews [FRI97], one that provides the most information at a given cost or the required information at minimum cost. In order to accomplish this, some important issues must be addressed before conducting the experiment. According to [BLI00], these issues are:

→ Population(s) to which inferences are to be drawn;

→ Variables to be measured and units of measurement;

→ Factors to be varied in the experiment (e.g., temperature, humidity, light-intensity);

→ Choice of levels of these factors;

→ Conditions under which the experiment is to be run;

→ Preparation of a complete list of other factors that could affect the results;

→ Preparation of a list of factors that cannot be controlled;

→ Limitations of the experiment;

→ Feasibility, cost issues, facilities, and so forth.

Design of experiments can take many forms, but its major distinguishing elements are [CON01]:

→ Simultaneous variation and evaluation of several factors, and

→ Systematic elimination of some of the possible test combinations to reduce experimental time and cost.

The procedure provides a means of determining which factors have the largest effect on performance. It also allows the optimum settings for the various factors to be determined.

Three types of experiments that could be designed are defined:

1. A one-factor-at-a-time experiment implies that with each run one factor is changed while the others remain the same [CON01].
2. All possible combinations of factors in one experiment. This is called a full factorial experiment [LEW96].
3. The fractional factorial, allows the experimenter to obtain information about all main effects and interactions while keeping the size of the experiment manageable, and also conducting it in a single, systematic effort. In a fractional factorial experiment only a fraction of all possible combinations are evaluated [CON01]. Taguchi has packaged techniques for performing fractional factorial experiments in a particular useful form called orthogonal arrays [LEW96]. These orthogonal arrays describe which level combinations of factors are used in each run.

After carrying out the experiments, the results of the experiments need to be analyzed. A quantitative method for determining whether the changes in factor levels are significant or are just the result of random effects or measurement errors is analysis of variance, ANOVA [MON99]. This statistical tool is especially valuable in the early stages of designed experiments, where many design factors must be screened to determine which have a significant impact on performance, and which can safely be ignored in optimization studies [LEW96].

The purpose of ANOVA is to determine whether individual factors of an experiment are significant by comparing their variation with the overall variation of the data. Many (statistical) software packages contain a certain ANOVA function.

Conformance with criteria

One of the strengths of reliability by DOE related methods is the fact that these methods take into account unit-to-unit variation and the influence of the unit-to-unit variation to the performance of the product. This is actually one of the main purposes of this testing strategy, to gather information about the influence of the variation, even from design parameter level, to the performance. So the score for the first criterion is "++".

In principle, DOE techniques are time-independent testing strategies. Therefore, the score would be "o" for the second criterion. However, Condra [CON01] describes an experiment performed by Tseng et al [TSE94] about combining DOE testing strategies with reliability goals through degradation testing. For this particular example, where a combination is made between DOE testing strategies and degradation testing strategies, the score would be "++". However, since in the example a combination of methods is used, in the reliability by DOE related class of methods only DOE methods will be judged. So, a score of "o" is justified, keeping in mind the remark of the example described by Condra [CON01].

For the same reasons as discussed previously, the third, foyrth and fifth criterion will be given a score “o”. Again, keep in mind the example worked out by Tseng et al [TSE94].

Finally, the last criterion is a strong point for DOE methods. A design can be made robust against noise factors and also the performance at time t = 0 can be optimized. However, it is not a guarantee that an optimized product for time t = 0 is also the optimal solution for reliability purposes. In chapter five a simulation experiment will be presented to prove this remark. But still, optimization is one of the strengths of this method and the score “+/++” is given.

3.4.4 Reliability by Accelerated Testing related methods

Lifetime data to model component or product reliability can be obtained from information out of the field or through testing. Estimating the time-to-failure distribution of highly reliable products that are designed to operate without failures for many years, is particularly difficult. Hence, few units will fail in the field or in a test of particular length at normal use conditions. Therefore, accelerated life tests (ALT) are used to obtain information on product-life in an acceptable time. Exactly for the reason of preventing long testing times, reliability by accelerated testing related methods is considered as one of the important classes in literature. And therefore many authors have put a lot of effort in researching possibilities of accelerating tests, as the amount of literature clearly shows (Nelson (1990) [NEL90], Viertl (1988) [VIE88], Kececioglu (1993, 1994) [KEC93] [KEC94], McSorley, Lu, and Li (2002) [MCS02], Meeker and LuValle (1995) [MEE95b]).

Generally, accelerated tests focus on one or a few degradation processes or well-understood failure modes. Then the results are extrapolated using an appropriate physics-of-failure based statistical model (e.g. Arrhenius model relating the lifetime distributions to temperature [KEC93]), to obtain the required lifetime data or to make predictions about reliability at normal use-conditions.

Accelerated tests are traditionally used to find flaws or weaknesses in the product design. But they can also be employed to assess and predict reliability. Lewis [LEW96] makes a distinction between two kinds of acceleration methods, namely:

1. Compressed-time tests;
2. Advanced-stress tests.

Compressed-time testing

Compressed-time testing is a way of testing in which the product is used more steadily or frequently during the test than in normal use, but the loads and environmental stresses are maintained at the level expected in normal use [LEW94]. An example could be a television set that is turned on and off very frequently and where channels are changed more often than during normal operating life. Precaution should be taken. If the cycle is accelerated too much, a situation can be established in which the conditions of operation change and no longer reflect the actual product life. A television set in real life is turned off; then it has time to cool down. When it is turned on again it makes a cool start. If an accelerated cycle is run too fast, capacitors within the television set may still be charged. This leads to different operating conditions and possibly earlier failure.

Advanced-stress testing

Some systems are in continuous operation during their life cycles. Other systems are constantly exposed to deterioration whether they are active or not. For these types of systems, compressed-time testing does not accelerate the failure mechanism. In these cases advanced-stress testing may be applied. The test uses an increase in load or a harsher environment to accelerate the failure mechanism. This only works if a decrease in reliability can be quantitatively related to an increase in stress level.

It has been made clear that accelerated tests are used to obtain information within an acceptable time on product-life or performance degradation over time. An appropriate physics-of-failure based statistical model is then fitted to the obtained test data to make extrapolative predictions about the product-life or performance at the normal use conditions. This way of testing immediately leads to questions. For example, is it possible to extrapolate the results to normal use conditions? Another question that immediately arises is: are the results unique for the test conditions? This pitfall and other serious concerns are described in Meeker and Escobar [MEE98c] and Nailen [NAI02]. They describe some of the dangerous pitfalls of accelerated testing and warn users of accelerated life tests to avoid these pitfalls. Next, some of these pitfalls are described in order to give insight into some of the shortcomings of accelerated testing.

→ ***Unrecognized Failure Modes***

Generally, in an advanced-stress test (AST) only one variable is accelerated in order to determine the higher level of stress that this accelerated variable causes on a specific component or product. Because of this higher level of stress, an increased failure rate may be observed. However, higher levels of stress may induce other failure modes that would normally not be observed. In less extreme cases, the failure mode might not be recognized and thus may also not be recognized in the data analysis, which might lead to incorrect conclusions.

→ ***Inadequate Use Of Statistical Models***

During an AST, valuable data is obtained that needs to be processed further in order to draw conclusions about the failure time under normal conditions. Therefore, an appropriate statistical model must first be fitted to the data. An estimate of F(t), the cumulative distribution function, a set of approximate s-confidence intervals for F(t), and a regression model are determined. The Weibull and lognormal distributions are consequently frequently used for the analysis of AST. These standard accelerated life test models are adequate for modeling e.g. simple chemical processes that lead to failure, but are not appropriate for more complex chemical processes, as described in [MEE95a]. One of the pitfalls of AST is therefore the fitting of a standard model to test data, when actually a customized model is needed which will fit the data better and will consequently provide more consistent extrapolations.

→ ***Multiple Factors Affecting Degradation***

In most AST, only one variable is accelerated, e.g. temperature, voltage or humidity. By testing only one variable, the results will show only the effect of this one factor and other factors that may influence failure time are not taken into account.

→ ***Faulty Comparison***

It is sometimes claimed that accelerated tests are useful for comparing alternative designs or vendors. However, one cannot, in general, use an ALT to compare products that have different kinds of failure modes. It is important to understand the life-limiting failure modes at use conditions before any comparison can take place. Otherwise, incorrect conclusions could be drawn.

→ ***Accelerating Variables Can Cause Deceleration***

An accelerating variable might cause another variable to 'slow down', causing misleading results and more failures in practice than was predicted. For example, increased temperature will often lead to lower humidity, so an AST where the temperature is accelerated will lead to more positive failure times if the primary failure mode in practice is corrosion due to humidity.

→ ***Few or No Failures Might Occur***

Even with acceleration, few or no failures might occur during a test. In that case, the obtained data will not be very reliable and there will be an enormous level of uncertainty, resulting in large confidence intervals and unreliable failure times. In this situation, it is difficult to assess reliability with traditional life tests that record only failure time.

Meeker and Escobar [MEE98b] address the problem of few or no failures. Since not much data can be collected about real failures in this case, degradation measures are used to describe a degradation model, which is used to make predictions about a failure time distribution. Since this degradation reliability model corresponds to physics-of-failure mechanisms instead of a commonly accepted test standard or generic list, Accelerated Degradation Test (ADT) also addresses the problem of inadequate use of statistical models.

For some products or devices it is difficult to obtain failure time data fast, because their time-to-failure is quite long. For these kinds of devices it may be possible to obtain degradation measurements over time. These measurements may contain useful information about product reliability [LU93]. Sometimes it is possible to measure physical degradation as a function of time. In other applications actual physical degradation cannot be observed directly, but measures of product performance degradation may be available.

In literature, various accelerated degradation tests are described, modelled and analyzed ([LU93], [MEE98a], [MEE98b], [CHI01], [HAM95], [TSE94], [YAN02]). They describe how degradation data can be used to estimate parameters of a degradation model and use this for the prediction of time-to-failure. This topic will be further discussed in section 3.4.5.

Conformance with criteria

In this class of methods a division is made between two types of accelerated testing methods. One of these is focused on finding failure times in a relatively short time, while accelerated degradation tests actually follow the real degradation path and extrapolate these results to failure times. ADT methods are very closely related to the next class of methods (section 3.4.5). However, this class of methods limits itself to the testing methods themselves. The scores of this class of methods are split up. The first score per criterion is for the accelerated failure tests (AFT). The second score is for ADT tests.

The first criterion is taken into account. With ADT tests unit-to-unit variation is even taken into account more than with accelerated failure tests. For AFT the same accounts as for the statistical failure analysis methods (class 1 methods). Unit-to-unit variation is not explicitly taken into account, but can be found in the results of the failure data. With ADT tests all units are separately followed until failure, or at least until a certain pre-specified period of time. Therefore, the scores are "+" and "++".

As previously mentioned, AFT tests do not provide information about the time-dependent behavior of products. This gives a score of "o" to the AFT tests. ADT tests, however, do provide information about the behavior of the products individually over time. So, the score for criterion two is "++".

For the same reason as given for criterion two, the scores for criterion three are “o” and “++” respectively.

Both testing methods can deal with censored data. However, as Meeker et al [MEE98b] explain, ADT tests provide more justification and credibility for extrapolating data to failure times. This has the following scores as a result: “+” and “++”.

The objective of both testing methods is to gather and analyze statistical failure data. This leads to a score of “++” for both testing methods.

The last criterion is about optimization of the design of a product. AFT tests do not take optimization into account. So the score is “o”. ADT tests however, can actually take this into account, when considering the example provided by Tseng et al [TSE94]. But then again, that was a combination of two classes of methods. Solely taken, ADT tests do not explicitly include information of the design parameters, which makes optimization impossible. The score therefore becomes “o” too.

3.4.5 Reliability by Degradation Analysis related methods

For highly reliable products, it is difficult to assess the lifetime of the products by using traditional life tests that record only time-to-failure. Even using the technique of censoring [LEW96] or accelerated life testing (see section 3.4.4) provides little help, because no failures are likely to occur in a reasonable amount of time. If characteristics exist whose degradation over time can be related to reliability, then collecting degradation data can provide information about product reliability. An example of such a characteristic is given in figure 3.4, where the length of a crack is linked to the number of cycles.

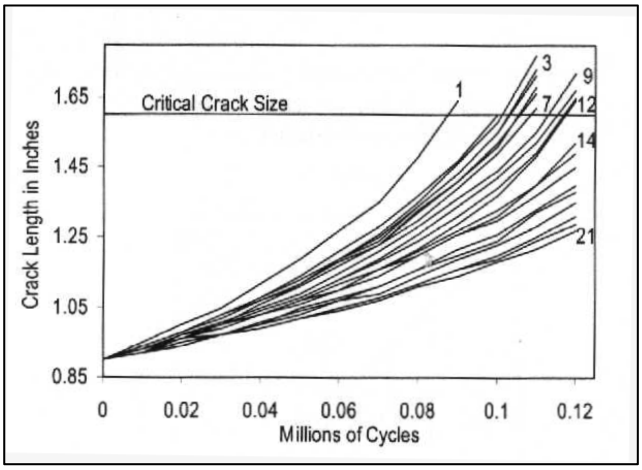


Figure 3.4: Fatigue crack growth data plot [MEE98a].

This figure also makes clear that failure needs to be defined in terms of a specified level of degradation. Then after modeling the degradation profile of a product, reliability characteristics as Mean Time To Failure (MTTF) could be predicted.

Many researchers think that degradation analysis can provide better reliability prediction methods, because degradation is a natural response and because of its ease to extrapolate. Hence, several degradation-modeling methods have been developed. Four typical examples are described in Lu and Meeker (1993) [LU93], Meeker and Escobar (1998) [MEE98a], Chiao and Hamada (2001) [CHI01], and Chinnam (2002) [CHI02].

These methods basically make use of the same kind of degradation model. The actual degradation path of a particular unit over time is denoted by $D(t)$, $t>0$. Values of $D(t)$ are in application sampled at discrete points in time t_1, t_2,.... 'Time' t could be real time or some other measure like miles for automobile tires or cycles in fatigue tests. The observed degradation y_{ij} of unit i at time t_j is [MEE98b]:

$$
\begin{aligned}
&y_{ij} = D_{ij} + \varepsilon_{ij} = D(t_{ij}; \beta_{1i}, \ldots, \beta_{ki}) + \varepsilon_{ij}, \qquad && i = 1, 2, ..., n, \\
&\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^2), && j = 1, 2, ..., m_i
\end{aligned}
\tag{3.4}
$$

where D_{ij} is the actual path of the unit i at time t_{ij} and ε_{ij} is a residual deviation for unit i at time t_j. The total number of inspections on unit i is denoted by m_i. For the ith unit, $\beta_{1i},...,\beta_{ki}$ is a vector of k unknown parameters.

Meeker et al give some advantages for the use of degradation analysis in [MEE98b], [CHI02]:

1. Degradation data can, particularly in applications in which few or no failures are expected, provide considerably more reliability information than would be available from traditional censored failure-time data.
2. Accelerated tests are commonly used to obtain reliability-test information more quickly. Direct observation of the degradation process may allow direct modeling of the failure-causing mechanism, providing more credible and precise reliability estimates and a firmer basis for often-needed extrapolation.
3. Degradation is a natural response for some tests. And degradation data can provide better information of degradation processes, which in turn can help find the appropriate functional relationship.
4. Degradation data may yield more accurate life estimates than accelerated life tests with few or no failures.
5. Degradation data can be analyzed earlier, before a failure actually occurs and can be invaluable in studying highly reliable products that may exhibit few or no failures during traditional life-tests.

6. There is more justification and credibility for extrapolation, because the modeling is closer to physics-of-failure, compared to time-to-failure data.

Next to these advantages Meeker et al also list some limitations of degradation analysis [MEE98b]:

1. Modeling degradation of performance output of a component or subsystem may be useful, but modeling could be more complicated because the output may be affected, unknowingly, by more than one physical/chemical failure-causing process.
2. Degradation data may be difficult or impossible to obtain.
3. Obtaining degradation data may have an effect on future product degradation.
4. Substantial measurement error can diminish the information in degradation data.
5. The degradation level may not correlate well with failure.
6. The analysis can be more complicated: it requires statistical methods that are not yet widely available.

However, currently a lot of research is done on the possibilities of using degradation analysis for the purpose of reliability prediction and improvement, as the numerous references showed ([CHI02], [CHI01], [DIB04]).

Conformance with criteria

The model presented in the previous section shows that design parameters are taken into account. The degradation models also take the unit-to-unit variation into account. However, this class of methods is more a modeling class of methods, and not specifically test related. This is why the score "+/++" is given, and not the full score.

Since the method completely concentrates on modeling and analyzing time-dependent behavior of products, the score for the second criterion is "++".

As mentioned before, this class of methods is more model oriented, and less test oriented. However, the information of the models provides a good basis for analyzing the status of a product over time. This justifies the score "+".

Also criterion four is one of the strengths of this class of methods. The methods are based on degradation data and physical degradation models. When a failure limit is known, the rest of the lifetime of the products can be predicted (score is "++").

Although this class of methods does not initially concentrate on failure data; it could be more or less included by taking a failure limit. Therefore, the score is "+".

And finally, this class of methods takes the influence of the design parameters into account. Information about design parameters over time makes optimization towards reliability characteristics possible. So the score is "++".

3.4.6 Robust Design related methods

In the industry, statistical techniques for improving quality have progressed in three broad stages. A first attempt to improve quality was product inspection. It is aimed at inspection of already manufactured products. This is done in an attempt to detect products not conforming to requirements [GOH93].

Subsequently, methods like process capability studies, process control charts and Statistical Process Control (SPC) were developed. These techniques can be situated more "upstream" of the Product Creation Process (PCP). Their intention is to avoid manufacturing of unsatisfactory products by monitoring the production itself [GOH93]. Like product inspection, there is no attempt made to improve quality of the product but only to master it. Both methods are known as on-line quality control techniques.

In an attempt to improve quality of a product it is necessary to stress efforts on the design phase of a product and production process. This means, designing quality into the product. Although it is difficult to predict future product behavior in the early design stage, much research has been done in order to accomplish this goal.

Among the many approaches for improving the quality of products and processes, a particularly cost-effective approach is that of robust design, introduced by Taguchi [PHA89]. The goal of robust design is to design a system or product so that its performance is insensitive to the effects of noise. The performance of a product as measured by the quality characteristic varies in the field due to a variety of causes. These causes are called noise factors [PHA89], and they are classified as follows:

1. *External;* The environment in which a product works and the load to which it is subjected are the two main external sources of variation of a product's function.
2. *Unit-to-unit variation;* The variation that is inevitable in a manufacturing process leads to variation in the product parameters from unit to unit.
3. *Deterioration;* When a product is sold, all its functional characteristics may be on target. As time passes, however, the values of individual components may change leading to deterioration in product performance.

Robust design is one of the three stages of overall product improvement as introduced by Taguchi [PHA89]:

1. *Concept design*. During this first step, the basic architecture and techniques are investigated for achieving the desired function of the product. The most suitable ones are selected for the product.
2. *Parameter Design (or robust design)*. In this second step, the setting of parameters that affect the response, which minimizes the quality loss without affecting manufacturing cost, is chosen. Such a parameter setting yields a situation where the response output is on the desired target value and product-to-product variability in the response is minimal. For further improvement of the product, one can proceed to the third step.
3. *Tolerance Design*. For further reduction of the response's variability, the tolerances of parameters are reduced selectively but this also increases manufacturing cost. In chapter 2 the description of Spence and Soin [SPE97] was used for the explanation of tolerance design. Phadke [PHA89] splits tolerance design up into parameter design and tolerance design, where Spence and Soin [SPE97] combine them.

Many books and publications can be found in literature on Robust Design and Tolerance Design (Wu and Wu (2000) [WU00b], Park (1996) [PAR96], Creveling (1997) [CRE97], Spence (1988) [SPE88]). In this section mainly the work of Phadke [PHA89] and Spence and Singh Soin [SPE88] will be used as reference books. Phadke, in [PHA89], defines robust design as a methodology for finding the optimum settings of the control factors to minimise the product or process sensitivity to noise factors. The methodology focuses on choosing mean values for design parameters such that the product performance characteristic is made less sensitive to parameter variance. After this the performance sensitivity to process variability will be reduced. The robust design methodology is illustrated in figure 3.5, from [LEW96].

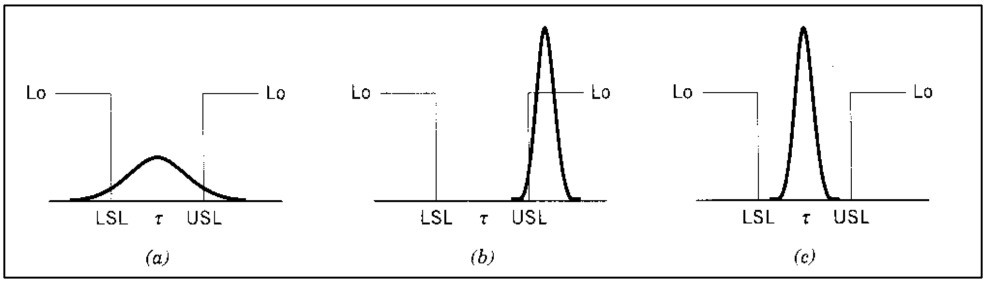


Figure 3.5: Steps in robust design method [LEW96].

In a formal approach Robust Design can be divided into two steps:

1. Optimization of the value of one or more design parameters to minimize the performance sensitivity to the value of that parameter, *regardless* of the effect on the performance means.
2. Identification of an adjustment parameter to bring the mean back on target without increasing the variance.

These two steps are illustrated in figure 3.5. At first, the mean of the performance characteristic is on target but the variance is too high (a). In the first step this variance is reduced (b) and subsequently, in the second step, the mean is brought back on target (c). In practice, these two steps are often performed simultaneously during a process called stochastic optimization.

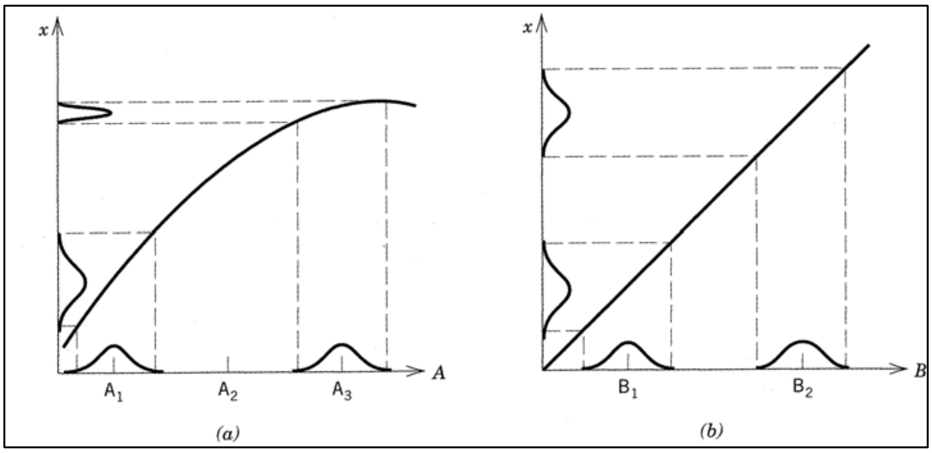


Figure 3.6:

a) *nonlinear effect [LEW96].*

b) *linear effect [LEW96].*

For the first step, design parameters are selected whose value influences the variance of the performance characteristic. This is illustrated in figure 3.6a, where increasing the value of the design parameter A, increases the mean value of the performance characteristic x, but decreases the variance in x.

For the second step, design parameters are selected whose values influence the mean of the performance characteristic but do *not* influence the variance of this performance characteristic. Assuming that after step 1 the variance of the performance characteristic is low, step 2 aims to get the mean on target. This is illustrated in figure 3.6b. The design parameter must have a linear effect on the performance characteristic. Increasing parameter B will increase the mean value of the performance characteristic x, while leaving the variance unaffected. However, the selection of such design parameters for step 1 and 2 is only possible in ideal situations. In practice, design parameters will be selected that *mainly* influence the variance of the performance characteristic and only *partly* influence the mean of the performance characteristic (or the other way around).

The explanation of Robust Design in this section concernes the quality characteristic of a product or product population. Similarly we may have a description of a performance characteristic over time, which may be seen as a characteristic that describes the degradation of a product or product population. In order to achieve robust reliability, design parameter settings need to be identified that minimize the variance of the performance characteristic over time while maintaining the mean value over time (degradation path) the same or better as before. This implies that these parameter settings reduce unit-to-unit variability over time to a minimum.

Literature describes various ways of improving reliability and to make it robust. Condra (2001) [CON01] describes how one can design for robust reliability. He describes a degradation experiment for a fluorescent lamp by Tseng, Hamada and Chiao [TSE94] and Hamada [HAM95]. In this experiment the effect of three factors or design parameters on the performance characteristic Light Intensity is evaluated. Design Of Experiments [CON01] is used for this purpose. The experimenters use four runs with different combinations of level settings at each run. For each run (or combination of level setting) five lamps are used in order to compensate for lamp production variability. Each of the twenty lamps is subjected to the same degradation test. The results of the degradation tests indicated that only two out of three factors were of influence on the Time-to-Failure (TTF) and they were set at the level that maximized their life span. The other factor was set at the level as it was before the experiment.

In another experiment using LEDs, Chiao and Hamada [CHI01] also take into account a noise factor. They estimate the parameters of a degradation model and the probability density function per run. Based on the PDF they calculate the reliability during the warranty period per run. The factor settings for the run that lead to the highest warranty reliability are selected. This way of design also takes into account the variance in TTF.

Although this *parameter design* approach can generate major operating cost reductions, it will not always lead to sufficiently high quality. After optimization through parameter design, further improvements could be obtained by controlling the causes of the variation. This can for example be done by using more expensive equipment and materials, improving the processes, and regulating the environment. This approach is called *tolerance design.*

Tolerance Design makes use of the relationship between the performance characteristic and its design parameters. Chapter two provides an extensive description of tolerance design. That description is included in the analysis of suitability.

Conformance with criteria

Robust design related methods are very appealing at first sight. However, these methods are in general focused on time-independent optimization of a design. As indicated at the beginning of the description of robust design, the book of Phadke [PHA89] is used as a reference book, because this is a very clearly written and well-known book. For judging the goodness-of-use for a method that fulfils all three design requirements, the method described in Phadke will be used. But remarks will be made about the other examples, to give some insight in how these methods would be judged.

The first criterion is clear. Unit-to-unit variation and variation effects of design parameters on the performance of the product are taken into account. This leads to the full score, namely "++".

The second, third, fourth and fifth criteria are all about time-dependent features related to reliability. Using the method Phadke described, the scores are all "o". Time-dependent behaviour is not modeled, the status of products is not analyzed during its lifetime, and neither does the method predict the missing, or censored, failure data. However, when considering the other examples mentioned, they actually do take the factor time into account. The examples are a combination of many methods, like degradation testing, DOE testing and, more or less, robust design. Then the scores would definitely be higher for these four criteria.

The last criterion is optimization of a product's design. This is one of the main goals of robust design, optimizing a design in such a way that it is insensitive to noise factors and variations on the design due to all kinds of different causes. A remark that has to be made here, is that robust design is a time-independent method, and focuses on optimizing the design for time $t = 0$. It is likely that this will also lead to a better performance over time, but it is not a guarantee, as an example in chapter 5 will show. So, for the last criterion the score is "+/++".

3.4.7 Maintenance/Condition Monitoring related methods

The title of this section refers to both maintenance and condition monitoring. These two topics are closely related through maintenance theory and therefore taken as one class of methods related to reliability. As reference book for this class of methods the book of Blischke and Murthy (2003) [BLI03] is used.

The performance of a product does not only depend on its design and operations, but also on the maintenance of the product during its operational lifetime. Thus, it could be stated that functioning over an extended time period requires proper servicing on a regular basis, adequate repair or replacement of failed parts or components and so on. These actions are part of maintenance and maintainability. **Maintenance** can be defined, according to Blischke and Murthy (2003) [BLI03], as:

> *"Maintenance compromises any actions (other than routine servicing during operation such as fueling or minor adjustments) that alter a product or system in such a way as to keep it in an operational condition or to return it to an operational condition if it is in a failed condition."*

Blischke and Murthy recognize two primary types of maintenance actions:

→ ***Preventive maintenance (PM)***, where the intention is to increase the length of its lifetime and/or its reliability and generally requires shutdown of an operational system.

→ ***Corrective maintenance (CM)***, where failed products or systems are restored to an operational state by repair or replacement actions of all failed parts and components necessary for successful operation of the product.

The emphasis of this thesis is more on preventive maintenance than on corrective maintenance. For this reason the rest of the discussion of this class of reliability related methods is on preventive maintenance. For more in-depth discussions on corrective maintenance, the author refers to books by Blischke and Murthy (2003) [BLI003], Hoang Pham (2003) [HOA03], Osaki (2002) [OSA02], and many others.

Preventive maintenance can be classified into the following categories [BLI03]:

→ **Clock-based maintenance**: PM actions are carried out at set times.

→ **Age-based maintenance**: PM actions are based on the age of the components.

→ **Usage-based maintenance**: PM actions are based on usage of the product.

→ **Condition-based maintenance**: PM actions are based on the condition of the component being maintained. This involves monitoring of one or more variables characterizing the wear process. This could thus be seen as condition monitoring.

→ **Opportunity-based maintenance**: When a maintenance action (CM or PM) is carried out it provides the opportunity to carry out PM actions on one or more of the remaining components of the system.

→ **Design-out maintenance**: This involves carrying out modifications through redesigning the component. As a result, the new component has better reliability characteristics.

In general, as Blischke and Murthy [BLI03] emphasize, preventive maintenance is carried out at discrete time instants. Many different types of model formulations have been proposed to study the effects of preventive maintenance on the degradation and failure occurrence of items to derive optimal preventive maintenance strategies. Pecht (1995) [PEC95] discusses concepts, modeling, and analysis of maintenance and reliability and related areas in detail.

One of the obvious conclusions that can be drawn from most of the literature on preventive maintenance related topics is that decisions are usually made on statistical failure data. This fits the first three classes of preventive maintenance, as suggested by Blischke and Murthy [BLI03]. One special class in the classification is the condition-based maintenance, which is often called condition monitoring in literature. In this class of PM the actual condition of the product needs to be monitored using variables that are directly linked to the performance of the product or system. However, this class of PM is only common in very big industrial systems (Hunt (1996) [HUN96], Rao (1996) [RAO96], Williams, Davies and Drake (1994) [WIL94]).

Conformance with criteria

Methods focused on maintenance usually do not include unit-to-unit variations. Preventive maintenance methods most often use statistical failure data and make maintenance decisions on those data. But in general, unit-to-unit variation, especially at the level of design parameters, is not included, leading to a score of "o" for criterion 1.

Criteria two and three are both about time-dependent behavior of products. Corrective maintenance does not model, or analyze time-dependent behavior. Preventive maintenance only takes this minorly into account in the case of condition-based maintenance. Therefore, the scores for criteria two and three are "o/+" and "o/+" respectively.

None of the maintenance methods predicts product behavior over time. Even condition-based maintenance methods are not meant to do this. In these methods the status of the products are monitored and when the levels come close to a pre-determined failure level, PM is applied. Thus, the score is "o".

Also the fifth criterion is not a point of strength of maintenance related methods in relation to the criteria that have been formulated in the beginning of this chapter. With corrective maintenance, no attention is given to the analysis of statistical failure analysis. With preventive maintenance, statistical failure data is analyzed on population level. Therefore, a score of "o/+" is given for this criterion.

And finally, the last criterion is optimization of the design. Maintenance is completely not focused on optimizing a product, but just to keep it in an operational condition, or to return to an operational condition if the product has failed. So, the score is "o".

3.5 Summary of literature analysis results

In the previous section a brief description is given of all classes of reliability related methods and tools. Then, with the brief description in mind, all classes of methods were judged on their goodness-of-use by judging how good the methods meet the criteria that were formulated and discussed in section 3.2. Table 3.2 gives an overview of the results of all the discussions about the goodness-of-use of all the different classes of methods related to reliability.

Table 3.2: Overview results of analysis of reliability related methods to criteria for reliability prediction and improvement.

		Criteria for Reliability Prediction and Improvement					
	Ability to	addres unit-to-unit variability	model and analyse product time-dependent behaviour to degradation data	analyse product status	predict product behaviour over time	analyse statistical failure data	design reliability optimisation
Reliability Related Methods	1. Statistical Failure Analysis	o/+	o	+	+/++	++	o
	2. Stress-Strength Reliability Analysis	+/++	+	+	+	o/+	o/+
	3. Reliability by DOE	++	o/+	o	o/+	o/+	+/++
	4. Reliability by Accelerated Testing (ALT|ADT)	+|++	o|++	o|++	+|++	++|++	o|o
	5. Reliability by Degradation Analysis	+/++	++	+	++	+	++
	6. Robust Design	++	o	o	o	o	+/++
	7. Maintenance/-Condition Monito-ring	o	o/+	o/+	o	o/+	o

When studying the table, it can easily be concluded that all classes of methods have their own strengths and weaknesses in relation with the criteria that have to be fulfilled in order to solve for the three design requirements. Again note that all methods have been judged using one book (when necessary) as reference for the particular classes of methods. In the text references were already made to methods that overlap a few classes of methods and, therefore, could perform better with respect to the criteria. However, the analysis on methods and tools available in literature shows that certain ideas, concepts, or approaches could be very useful for the development of a method that does meet all criteria to solve for the design requirements.

After this analysis it is possible to answer the two research questions that were given in section 3.1. The research questions are:

Are methods available in literature that connect, or take into account, the necessary information for the three design requirements?

And:

Which methods, concepts, or ideas available in literature could serve as a basis for a new method and what adjustments are necessary to these methods in literature to connect, or take into account, the necessary information for the three design requirements?

Table 3.2 clearly shows that all methods have their strengths and weaknesses in relation with the criteria that were examined in this chapter. But none of the methods is able to fulfil all criteria in an optimal manner. This is why the answer to the first research question is negative, meaning that literature does not provide one method solving the three design requirements at once. However, all methods have very useful ideas and concepts that could definitely serve as a starting point for the development of a new method. The strengths of all classes of methods are indicated with a '++' in table 3.2. In chapter four a new theoretical approach is presented that meets all criteria as presented in this chapter. The approach incorporates many ideas, concepts and approaches of the methods that have been described in this chapter.

4 Reliability Optimization Method using Degradation Analysis (ROMDA)

4.1 Introduction

The ultimate objective of this research is to develop a method that is applicable by designers that can tackle the three design requirements. Chapter 3 presented the results of a literature study that has been carried out to research if methods are available in literature that could be used to reach the research objectives. This has been done by judging how good the available methods and tools in literature meet a set of criteria that a method has to meet in order to solve for the three design requirements. The summary of the results presented in section 3.5 shows that not one method is capable of providing a good solution for all criteria. However, all methods definitely have their strengths, as was indicated in table 3.2.

This chapter presents a theoretical framework taking into account all criteria that have to be complied with, to come to a solution method that can be used to solve for the three design requirements. For the development of the theoretical framework the knowledge of all classes of reliability related methods and tools is used. This chapter limits itself to a theoretical framework. Chapter 5 presents computer simulation experiments verifying the theoretical validity and value of the theoretical method that is presented in this chapter. Next, a critical analysis on the practical validity and value of ROMDA is presented.

4.2 Theoretical framework

The theoretical framework of the Reliability Optimization Method Using Degradation Analysis (ROMDA) method will be explained using figure 4.1. Figure 4.1 is divided in three stages. The first stage is the 'Product Design' stage where products are designed or designs can still be changed or adjusted. The second stage in figure 4.1 is the 'Quality' stage. In this stage products are already manufactured and sold to the customers. This stage represents the time-independent quality of products taking into account all causes of variation influencing the performance of products. Basically, since in this thesis quality is defined as reliability at time $t = 0$, this stage can be considered as how good products or systems fulfill their intended purpose considering all causes of variability, except variability due to degradation effects. And the third stage is the 'Reliability' stage. Reliability is quality over time and takes all causes of variability and all failure mechanisms into account. The first stage is where the products are designed and where the values for the design parameters (DP's) and the performance characteristic of the product design concept are decided. In the second stage the results of the choices made for the values of the DP's and the output parameters can be seen and measured. And the third stage makes the translation to failures over time of the complete product population.

Chapter 3 presented a set of criteria for reliability prediction and optimization that should be incorporated in a reliability prediction and optimization method in order to provide a way of solving for the three design requirements.

The six criteria are:

1. Ability to address unit-to-unit variation
2. Ability to model and analyze product time-dependent behavior

3. Ability to analyze the product status
4. Ability to predict product behavior over time
5. Ability to analyze statistical failure data
6. Ability to optimize the product design in terms of reliability

All these six criteria are indicated in figure 4.1 according to the criterion number. Criterion 1 deals with the ability to address unit-to-unit variation due to manufacturing causes, and environmental causes. In figure 4.1 at the 'Quality' stage the variation of products at time $t = 0$ is clearly shown by a statistical distribution. The statistical distribution represents the unit-to-unit variation of the performance characteristic in the performance space, which is taken in consideration in this theoretical framework. It is possible to take more performance characteristics into account, but for the purpose of explaining the theoretical line of reasoning, the method will be explained by using only one performance characteristic.

Criteria 2 to 4 can all be placed on the link between 'Quality' and 'Reliability'. Criteria 2 to 4 deal with the time-dependent performance of the complete product population. Criterion 5 deals with the ability to analyze statistical failure data. One way of representing statistical failure data is by means of a failure rate curve. And finally criterion 6 is placed in the complete loop of figure 4.1. Products are designed and manufactured. This results in a certain unit-to-unit variation of the performance characteristic. And due to the time-dependent behavior (degradation) the performance of the products will degrade over time. When the performance degradation exceeds the failure limits the products will eventually fail.

The next section presents a theoretical framework taking into account all criteria necessary for a stochastic reliability prediction and optimization method. The theoretical line of reasoning finally leads to a step-by-step protocol for ROMDA.

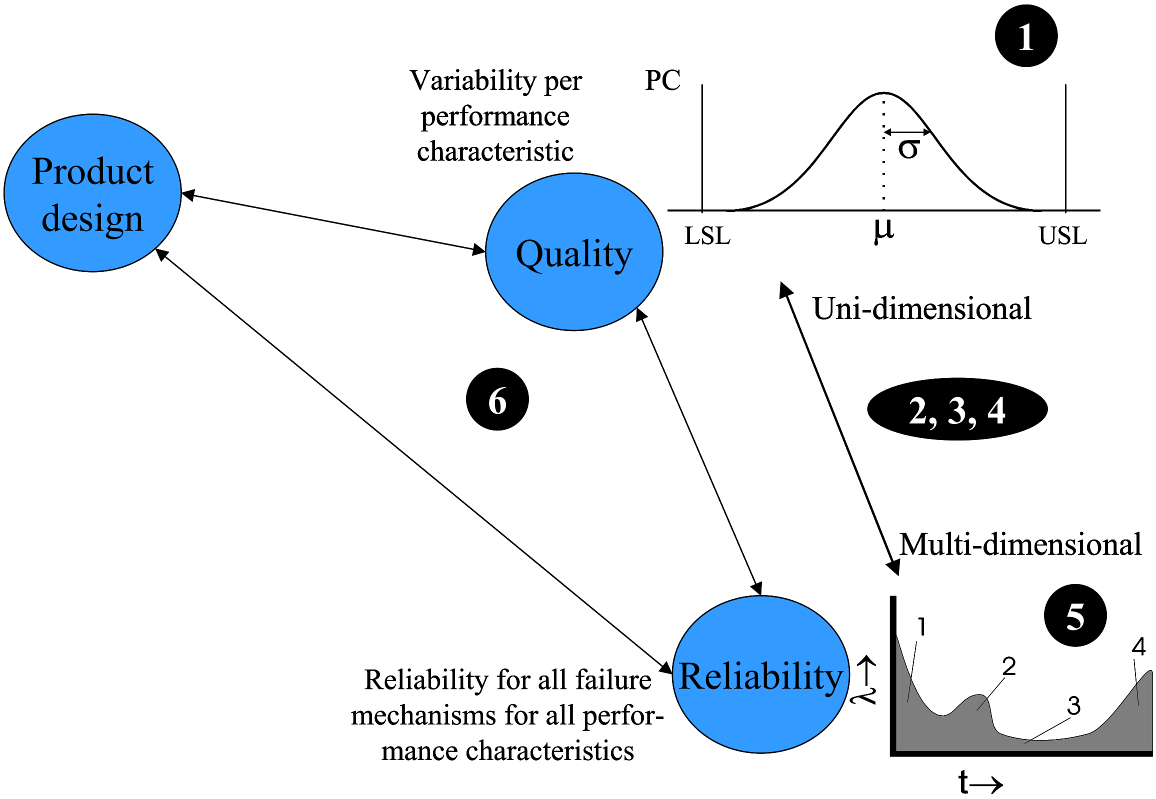


Figure 4.1: Overview of the theoretical framework of ROMDA.

4.2.1 Line of arguments for theoretical framework

The typical failure rate curve, as described in chapters 2 and shown in figure 4.1 at the 'Reliability' stage, contains compounded information of a variety of modes of failure at a given time. In other words, the failure rate curve represents all products failing to perform their intended functions considering all performance characteristics due to all possible failure mechanisms at a given time. Therefore, the failure rate curve consists of all failure mechanisms of all performance characteristics. However, typically variability information is only available pertaining to a single performance characteristic. Figure 4.1 shows variability information of a single performance characteristic (see statistical distribution at 'Quality' stage).

The contradictory link between variability per performance characteristic at the time-independent 'Quality' stage and the time-dependent 'Reliability' stage for all failure mechanisms for all performance characteristics provides a first problem that has to be solved.

Hence, as a first step in the exploration to the existence of the link between variability of the studied performance characteristic at time t = 0 and reliability at time t, the dominant failure modes have to be studied separately in conjunction with variance of the associated performance characteristics. This information provides the possibility to come to a failure rate curve consisting of one performance characteristic for one dominant failure mode. The failure rate curve then becomes a failure rate curve representing a single failure mode. When such a dominant failure mechanism has been identified, the contradictory link is solved. Since the failure rate curve is now only dependent on the dominant performance characteristic representing the most dominant failure mechanism, it becomes possible to formulate a causal relationship between product variability and reliability with respect to that performance characteristic. Essentially two types of data are necessary to overcome the contradictory link problem:

→ Performance characteristics data at zeroth hour ('Quality' stage)

→ Time-dependent data with respect to the performance characteristic that is being studied. This will yield information on change of the performance characteristic over time and hence will be crucial in mapping the failure rate information.

Chapter 2 already shows that from an initial set of products, product failure may be conceptualized as being due to a change in the variance over time, a drift in the mean over time, or a combination of both over time of the dominant performance characteristic. These three degradation mechanisms in combination with the failure limits (when the failure limits would be constant values) lead to failure and can be used to explain the failure rate curve, as figure 4.2 shows.

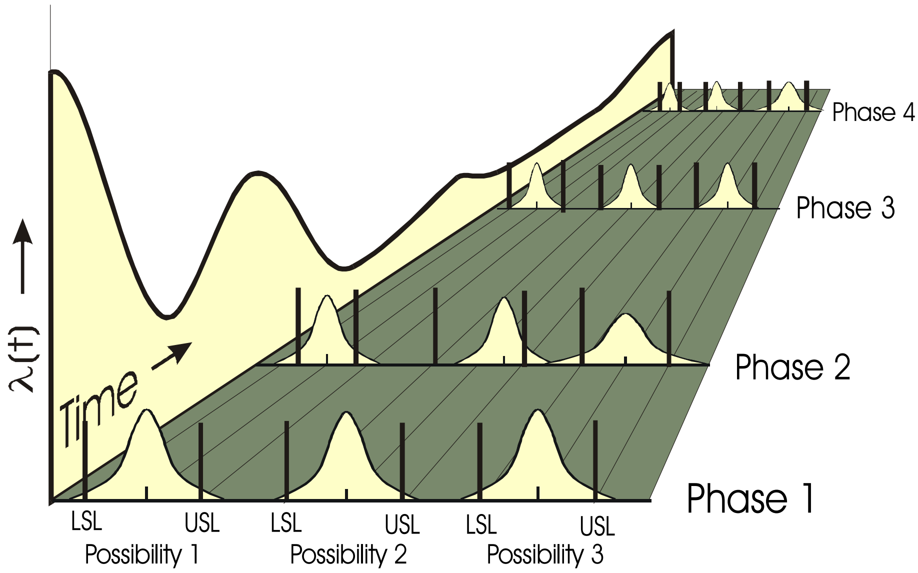


Figure 4.2: Possible effects of variability.

Now that the time-dependent behavior of the performance characteristic in combination with the variation effects is known, the next step is to identify design parameters that influence the behavior of the performance characteristic. The purpose for this step has been explained in section 2.3 (Tolerance Design). So, if the change in variance and a drift in the mean value of the performance characteristic could be modeled in terms of the dominant time-dependent design parameters influencing the performance characteristic under study, and a 'Physics of Failure' based degradation mechanism (like e.g. the Arrhenius model) could be 'superimposed' on these design parameters in the model, then the mean drift and variance change of the performance characteristic could be modeled in terms of design parameter values and time. Figure 4.3 schematically shows this line of arguments.

The challenge then would be to use the variance degradation and the mean drift model of the performance characteristic as a causal reason to explain the failure rate curve for the performance function. First the dominant design parameters are defined. Then "Physics of Failure" degradation mechanisms are superimposed on these dominant design parameters. With this the change in variance and the mean drift of the performance characteristic under study can be mathematically modeled by the degradation models of the design parameters, which makes it eventually possible to describe the failure rate curve of the performance characteristic in terms of the dominant design parameters and time. Note that the link between the design parameters and the performance characteristic describes the link between the parameter space and the performance space.

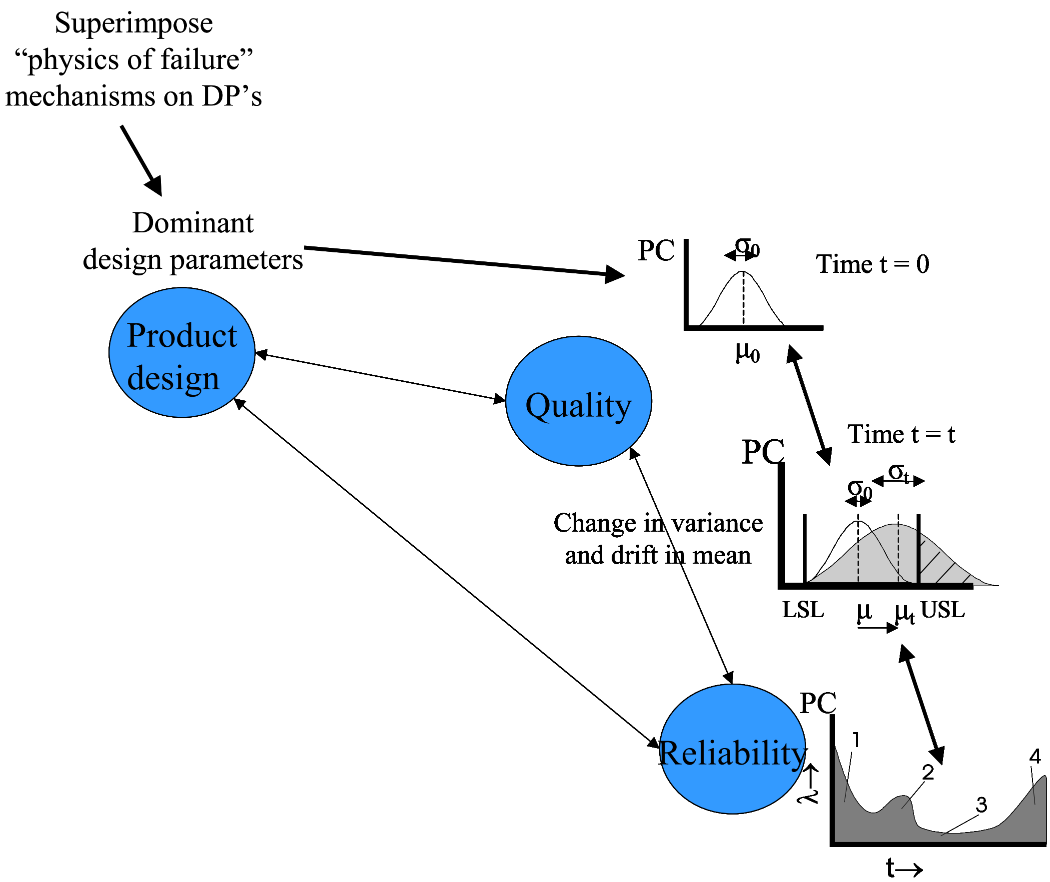


Figure 4.3: Overview ROMDA with degradation of performance characteristic.

The theoretical approach attempts to establish a relationship between product reliability and product design, and investigates failure of products with respect to a dominant performance characteristic, where performance characteristic is defined as a measure expressing how good a product fulfils its function. The crux of the method is that the performance characteristic characterizes the reliability of the product as a function of the dominant design parameters (= physical product parameter that can be influenced by the designers) and the degradation behavior of these dominant design parameters over time. The degradation profiles of the design parameters are superimposed on the performance characteristic in a model describing the functional relationship between the degradation of the performance characteristic and the design parameters. This relationship is then used to derive reliability characteristics (e.g. mean time to failure (MTTF), variance time to failure (VTTF)) of the stipulated performance characteristic. In essence, this approach can be used to establish the behavior of the statistical properties of the 'time to failure' of the performance characteristic given the statistical properties (like the mean and the variance) of the design parameters at time $t = 0$ and their degradation models. A graphical representation of this concept is illustrated in figure 4.4.

In figure 4.4 the three figures on the left represent the statistical properties of the dominant design parameters and the degradation of these design parameters over time, where the z-axis represents time. These three figures are in the parameter space.

The figure in the middle represents the performance characteristic in the performance space. The performance characteristic is also of statistical nature and degrades over time due to the effects of degradation of the dominant design parameters. The performance characteristic is linked to the dominant design parameters by a mathematical functional relationship. Therefore, the functional relationship describes the link between the parameter space and the performance space. When specification limits for the performance characteristic are known (in figure LSL = Lower Specification Limit and USL = Upper Specification Limit), a translation can be made to a reliability characteristic like the failure rate curve, which is shown on the right of figure 4.4 (e.g. the roller-coaster failure rate curve of K.L. Wong [WON88]).

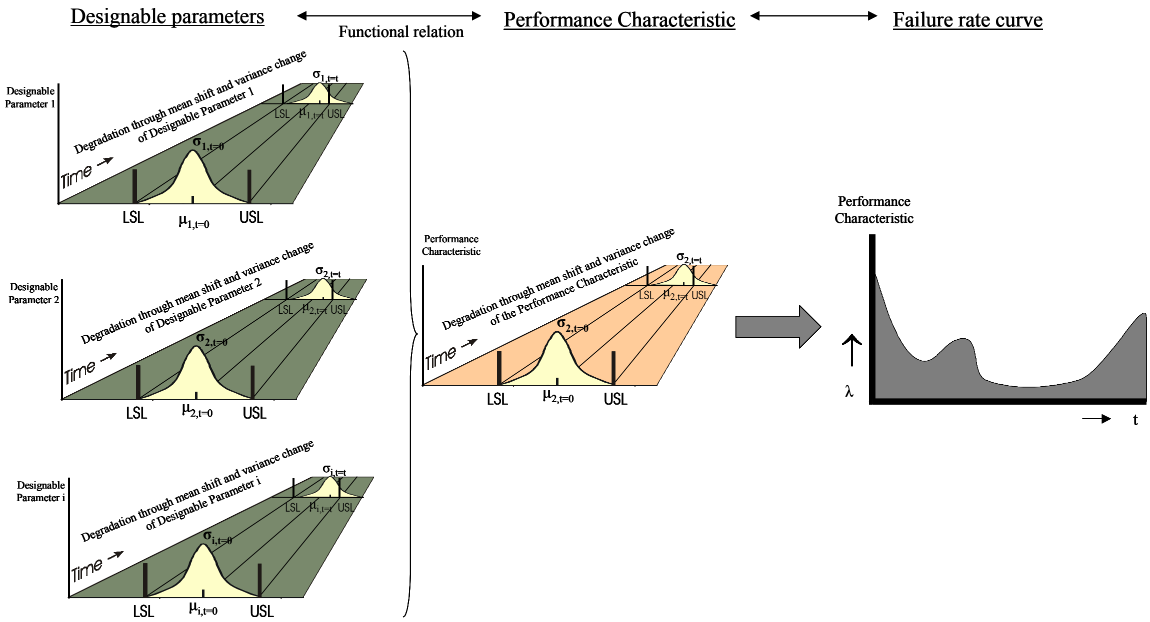


Figure 4.4: Overview of the theoretical line of reasoning behind ROMDA.

4.3 Link to three design requirements

The theoretical framework of ROMDA has been explained in section 4.1 and 4.2. This section explains the link between the theoretical framework and the three design requirements. The objective of this research is to develop a method that provides a solution for the three design requirements.

In order to explain how the line of argument provides the possibility to solve for the three design requirements, consider figure 4.5.

In order to optimize a product towards reliability and robustness, the link between the design parameter values and the performance of a product is obvious. Chapter 3 extensively explains that adjusting the initial design parameter values can improve the reliability performance using the functional relationship between the PC en the DP's. Therefore, design parameter information in relation with the performance characteristic is crucial. This has been explained in chapter 2.

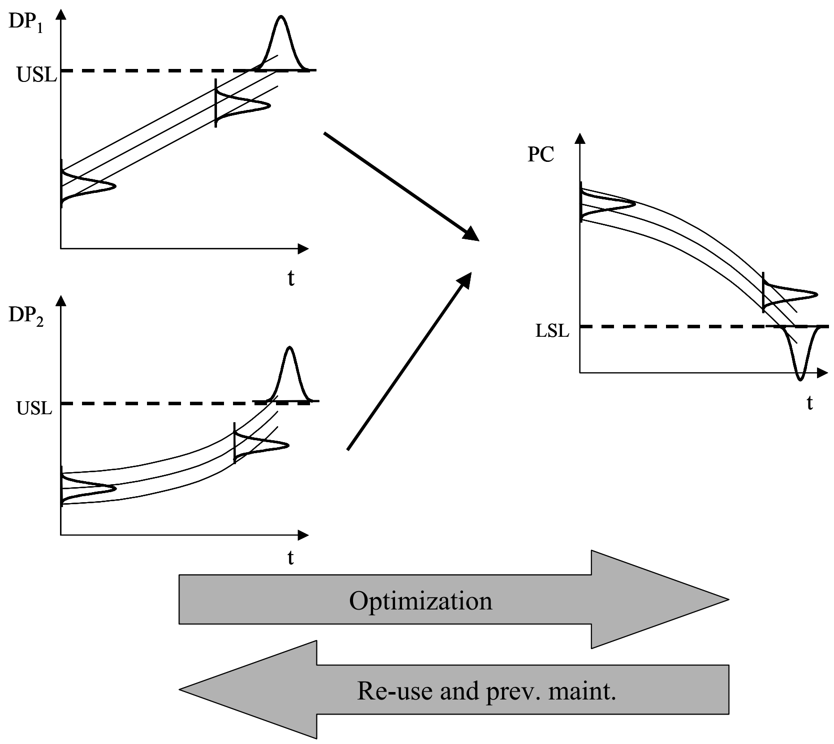


Figure 4.5: Link between theoretical framework and the three design requirements.

In chapter 2 it is argued that having time-dependent design parameter information can improve applicability of preventive maintenance and re-use decisions. Consider figure 4.6 as an example.

Imagine, for example, that an engineer has to make a preventive maintenance decision. It is very hard to measure the performance characteristic online, because this factor is not a physical parameter. Consider the simple example of a car braking system. Imagine the brake power is the important performance characteristic. Brake power is not easy to measure directly. Now, the engineer knows the important design parameters (e.g. brake disk thickness, piston margin, etc.) and the link between the design parameters and the performance characteristic. Now, by simply measuring the design parameters and using the functional relationship between DP's and the PC, he is able to make a good preventive maintenance decision. When studying figure 4.6 it is easy to understand that when having measured the two values of the design parameters (the x-s in the two left graphs) and knowing the functional relationship, the value of the performance characteristic has to be somewhere within the Δt time span.

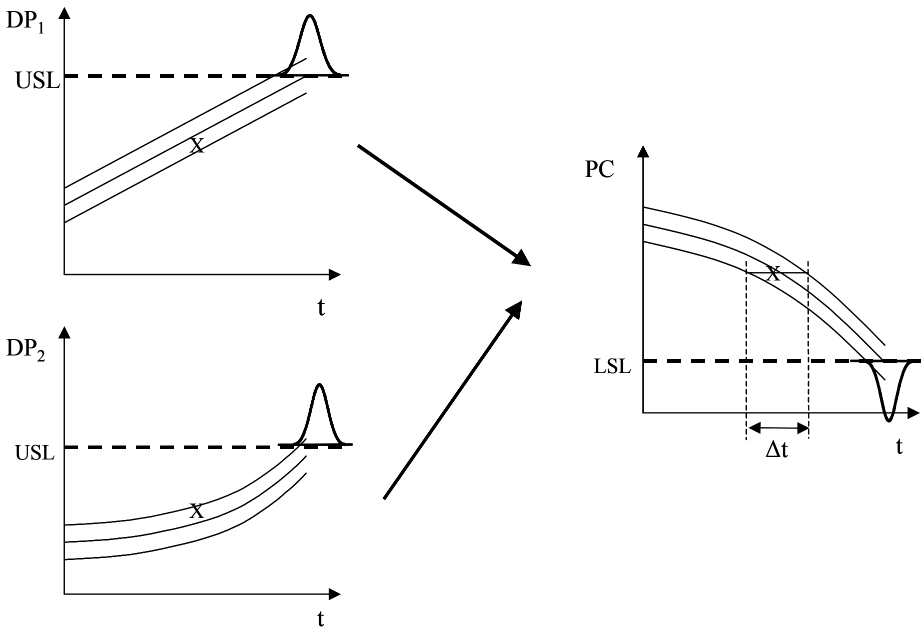


Figure 4.6: Example for preventive maintenance decisions.

A same line of reasoning can be used for re-use decisions.

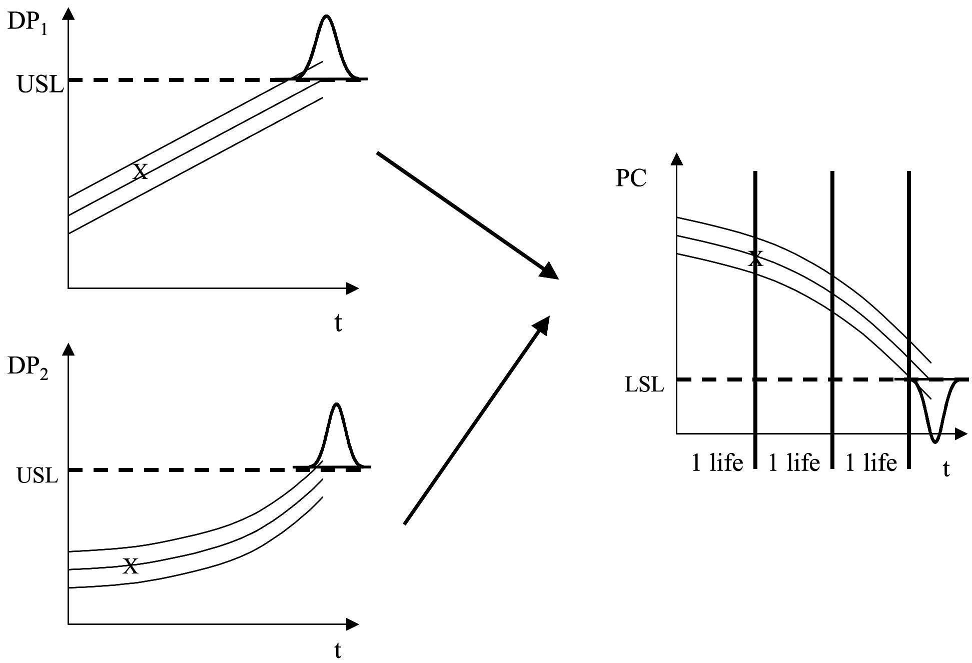


Figure 4.7: Example for re-use decisions.

Figure 4.7 shows an example of measurements that make re-use decisions possible. Consider a photocopier. A photocopier consists of 24 modules. The innovation of the copier is generally limited to the copying process itself (from analogue to digital). But the paper transport system is not changing in a new copier. Then it would be highly cost efficient and environmentally conscious if the modules that have not changed in the new design could be re-used. In the case of a copier machine this is an actual question (and it will be used as one of the case studies in chapter 7). The copiers are designed for an average technical operation time of 16 years. However, most customers exchange their copier for a newer model after approximately 1,5 years. This means that the copier still has a considerable technical, and thus, economical value. However, a manufacturer cannot take the risk to just re-use modules with the risk of not surviving another lifetime in a new copier. Imagine that the values shown in figure 4.7 are measured and that the second life should approximately end at the second vertical line in the graph on the right. Then, with high certainty, the manufacturer can re-use the module for a next lifetime, since the PC is not expected to become below LSL during the 2nd life.

The above-described examples in combination with the discussion in section 2.3 illustrate how the theoretical framework works for the three design requirements. Next, a general step-by-step protocol that makes the theoretical framework applicable will be explained.

4.4 General step-by-step protocol

ROMDA aims to optimize the product design by establishing a relationship between the reliability of products by means of a performance characteristic and the design parameters. This way also an understanding of the link between the robustness of the initial product design and the reliability of the product is established. In this method, the reliability of a population of products is only expressed by one performance characteristic. More performance characteristics are possible. In the next sections, ROMDA will be discussed according to three steps, namely:

1. Determination and modeling of the Performance Characteristic and the Design Parameters;
2. Determination of the functional relationship between the Performance Characteristic and the Design Parameters;
3. Reliability prediction and optimization of the complete product population.

4.4.1 Determination and modeling of the Performance Characteristic and the Design Parameters

The first step is to identify the performance characteristic (PC) and the dominant design parameters (DP's). In theoretical problems the DP's and the PC are usually known from literature.

After the identification of the PC and the dominant DP's, a degradation function needs to be developed that describes the degradation of these DP's over time. These functions are stochastic in nature due to the natural unit-to-unit variation. For explanation purpose only normal distributions will be considered. The same line of arguments applies for other distributions. Only the mathematical treatment becomes increasingly difficult. The initial statistical distribution due to the unit-to-unit variation can, respectively for the DP's and the PC, be expressed as:

$$DP_i(t=0) \cong f_i(\mu_{DP_{i0}}, \sigma^2{}_{DP_{i0}}) \quad i = 1,2,...,n \tag{4.1}$$

$$PC_j(t=0) \cong k_j(\mu_{PC_{j0}}, \sigma^2{}_{PC_{j0}}) \quad j = 1,2,...,m$$

with n being the number of dominant design parameters (DP_i) and $\mu_{DP_{i0}}$ and $\sigma_{DP_{i0}}$ being the mean and the variance of design parameter i at time t = 0, and with m being the number of performance characteristics and $\mu_{PC_{j0}}$ and $\sigma^2_{PC_{j0}}$ being the mean and variance of these performance characteristics at time t = 0.

This is a description of the nominal values of the design parameters and the variance of the design parameters around these nominal values. As a result of degradation (wear) of the products, the properties of the statistical distribution will change over time. This can be expressed as:

$$DP_i(t) = g_i(DP_i(t=0), t) \quad i = 1,2,...n \tag{4.2}$$

$DP_i(t=0)$ represents the initial value of the design parameter *i*. So, the design parameter over time is a function of the initial value of the design parameter and time.

As a result, the design parameters' mean and variance are functions of the value of that design parameter at t = 0 and time. This can be expressed as:

$$\mu_{DP_i}(t) = g_{1i}(\mu_{DP_{i0}}, \sigma^2{}_{DP_{i0}}, t)$$

$$\sigma^2_{DP_i}(t) = g_{2i}(\mu_{DP_{i0}}, \sigma^2{}_{DP_{i0}}, t) \qquad i = 1,2,...,n \tag{4.3}$$

4.4.2 Determination of the Functional Relationship between the Performance Characteristic and the Design Parameters

In the next step, a functional relationship needs to be established between the design parameters and the performance characteristic. The functional relationship between the design parameters and the performance characteristic will be of the following form:

$$PC_j(t) = F_j(DP_1(t), DP_2(t),..., DP_n(t)) \quad j = 1,2,...,m \tag{4.4}$$

with m being the number of performance characteristics (m = 1 in this thesis).

The functional relationship between the performance characteristic and the design parameters (4.4) can be combined with the degradation profiles of the critical design parameter (4.2) to form a function that describes the degradation function of the performance characteristic over time. This change over time is again divided in a shift in mean and a change in variance. The following functions describe the behavior of the performance characteristics over time:

$$\mu_{PC_j}(t) = f(\mu_{DP_i}(t), \sigma^2{}_{DP_i}(t))$$
$$\sigma^2{}_{PC_j}(t) = f(\mu_{DP_i}(t), \sigma^2{}_{DP_i}(t)) \quad j = 1,2,...m \quad i = 1,2,...n \tag{4.5}$$

Appendix 2 shows a validation of the form of these functions by means of Taylor series expansions. With the form of the function in this case is meant that the mean of PC over time is a function of both the mean and the variance of the DP's over time. The same applies for the variance function of PC over time. This function is also dependent on the mean and the variance of the DP's over time.

At any moment in time, the value of the performance characteristic can be found by using this function (4.5). Linking these values to the specification limits of the performance characteristic gives insight into reliability characteristics of this performance characteristic. An example of such a reliability characteristic is the mean time-to-failure (MTTF). According to Lewis [LEW96] the MTTF can be expressed as:

$$MTTF = \int_0^\infty R(t)dt \tag{4.6}$$

with R(t) being the reliability at time t (see equation (2.4).

4.4.3 Reliability Prediction and Optimization

The last step in ROMDA is the step of reliability prediction and optimization by using the functions and reliability characteristics of the previous two steps. The initial design parameter values (at time t = 0) can be set at various levels in the design stage. This means that, in case of parameter design, μ_{DP_i} at t = 0 can be changed. This will result in different performance of the performance characteristic over time. Similarly, tolerance design could be applied.

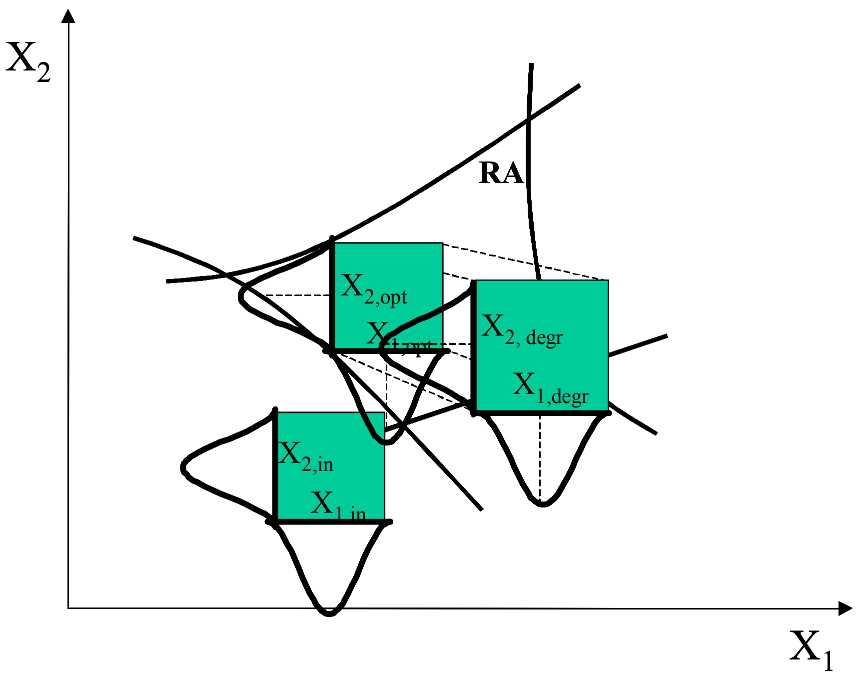


Figure 4.8: Schematic overview of optimization in terms of reliability.

For each setting of the design parameter values, the model of the performance characteristic can be obtained and the related relevant reliability characteristics, like MTTF and VTTF, can be determined. Subsequently, these reliability characteristics can be optimized using an optimization method like Robust Design (§ 3.4.6). The goal of this optimization method is to maximize the nominal value and minimize the variance values of the reliability characteristics. This can give better results than using traditional reliability or quality related optimization methods. Figure 4.8 illustrates this. In figure 4.8 the region of acceptance (RA), as Spence and Soin [SPE97] use it, is shown. Assuming that the tolerance region of a product with two parameters looks like the rectangular block with ($X_{1,in}$, $X_{2,in}$) as the initial design values (before optimization), it is obvious that the complete product population is outside the region of acceptance. In that case all products would fail. When using robust design optimization techniques, an optimal design would be exactly in the middle of the region of acceptance. Optimizing in terms of reliability means that the products remain as long as possible within the region of acceptance. So, when knowledge is available on the direction of the degradation of the dominant design parameters over time, a better optimal solution in terms of reliability could be obtained. This approach is already explained in chapter 2. Figure 4.8 shows that the parameters degrade to the right of the region of acceptance. And because the optimal solution is now on the upper left corner, most products will not fail for a maximum, or optimal, period of time.

4.5 Summary of step-by-step protocol

A general systematic approach of ROMDA to predict and improve (optimize) reliability in a robust way is:

1. Identify the dominant failure mechanism and relate this dominant failure mechanism to a performance characteristic.
2. Identify the time-dependent dominant design parameters influencing the performance characteristic under study dominantly.
3. Obtain time-dependent stochastic models that describe the degradation of the performance characteristic through the physical degradation of the dominant design parameters, as graphically shown in figure 4.3 and 4.4.
4. Introduce the stochastic properties of the design parameters into the performance characteristic/design parameter functional relationship to obtain a stochastic time and design parameter dependent model for the performance characteristic under study.

5. Use this functional relationship with respect to certain chosen specification limits to obtain reliability characteristics, like the mean time-to-failure (MTTF) and variance of time-to-failure (VTTF).
6. Use an optimization method, like Robust Design, to improve or optimize these reliability characteristics by setting the nominal value of the design parameters at certain values (*parameter design*). The goal of this optimization method could be to optimize the nominal values and to minimize the variance values of these reliability characteristics.

This chapter provides a theoretical description of the ROMDA method. The next chapter presents simulation experiments that show how ROMDA works. The simulation experiments also provide a good insight and understanding in the method and the usefulness for optimizing a product design towards robust reliability.

5 Simulation experiments

5.1 Introduction

Very little literature is available on prediction and optimization of reliability through degradation analysis of the design parameters themselves in relation with a performance characteristic. In this chapter two simulation experiments are presented. The purpose of these simulation experiments is to obtain a general idea of how ROMDA works in theory. In these experiments the functional relationship between the performance characteristic and the design parameters is known in an analytical form. Furthermore, standard design-parameter degradation models, available in literature, are used for the degradation of the design parameters. Also design parameter variations around their nominal values, due to manufacturing tolerances and environmental variation, are described through parametric statistical distributions. Hence, through simulation, the performance characteristic values over time of a batch of products can be established. Given certain specification limits, a reliability characteristic, like the time-to-failure (TTF) of each simulated product, is obtained, which results in the estimation of the mean time-to-failure (MTTF) and the standard deviation of the time-to-failure (SDTFF) of a batch of products.

These simulation experiments show a first attempt to predict product reliability at the design stage. The results of the predictions are used to improve product reliability through *parameter design* [PHA89], which means setting the initial nominal design parameter values at certain levels that optimize product reliability, taking the degradation profiles of these design parameters into account.

The first simulation experiment is the first attempt to predict and improve product reliability. In this simulation experiment for the optimization, robust design technology is used. The second simulation experiment is a more extensive, and complex product. Also the optimization step is more reliability oriented. This simulation experiment is followed by a discussion on the practical applicability of the results of the simulation experiments.

5.2 Simulation Experiment 1: Simple electrical circuit

This simulation experiment makes use of a simple electrical circuit [SPE88], which contains two resistors, an input voltage and a voltmeter to measure the output voltage. A diagram of this model is shown in figure 5.1a. This model is chosen because of two main reasons. First of all this model is relatively simple and can easily be described in a mathematical form.

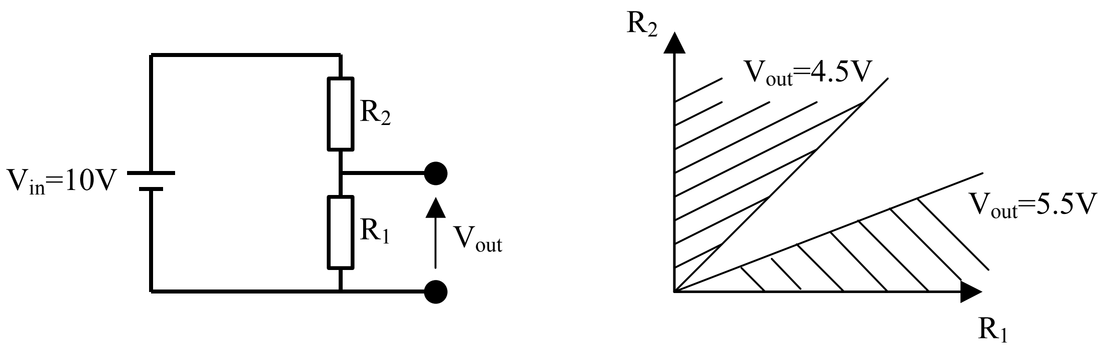


Figure 5.1:

a) *Electrical circuit.*

b) *Specification limits.*

Secondly, and most importantly, this model can easily be used to understand the failure process linked to variability and degradation in the design parameters. This second reason makes this model extremely useful for the purpose of this simulation experiment.

The structure of the rest of this section follows the steps of the protocol presented in chapter 4.

<u>Step 1</u>: Identification of the Performance Characteristic and the Design Parameters

The output voltage is the measured performance characteristic, while the resistors, R_1 and R_2, and the input voltage V_{in} are the controllable design parameters. The following equation describes the link between the performance characteristic and the design parameters [SPE88]:

$$V_{out} = \frac{R_1}{(R_1 + R_2)} \cdot V_{in} \tag{5.1}$$

Figure 5.1b shows the specification limits of the performance characteristic, the output voltage in the parameter plane for a fixed value of V_{in}. An output voltage of 4.5 Volts is chosen as the lower specification limit while 5.5 Volts is chosen as the upper specification limit. Taking these specification limits into account, the yield (at time t=0) and the failure rate λ at a given time t may be estimated.

In this experiment the input voltage V_{in} is set on a constant value of 10 V. Of course, in practice there will be some variations in this voltage, but initially these variations will not be taken into account. This is primarily done to get a better insight on the effects of variability and degradation in the resistance of the resistors (DP's).

To introduce variability in the design parameters of products, due to the effect of manufacturing tolerances, the values of the resistors R_1 and R_2 are assumed to be non-constant, but to inhabit a statistical distribution. The values of these design parameters at time t=0, R_0, are assumed to be uniformly distributed with a certain mean and variance. Due to temperature effects the resistor values slightly degrade over time. These small changes are often referred to as resistance drift ($\Delta R/R$). The change in resistance, due to this thermal degradation, depends upon ageing time and temperature and is caused by several different mechanisms. This dependency is generally fitted to an equation of the type [BEL00]:

$$\frac{\Delta R}{R} = \alpha \cdot t \cdot e^{\frac{-E_a}{kT}} \tag{5.2}$$

where T is the temperature in Kelvin, k is Boltzmann's constant, t is the time, E_a is the activation energy, and α is a proportionality constant characteristic of a particular degradation mechanism.

Since $R=R(t=0)=R_0$ and $\Delta R=R(t)-R_0$, equation (5.2) can be rewritten as:

$$R(t) = R_0 \cdot (1 + \alpha \cdot t \cdot e^{\frac{-E_a}{kT}}) \tag{5.3}$$

Table 5.1 summarizes the values of the constants and variables for the degradation model. Also the value of the input voltage, which is set at a constant value in this simulation experiment, is shown.

Table 5.1: Values of variables and constants used in the first simulation experiments.

Variable or constant	**Value**
Input voltage V_{in}	10 Volts
Temperature T	293 K
Boltzmann's constant k	$8.6*10^{-5}$ eV/K
Activation energy E_a	0.9 eV
Constant α	$3.25*10^{5}$ Ω/time unit

The values of table 5.1 combined with equation (5.3) provide the following degradation model of the design parameters:

$$R_i(t) = R_{i0} \cdot (1 + 5 \cdot 10^{-3} \cdot t) \qquad (5.4)$$

with R_{i0} the value of the nominal designed resistor value at time t=0.

The simulation experiments use the Monte Carlo Principle to randomly generate a number of values for products of a nominal design, used in this experiment. *Matlab* is used to run these simulation experiments. From the experiments time-dependent distributions of the design parameters and the performance characteristic can be obtained, while failure rates can be estimated taking the specification limits into account.

In the next subsection, a screening simulation experiment will be discussed where both design parameter (resistor R_1, and R_2) are subjected to variability and degradation.

<u>Step 2</u>: Determination of the Functional Relationship between the Performance Characteristic and the Design Parameters

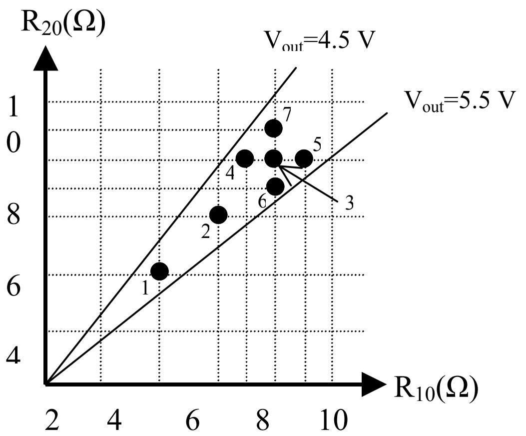
The screening simulation experiments are performed for several combinations of resistor values R_{10} and R_{20}. The Monte Carlo method is used to simulate thousand products of a nominal design. Hence, the performance characteristic shows a certain statistical distribution around its value of the nominal design, due to the variability in the design parameters. In some runs of the experiments the two design parameters (resistors R_1 and R_2) both have the same value and the performance characteristic is on the so-called "target-line", which means that the output voltage should be 5 Volt. While in other runs of the experiments these design parameters each has a different value and the value of the performance characteristic is near one of the two specification limits (LSL = 4.5 V and USL = 5.5 V).

Next step in the simulation experiments is to introduce uniform distributions at time t=0 and a degradation profile for both design parameters, resistors R_1 and R_2. The uniform distributions of R_{10} (t=0) and R_{20} (t=0) have various mean values with a constant value of the standard deviation of 0.3 Ω (σ=0.3 Ω) for each run of the experiment. The combinations of the mean values are shown in figure 5.2.

The degradation models used for design parameters R_1 and R_2 are:

$$R_1(t) = R_{10} \cdot (1 + 5 \cdot 10^{-3} \cdot t) \tag{5.5}$$

$$R_2(t) = R_{20} \cdot (1 + 5 \cdot 10^{-4} \cdot t) \tag{5.6}$$



Run	Levels (mean values)	
	R**$_{10}$ **(Ω)	***R**$_{20}$ **(Ω)***
1	4	4
2	6	6
3	8	8
4	7	8
5	9	8
6	8	7
7	8	9

Figure 5.2: Mean values of design parameters R1 and R2 (at t=0).

The degradation models for the design parameters are not equal, otherwise, almost no failures would occur due to the shape of the functional relationship, eqn. (5.1), between the performance characteristic and the design parameters. It is also more realistic that products consist of different components, instead of only two equal components.

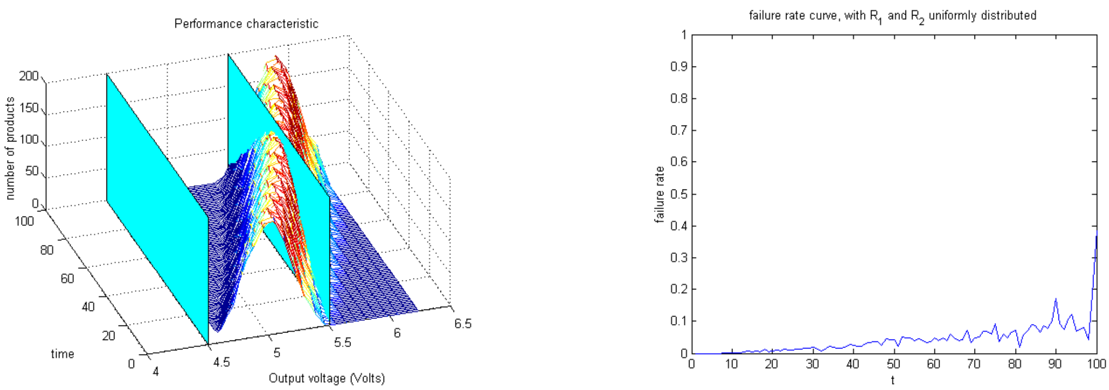


Figure 5.3: Results of Simulation Experiment with R1 and R2 uniformly distributed (m=6 Ω and σ=0.3 Ω).

a) Time-dependent distribution.

b) Failure rate curve of performance characteristic.

Figure 5.3 shows the results of *run 2* where design parameters R_1 and R_2 are both set at a mean value of 6 Ω.

Results of all the runs of this experiment are shown in appendix 3. These results lead to the following conclusions:

→ An increase of values of design parameters R_1 and R_2, for which R_1=R_2 and the performance characteristic should be on the "target-line", results in a failure rate that increases faster over time. The reason for this behavior is due to the faster degradation (increasing value) of design parameters R_1 and R_2 as levels of R_1 and R_2 increase. As a result the value of the performance characteristic moves faster to the USL and failures occur earlier in time.

→ Combinations of values of design parameters R_1 and R_2, which result in a performance characteristic (*PC*) value closer to the USL, fail faster than combinations of design parameters R_1 and R_2, which result in a *PC* value closer to the LSL. This is caused by the fact that design parameter R_1 degrades and thus increases faster than design parameter R_2 (compare eqn. (5.5) and (5.6)). This causes the value of the performance characteristic to move towards the USL, which results in failures occurring earlier in time.

→ The distribution of "passed" products will change over time. This is due to the fact that the sample size in the experiments is relatively small (n=1000). As a result, only a few products are left after a certain time and the shape of this distribution will not necessarily be the same over time. Hence, conclusions based on the final part of the failure rate curve have to be considered carefully.

<u>Step 3</u>: Robust Optimization

The screening experiments are conducted with a design, which was not optimized at time t=0. Therefore, the design parameters of each run were selected arbitrarily and no attention was given to the quality of the products. In the original design both design parameters R_1 and R_2 were set at a value of 5 Ω, while the other non-designable input parameter (V_{in}) was set at 10 V, which resulted in a nominal output voltage (V_{out}) of 5 V. This section discusses the quality optimization of this product with the use of *parameter design* to see if this optimization also leads to reliability improvement. Hence, a failure rate plot is estimated from the optimized design to observe if reliability improvement is obtained.

The results of these new experiments, expressed in a failure rate curve, are compared with the results of a non-optimized run to see if the failure rate curve improves. The optimization is performed using a full factorial experiment with 3 different levels of design parameters R_1 and R_2. The values of these levels are given in table 5.2.

Table 5.2: Level settings of design parameters R1 and R2.

Variables	**Levels**		
	1	2	3
R_1(Ω)	2	6	10
R_2(Ω)	2	6	10

The full factorial experiment is chosen because only two design parameters are considered, thus such an experiment only contains 3^2=9 runs. The target value of the performance characteristic, the output voltage, is set on 5 Volts. The goal is to minimize the variation of the performance characteristic value around this target value (at time t=0), by making the design robust against the variability in the design parameters using *parameter design*.

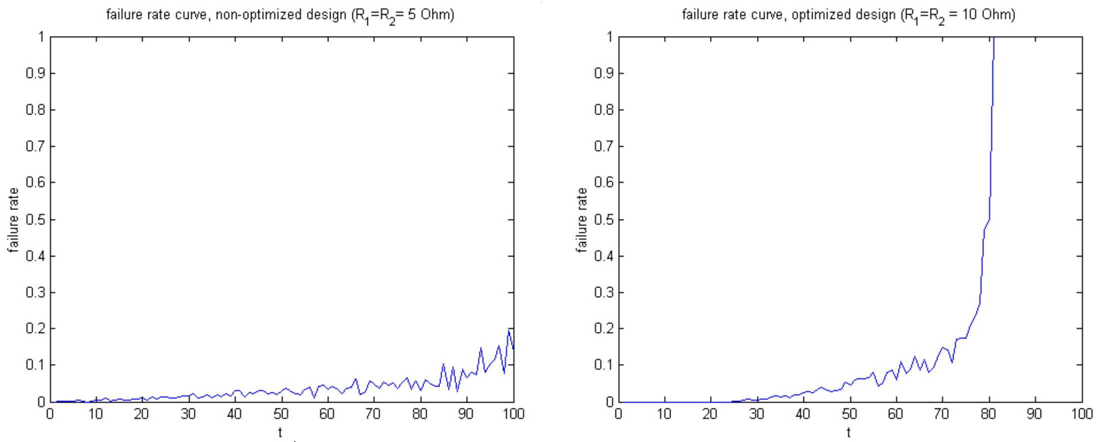
The values of the two design parameters (again at time t=0) must remain in the region between 0 Ohm and 10 Ohm. Using the Signal-to-Noise (S/N) ratio, η [PHA89], for a nominal-the-best problem, it is possible to determine the optimum levels of the design parameters R_1 and R_2 to obtain an "optimal" robust design.

The used Signal-to-Noise (S/N) ratio, η, is defined as [PHA89]:

$$\eta = 10 \cdot \log_{10}\left(\frac{\mu^2}{\sigma^2}\right) \tag{5.7}$$

where μ and σ are the mean and standard deviation of the performance characteristic. The S/N ratio must be maximized to obtain an optimized robust design [PHA89].

In this case it is obvious that this occurs when both design parameters are set on 10 Ω, since the standard deviation of the design parameters are constant and, at this level, relatively small compared to the mean value. Figure 5.4 shows the failure rate curves of the non-optimized design (R_1=R_2= 5 Ω) and the optimized design (R_1=R_2=10 Ω). However, the results clearly show that the optimization does not lead to an improvement in the failure rate. This leads to the conclusion that optimizing for quality purposes, in this case robust optimization, does not always lead to a better performance in terms of reliability (here represented by a failure rate curve). Note that the failure rate curve is only used for illustrative purposes and cannot be used solely as a reliability characteristic. In this thesis the choice has been made to use the Mean Time To Failure and the Variance Time To Failure as reliability characteristics.



a) *b)*

Figure 5.4: Failure rate curves of 1000 products with the design parameters R1 and R2 uniformly distributed.

a) Non-optimized design: R1=R2= 5 Ω (s=0.3).

b) Optimized design: R1=R2= 10 Ω (s=0.3).

Quality

Quality, as defined in chapter 2, is the ability of a product or system to fulfill its intended purpose. A possible way of measuring quality is one introduced by Phadke (1989) [PHA89]:

$$Q = (\mu - \tau)^2 + \sigma^2 \tag{5.8}$$

where the first part represents the bias, which is the difference between the target mean value (τ) and the measured mean value (μ) of the performance characteristic. The second part represents the variance of the performance characteristic. By minimizing both the bias and the variance the quality (at time t=0) can be optimized. Here, the definition is more precise than the definition given in chapter 2, because here a distinction is made between "within specifications" and "closer to the target values with a small variance is better then close to the specification limits with a large variance". Another characteristic to measure the quality is the S/N ratio as defined above.

Yield

The yield of a product is the percentage of products in a batch meeting specification at time t=0. Improving the yield does not automatically mean that the quality of a product is improved, only that more products meet specification. An improvement in the yield can result in an increase as well as a decrease in quality. This totally depends on the design of a specific product. For example, assume that more products meet specification, thus the yield is improved. However, the quality characteristic of these products is very close to the lower specification limits. Hence, if this quality characteristic should be as large as possible, the quality of these products is decreased.

Failure rate (reliability)

The failure rate is a frequently used reliability measure. The commonly used definition of failure rate is given in section 2.1. This definition can be translated to these experiments as the number of products failing during a certain time period divided by the total number of not failed products at that time period. As mentioned before, different levels of design parameters can optimize a product with respect to quality and/or reliability (expressed in failure rate). So, by optimizing the quality of a product it is possible that the failure rate of a product increases or decreases.

A same line of reasoning can link the yield to the failure rate. For example, if the yield decreases, fewer products meet specification. But maybe those products that meet specification are more reliable and thus the failure rate decreases. However, it is also possible that these products are close to the specification limits and will fail shortly after time t=0 and thus the failure rate increases. Both situations could occur.

The above discussion shows that it is most of the time impossible to optimize a design with respect to all three aspects. Therefore, normally a compromise between the three aspects has to be made to optimize a product at time t=0.

When focusing on both the quality and the reliability this leads to the following conclusions:

→ Either different design parameters have to be used to optimize a product with respect to quality and reliability.

→ Or different settings of these design parameters should be used to optimize a product with respect to quality and reliability.

→ It can be expected that a trade off has to be made in order to optimize a product with respect to reliability and quality simultaneously.

Since the main focus of this research is to predict and optimize the reliability of a product, with the use of degradation models of the design parameters, further experiments are conducted to improve product reliability.

5.3 Simulation experiments 2: Temperature Control System

In order to extend the simulation experiments, a second example will be used to examine the influence of interactions between more than two design parameters. This example, a temperature control system, is shown in figure 5.5 and is discussed in chapter 9 of *“Quality Engineering using Robust Design”* by Phadke [PHA89]. To make this simulation experiment more realistic customer use is introduced in the simulations. This is done by introducing a little different usage behavior of the customer at the beginning of operating the temperature control system. A detailed explanation is given in the simulation experiment.

The function of a temperature control system is to maintain the temperature of a room, a bath, or some object at a target value. A temperature control system can be divided into three main modules (see figure 5.5a): a temperature sensor (thermistor), a temperature control circuit and a heating element. The temperature, for example of a bath, is sensed by a thermistor, which is assumed to have a negative temperature coefficient. This means that the thermistor resistance, R_T, decreases with an increase in the temperature of the bath. When the bath temperature rises above a certain value, the resistance R_T drops below a threshold value so that the difference in the voltage between terminals 1 and 2 of the amplifier becomes negative. This actuates the relay and turns the heater off. Likewise, when the temperature falls below a certain value, the difference in voltages between the terminals 1 and 2 becomes positive so that the relay is actuated and the heater is turned on.

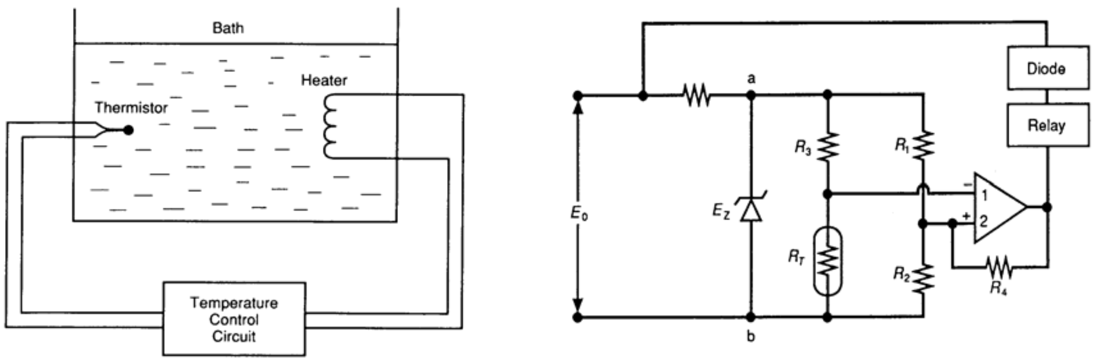


Figure 5.5:

a) Block diagram of a temperature.

b) Temperature control circuit control system.

<u>Step 1</u>: Identification of the Performance Characteristic and the Design Parameters

The temperature control circuit (see figure 5.5b) provides a way of setting the threshold value of the resistance R_T and thus setting a target temperature. During the simulation experiments, only attention is given to the setting of the threshold value of R_T when the heater turns on. So, this resistance value of R_T will be used as performance characteristic. The required resistance value of R_T can change due to variability and degradation in the values of the various circuit components (design parameters).

Through standard techniques of circuit analysis, one can express the value of the required resistance value of R_t as the following mathematical function of all circuit design parameters:

$$R_T = \frac{R_3 R_2 \left(E_z R_4 + E_0 R_1\right)}{R_1 \left(E_z R_2 + E_z R_4 - E_0 R_2\right)} \tag{5.9}$$

where R_1, R_2, R_3 , and R_4 are the resistance values of the four resistors, E_0 is the power supply voltage (input voltage), and E_z the nominal voltage of the Zener diode. The purpose of the Zener diode in the circuit is to regulate the voltage across the terminals a and b (see fig. 5.5b). Thus, the Zener diode is used to take care of fluctuations and drifts in the power supply voltage.

For proper operation of the circuit E_z must have a smaller value than E_0. Also R_4 has to be higher than R_1, R_2 or R_3. The nominal values of the circuit design parameters under the starting conditions are shown in table 5.3. This table also shows the standard deviation of these parameters, which is assumed to be one-third of the tolerances. This time the tolerance is taken as 5% of the mean nominal values.

Table 5.3: Nominal values of circuit parameters.

Parameter	Nominal mean value (μ)	Standard deviation (σ)
R_1	4.0 kΩ	0.067 kΩ
R_2	8.0 kΩ	0.133 kΩ
R_3	1.0 kΩ	0.017 kΩ
R_4	40.0 kΩ	0.667 kΩ
E_0	10.0 V	0.167 V
E_z	6.0 V	0.100 V

Step 2: Determination of the Functional Relationship between the Performance Characteristic and the Design Parameters

Similar as to the first simulation experiments (§ 5.2), the values of the resistors R_1 till R_4 at time t=0 are assumed to be uniformly distributed with a mean and standard deviation as shown in table 5.3. These design parameters also show degradation over time. Again the same equations for the degradation model, see equation (5.3), as in the first simulation experiment are used in these experiments. The degradation models for these four design parameters are:

$$\begin{aligned} R_1(t) &= R_{10} \cdot (1 + 1.5 \cdot 10^{-3} \cdot t) \\ R_2(t) &= R_{20} \cdot (1 + 1.5 \cdot 10^{-3} \cdot t) \\ R_3(t) &= R_{30} \cdot (1 + 1.5 \cdot 10^{-3} \cdot t) \\ R_4(t) &= R_{40} \cdot (1 + 1.5 \cdot 10^{-3} \cdot t) \end{aligned} \quad , R_1 \text{ till } R_4 \text{ in k}\Omega \tag{5.10}$$

Besides the resistors R_1 till R_4 the other two non-designable input parameters, E_0 and E_z, have to be discussed. The Zener Diode (E_z) regulates the input voltage (E_0). This is why the Zener Diode will be used to introduce customer use in these experiments. The following two points describe the way customer use is introduced in these simulation experiments:

→ Introduce a normally distributed input voltage, E_0, and Zener Diode voltage, E_z, to describe customer use. Then by shifting the mean value of this normally distributed Zener Diode voltage from 6 V to 5.5 V, the input voltage is not properly regulated, which leads to an increase of this input voltage and "overstress" due to "wrong use" of the customer, is being modeled. After a few time steps the mean value of the Zener Diode voltage returns slowly to the nominal value of 6 V. Mathematically this can be described as:

$$\begin{aligned}
&t = 0 \rightarrow 10 \Rightarrow E_z = 5.5 \\
&t = 11 \rightarrow 20 \Rightarrow E_z = 5.5 + 0.05 \cdot (t - 11) \text{ , } E_z \text{ in Volts} \\
&t = 21 \rightarrow \infty \Rightarrow E_z = 6.0
\end{aligned} \tag{5.11}$$

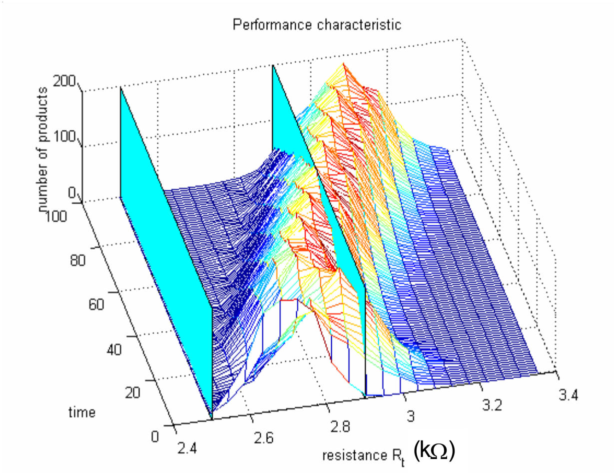
→ Model different "starting points" at which products or functions of products are being used for the first time. This is done to explain the fact that certain failures are detected and reported only after a while, although these failures may have already existed at time t=0. This is in line with the explanation given on the roller coaster curve.

The variability, degradation, and customer use introduced in these design parameters influence the performance characteristic, R_T, according to the stated mathematical equation (5.9). Taking into account the lower and upper specification limits the failure rate can be estimated. In these experiments, the following specification limits are chosen:

- LSL= 2.5 kΩ
- USL= 2.9 kΩ

These limits were chosen arbitrary, but such that reasonable lifetimes of products could be obtained with the design parameters set on the nominal mean values (see table 5.3).

Results of a failure rate curve obtained with these specification limits can be seen in figure 5.6. All design parameters in this experimental run were set at the values shown in table 5.3. Also customer use is included in this model, which results in the fact that 500 products were started being used at time t=0 and every next time step 50 products were started being used, until all 1000 products were in use.



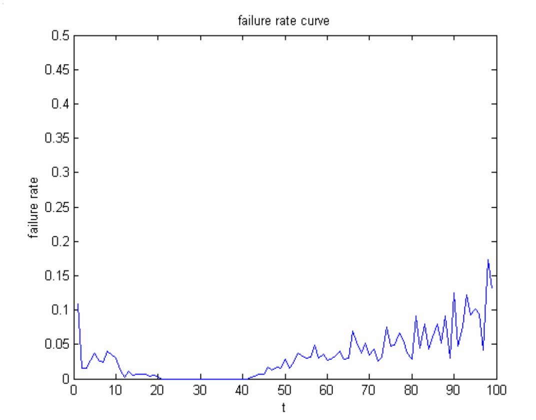


Figure 5.6: Time-dependent distribution of the performance characteristic and the failure rate curve of the "Extended Model".

<u>Step3</u>: Reliability Prediction and Optimization

Since the first simulation experiments have improved the understanding of the influence of variability and degradation in design parameters on product reliability, the next step will be to make an attempt to predict and improve product reliability by controlling these dominant design parameters at the design stage. Before this is possible, product reliability has to be quantified first.

Two characteristics will be used to quantify product reliability, namely:

1. Mean time-to-failure (MTTF), μ
2. Standard deviation of the time-to-failure (SDTTF), σ

The purpose of these experiments is to determine the possibility to use *parameter design* to maximize the MTTF of a product and, simultaneously, make a product insensitive to variability in the design parameters, to improve product reliability (minimize SDTTF).

The first step to achieve this purpose is to predict product reliability. This can be done using the presented approach of chapter 4.

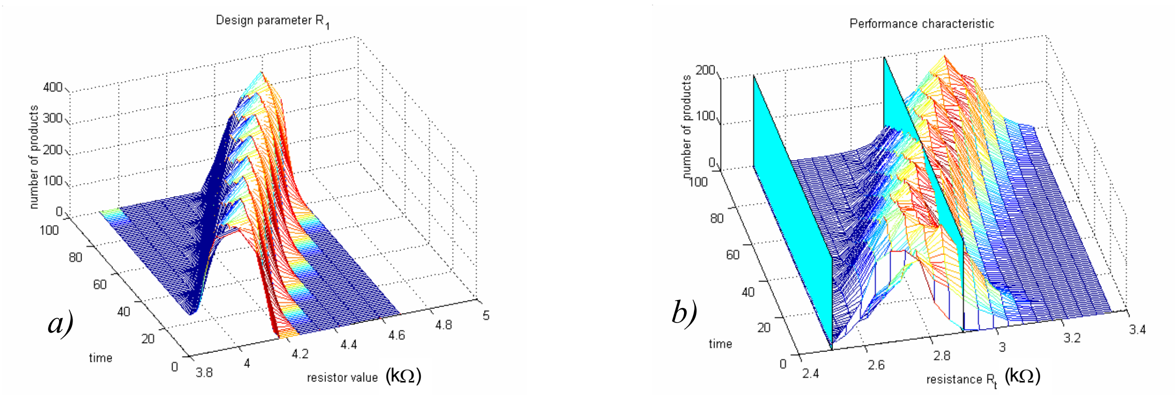


Figure 5.7:

a) Time-dependent distribution of design parameter R1(t).

b) Time-dependent distribution of performance characteristic: $R_T(t)$.

The degradation models of the dominant design parameters are known. Such a time-dependent distribution of design parameter R_1 is shown in figure 5.7a. As can be seen the mean of this design parameter shifts over time and the variance is also slightly increasing over time due to the degradation model applied on this design parameter.

The time-dependent distributions of the design parameters combined with the analytic functional relationship (eqn. (5.9)) between the performance characteristic and the design parameters, provide time-dependent distributions of the performance characteristic, R_T. An example of such a distribution is shown in figure 5.7b.

Figure 5.7b shows, besides the time-dependent distribution of the performance characteristic, also the specification limits (two planes) of this performance characteristic. These specification limits can be used to estimate the time-to-failure (TTF) of all the simulated products. Hence, estimations of the MTTF and SDTTF may be established.

Thus by conducting simulation experiments, it is possible to collect degradation data of the performance characteristic, which can be used to optimize the lifetime of these products. Now a distinction has to be made between the optimization of the first part of the performance characteristic, in which customer use plays an important role, and the second part, which is dominated by the degradation of the design parameters. The optimization focuses on the degradation part in order to improve the product reliability, because the main purpose of these experiments is to make the product insensitive to variabilities in design parameters, like degradation. Including customer use in the optimization process would also greatly complicate the optimization.

The following approach is provided in order to improve the product reliability:

1. Use Design of Experiments (DOE) to identify the influence of different settings of the design parameters on the product reliability. Results of these experiments are then used to link the reliability characteristics (like MTTF and SDTTF) to the design parameters (see also *step 6*).
2. Obtain degradation data of the performance characteristic for each DOE run using simulation experiments of the temperature control system model.
3. Determine Least Square Estimation (LSE) fits to calculate the degradation paths of all products from each DOE run. These LSE fits are determined, since only degradation data of the first 100 time steps are obtained from the simulation experiments.

4. Use these fits together with the specification limits to estimate the TTF of all products.
5. Calculate the MTTF and the SDTTF of each DOE run.
6. Link the MTTF ($\hat{\mu}$) and the SDTTF ($\hat{\sigma}$) to the nominal (mean) values of design parameters R_1 till R_4 using a 2nd order regression model, which makes it possible to include non-linear effects of the design parameter values on the ($\hat{\mu}$) and ($\hat{\sigma}$):

$$\begin{aligned} \hat{\mu} &= \left[\alpha_0 + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \alpha_{ij} x_i x_j + \sum_{i=1}^{n} \alpha_{ii} {x_i}^2 \right] \\ \hat{\sigma} &= \left[\phi_0 + \sum_{i=1}^{n} \phi_i x_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \phi_{ij} x_i x_j + \sum_{i=1}^{n} \phi_{ij} {x_i}^2 \right] \end{aligned} \tag{5.12}$$

where x_i and x_j are the mean values of the design parameters. In this experiment the x's are the four resistors R_1 till R_4.

Conduct a Combined Multiple Response Optimization using the *Desirability Approach* [DER80] to optimize these functional relationships. This means maximize the MTTF and simultaneously minimize the SDTTF.

This approach will be discussed next.

Design of Experiments (step 1)

This Design of Experiments (DOE) makes use of the four design parameters, namely R_1, R_2, R_3, and R_4. Similar as in the simulation experiments, these design parameters exhibit a certain variability at time t=0 and experience degradation over time. Only in the previous simulation experiments the values of $R_{t=0}$ were uniformly distributed, while in this DOE a normal distribution is used. This is done in order to obtain better regression models that link these design parameters to the MTTF and SDTTF.

The DOE is designed using a Central Composite Design (CCD). Such a CCD contains an imbedded factorial design with centre points, which is augmented with a group of “star points” that allow estimation of curvature. A CCD always contains twice as many “star points” as there are parameters in the design. Different CCD’s exist, each with different locations of these “star points”. In this design the “star points” are at the middle between the centre point and the +1 level and –1 level. The imbedded two-level full factorial design contains 2^4=16 runs with the four design parameters either at the +1 level or -1 level. The +1 level and the –1 level values for the four design parameters are given in table 5.4. The values of the design parameters for the centre point run are given in the last column of this table.

Table 5.4: Values of DOE levels for each design.

Design parameter	+1 level	-1 level	Center point
R_1 (kΩ)	4.25	3.75	4.0
R_2 (kΩ)	8.5	7.5	8.0
R_3 (kΩ)	1.05	0.95	1.0
R_4 (kΩ)	42.5	37.5	40.0

The Central Composite Design is used to capture the non-linear effects between the design parameters and the MTTF and SDTTF. The group of "star points" consists of 2*4=8 runs. Thus, in total this DOE contains 2^4+4*2+1=25 number of runs. For each run, 30 products are randomly simulated and degradation data of the performance characteristic of each product is obtained. Appendix 4 contains the design matrix used for these 25 runs.

Degradation data and Least Square Error (LSE) fits (step 2 and 3)

The degradation data of the performance characteristic of the products, obtained from the 25 runs of the DOE, only contain values from time t=20 till t=100. Although not all products have failed at time t=100, the simulation experiments are stopped at this point of time. This is done since normally these data are obtained by testing, which is very time consuming and expensive and, therefore, it is impossible to continue testing until all products have failed. Also the data of the performance characteristic from time t=0 till t=20 are not used, because in this time period customer use influences the value of R_T, while this optimization focuses on the degradation part.

The next step in this approach is to fit a Least Square Estimation (LSE) line through the obtained degradation data in order to capture the degradation path of each product. The LSE lines are of the form:

$$R_T = a + b \cdot t \tag{5.13}$$

These LSE fits are chosen linear since the linear degradation models of the design parameters, eqn. (5.10), and the form of the analytical expression of the functional model, eqn. (5.9), results in linear behaviour of the performance characteristic. These LSE lines can be extrapolated after time t=100 and used to estimate values of R_T. These fitted values of R_T combined with the specification limits provide all the necessary information to predict the TTF of all 30 products for each DOE run.

Estimation of MTTF and SDTTF (step 4 and 5)

Once the fitted values of the performance characteristic are available, the specification limits are used to estimate the time-to-failure (TTF). The specification limits chosen in section 5.3.2 are not suitable for these experiments, since these limits were chosen to obtain failures when the design parameters were set on the mean nominal values. In these experiments the settings of the design parameters will change within a certain range (see table 5.4) and the chosen limits would be too narrow, which would result in many early failures due to the simulated customer use. Therefore, the specification limits are set on different levels, namely:

- LSL=1.9 kΩ
- USL=4.0 kΩ

Thus, for each DOE run 30 time-to-failure values (TTF) are predicted. These predictions are used to estimate the MTTF and SDTTF for each DOE run with certain settings of the design parameters. The MTTF and SDTTF for each DOE run are shown in the design matrix in appendix 5.

Regression Models of MTTF and SDTTF (step 6)

In order to improve product reliability by controlling the design parameters (*parameter design*), the MTTF and SDTTF must be linked to the nominal (mean) values of the design parameters R_1, R_2, R_3, and R_4. This is done using a Multiple Linear Regression Model.

Before this, the results of the experiments are analyzed using ANOVA (Analysis of Variance) to determine the statistical significance of effects from the main factors, two-way interactions, and second-order terms of these design parameters on the MTTF and SDTTF. Once the dominance of the various terms is determined it is possible to build a regression model, which describes the functional relationship between these dominant terms of the design parameters and respectively the MTTF and the SDTTF, like eqn. (5.12).

The *Coefficient of Determination* (R^2) can be used to determine the amount of variability in the data explained, or accounted by the effects of the design parameters. The R^2 value can vary between 0 and 1. The various terms of the design parameters explain the variation in the MTTF well (R^2= 0.99). However, these terms only account for 57% (R^2=0.57) of the variation in the SDTTF. This indicates that the design parameters are not strongly influencing the SDTTF. Nevertheless, a model will be obtained, which links the SDTTF to these design parameters, in order to follow the proposed approach and to see if reliability improvement through *parameter design* is possible.

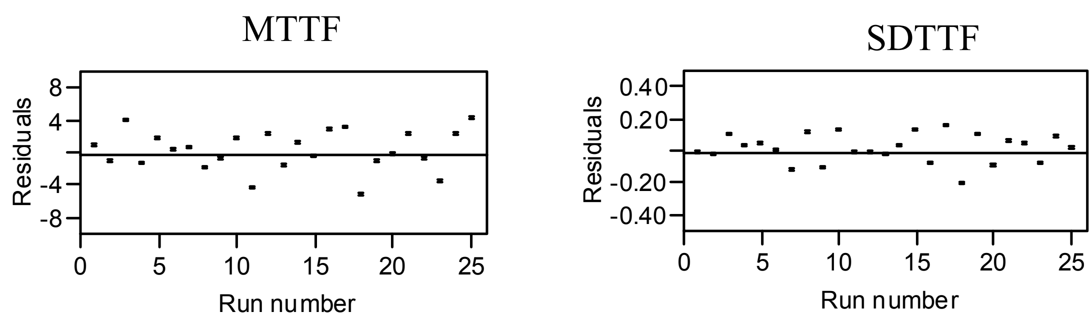


Figure 5.8: Residuals plots of MTTF and SDTTF.

As stated before, models for the MTTF and the SDTTF are of the form of eqn (5.12). The parameter coefficients α_i and ϕ_i of the dominant terms of the design parameters are determined by conducting the Least Square Estimation (LSE) regression method. The LSE regression method minimizes the sum of the squares of the deviations between observed data (in the simulation experiments) and the estimated or fitted data (of the model). This method results in the following models for the estimated MTTF ($\hat{\mu}$) and estimated SDTTF ($\hat{\sigma}$):

$$\hat{\mu} = 327.23 + 52.44 \cdot R_1 - 71.28 \cdot R_2 - 51.95 \cdot R_3 + 16.72 \cdot R_4$$

$$-24.68 \cdot R_2^{\ 2} + 24.00 \cdot R_4^{\ 2} - 4.86 \cdot R_1 R_2 - 3.77 \cdot R_1 R_3 \tag{5.14}$$

$$-1.98 \cdot R_2 R_4 + 4.43 \cdot R_2 R_3$$

$$\hat{\sigma} = \exp(3.46 + 0.03 \cdot R_1 - 0.05 \cdot R_2 - 0.06 \cdot R_3 - 0.02 \cdot R_4 \tag{5.15}$$

$$-0.44 \cdot R_2^{\ 2} + 0.46 \cdot R_4^{\ 2} - 0.05 \cdot R_1 R_4)$$

where R_1 till R_4 represent respectively design parameters R_1 till R_4.

Note that the exponential term in the equation (5.15) is introduced since the regression model is obtained linking the $ln(\hat{\sigma})$ to the design parameters in order to establish a more accurate fit of the SDTTF with respect to the design parameters.

Next, residual plots provide information whether additional terms have to be added to the chosen model. The residuals should be random variables with mean zero and a constant variance. Figure 5.8 shows the residual plots of both the MTTF and the SDTTF. These plots indicate that the residual terms are random variables. Also no patterns can be observed in the residuals, which means that no additional terms have to be inserted in both the models that could possibly improve them.

Validation of regression models

The models obtained using the LSE method are validated to check if they predict the MTTF and the SDTTF without any systematic errors. The error in the prediction is defined as the difference between the value of the simulation experiments (observed value) and the predicted value of the models. The error should be a random variable with mean zero. The validation test consists of 20 runs with 30 products, each with randomly selected settings of the design parameters. These tests are conducted and both the MTTF and the SDTTF are determined with use of the simulation experiment. Also the models of eqn. (5.14) and (5.15) are used to predict the MTTF and the SDTTF. The results of this validation test and the settings of the design parameters for each run are tabulated in Appendix 6.

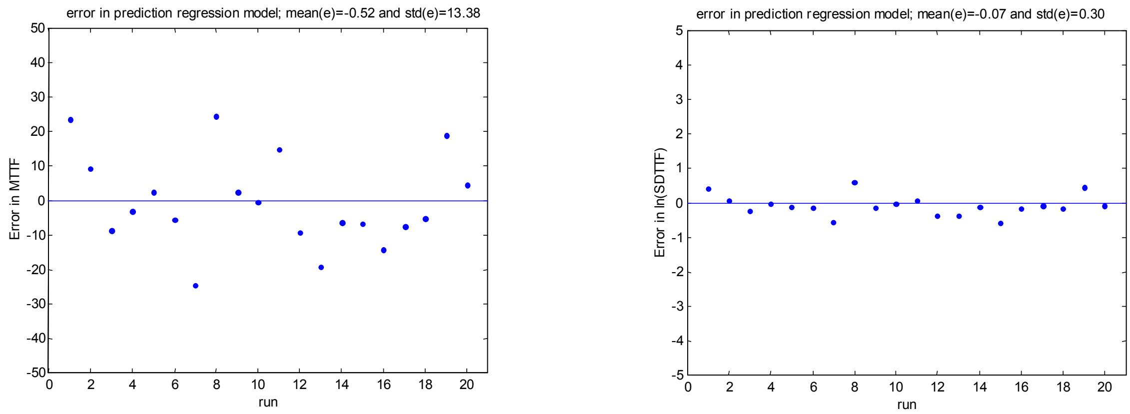


Figure 5.9: Error in MTTF and ln(SDTTF).

Figure 5.9 shows both the error in the prediction of the MTTF and the error in the prediction of the SDTTF for each run of the validation test. Both plots show that the mean value of the error terms is approximately zero and that these error terms are randomly distributed around this mean value. Hence, it can be concluded that the predictions of the MTTF and the SDTTF contain no systematic errors.

Next, the two models linking the MTTF and the SDTTF to the four design parameters are optimized to improve product reliability.

Combined Multiple Response Optimization (step 7)

In this multiple response case, two reliability characteristics have to be optimized simultaneously, namely:

→ Maximize the estimated MTTF ($\hat{\mu}$)

$\rightarrow$ Minimize the estimated SDTTF ($\hat{\sigma}$)

Optimizing these two characteristics simultaneously is quite difficult and probably impossible; so a trade-off has to be made in order to find design parameter levels, which are satisfactory for both the characteristics. An effective manner to make this trade-off is to use the *Desirability Approach* [DER80]. Appendix 7 gives a short elaboration on the *Desirability Approach*.

The approach that is explained in appendix 7 to improve product reliability through *parameter design* is applied to the temperature control system model presented in this simulation experiment to see if it is feasible to obtain reliability improvement.

Simulation experiments have been run to gather the degradation data of the performance characteristic. These data are transformed into MTTF and SDTTF, to optimize these two reliability characteristics the desirability approach and a sequential optimization scheme have been used.

The "starting values" of the design parameters in the optimization scheme, which are the nominal design values, are given in second column of table 5.5. This column also contains the MTTF and the SDTTF corresponding with these settings of the design parameters. The third column of table 5.5 shows the design parameter settings that realize the maximum *Overall Desirability* and thus the "optimal" trade-off in maximizing the MTTF and simultaneously minimizing the SDTTF.

Table 5.5: Results of Reliability Improvement.

DP	"Starting values"	"Optimal values"
R_1 (kΩ)	4.0	4.25
R_2 (kΩ)	8.0	7.5
R_3 (kΩ)	1.0	0.95
R_4 (kΩ)	40.0	40.6
MTTF	331	519
SDTTF	31.9	28.7

The results show that it is possible to achieve an improvement of 57% in the MTTF. However, only a slight improvement of the SDTTF is obtained.

This small improvement of the SDTTF is mainly caused by the choice of the degradation models of the design parameters. The variance in the design parameters is independent of the level of the mean values of the design parameters. Hence, the variance of the performance characteristic, which is dependent of the variance in the design parameters, is not affected by changes in the mean values of the design parameters. Therefore, the SDTTF, which is dependent of the variance in the performance characteristic, cannot be improved by *parameter design*. Thus, in these simulation experiments *parameter design* can only be used to improve the MTTF.

The SDTTF is almost not improved using this approach of Robust Design. Hence, *tolerance design* may be a next step in improving the SDTTF. This would mean linking the SDTTF to the variation of the design parameters over time and optimize the SDTTF by reducing the variation of those design parameters that influence the SDTTF most.

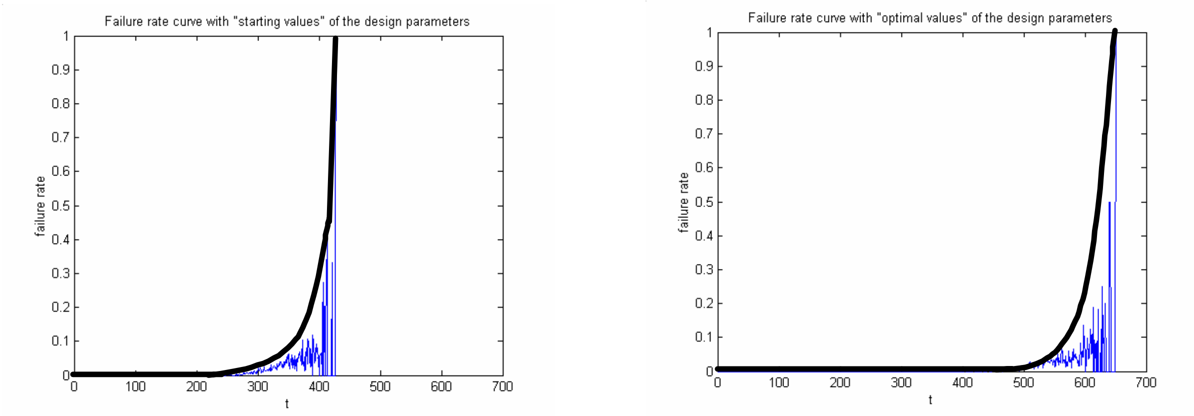


Figure 5.10:

a) *Failure rate curve: Before Reliability optimization.*

b) *Failure rate curve: After Reliability optimization.*

This reliability improvement can be translated back to the failure rate curves. Figure 5.10a shows the failure rate curve of the design before the reliability optimization. A thousand products are randomly created with the nominal settings of the design parameters as given in the second column of table 5.5. Figure 5.10b represents the failure rate curve of products (also a thousand) with the design parameters set on the "optimal" values determined in the reliability optimization. These plots clearly show the reliability improvement due to the change of settings of the design parameters. Note that the specification limits have been chosen such that customer use causes no early failures and, thus the first two phases of the Roller-coaster curve are not present in these failure rate curves.

5.4 Discussion of simulation results

Chapter 4 presented a method to predict and optimize product reliability through degradation analysis of the dominant design parameters. In this chapter simulation experiments are discussed, which are conducted to obtain some general sense of this method. First, a model of an electrical circuit is discussed and used as an example to run simulation experiments. Mechanical components or products could also be used, but in these simulation experiments electrical circuits were chosen, since more literature is available on degradation in electronics.

This simulation experiment improved the understanding of the influence from variability and degradation of the design parameters on product reliability. The simulation experiment also showed that the proposed concept enables the possibility to predict reliability (TTF) early at the design stage. The simulation experiments included early reliability behaviour (1^{st} and 2^{nd} phase of the Roller-coaster curve) by the introduction of “customer use”. However, besides “customer use” also weak sub-populations are causing these early wear-out failures. Therefore, bi-modal distributions could be used to describe the early reliability, which would give a more complete description of the reliability behaviour of products.

Subsequently, reliability could be optimized through *parameter design*. This optimization results in a substantial improvement of the MTTF and hence in the reliability of the used example in these simulation experiments. The SDTTF is almost not improved, which is caused by the chosen degradation models of the design parameters. Different degradation models or *tolerance design* could be used in future research to see if the SDTTF can be improved. However, as the first simulation experiment showed, it is not a guarantee that the reliability is also optimized, when a quality oriented optimization method, like robust design, is used. For this reason a different optimization strategy was used in the second simulation experiment. This lead indeed to a substantial improvement of the MTTF, which is a reliability characteristic.

The reliability improvement is concentrated on the wear-out part (fourth phase) of the Roller-coaster curve. It is assumed that in this part the population of products is homogenous (no weak sub-populations) and that customer use is not important anymore. Hence, the early part of the performance characteristic is not taken into account. However, to include this early reliability, the same approach could be used to model these early wear-out failures and to link the TTF's to the design parameters.

In the simulation experiments the functional relationship between the performance characteristic and the design parameters is known in the form of an analytic equation. Further, standard linear degradation models, available in literature, are used for the degradation of the design parameters.

5.5 Discussion on practical value of assumptions and preconditions of the simulation experiments

This section follows the protocol of the theoretical approach for reliability prediction and optimization.

The first step in the protocol is to identify the critical design parameters and performance characteristic. In a theoretical problem these dominant design parameters and the performance characteristic are known. Also the nominal values of the parameters under the initial conditions in the simulation experiments were known. This leads to the first precondition:

Precondition 1*: The performance characteristic and the dominant design parameters are known.*

In practice it is highly unlikely to know the dominant design parameters and the performance characteristic. Products or systems are becoming increasingly complex resulting in complex gradual degradation behavior of a product or system. This fact results almost in the impossibility of knowing the parameters and performance characteristic. Qualitative methods, i.e. Failure Modes and Effects Analysis (FMEA) or Fault Tree Analysis (FTA), and quantitative methods, i.e. Design Of Experiments (DOE), could provide a practical approach for determining the performance characteristic and the dominant design parameters.

Next, in the simulation experiments distributional assumptions are made for the unit-to-unit variance.

> ***Assumption 1:*** *The parameters are assumed to be normally distributed and the standard deviations of the design parameters are taken to be one-third of their tolerances. The tolerance is taken as 5% of the mean nominal values of the design parameters.*

Distributional assumptions can definitely have a big influence on the rest of the analysis. Especially when models or curves need to be estimated, the estimation error is much bigger if the distribution function is not known and different estimation methods may be needed.

The resistor values slightly degrade over time due to temperature effects (degradation process). These small changes are often referred to as resistance drift (*ΔR/R*). The change in resistance, due to this thermal degradation, depends upon ageing time and temperature and is caused by several different mechanisms with different time dependencies. This dependency is generally fitted to an equation of the type [BEL00]:

$$\frac{\Delta R}{R} = \sum_i \alpha_i t^{n_i} e^{\frac{-E_i}{kT}} \tag{5.16}$$

where T is the temperature in Kelvin, k is Boltzmann's constant, t is the time, n_i is the time dependence, E_i is the activation energy, and α_i is a proportionality constant characteristic of a particular degradation mechanism.

> ***Assumption 2:*** *The degradation profiles of the dominant design parameters are known and follow a pre-specified degradation relationship (parameter degradation).*

In practice the resistance change is dependent on the sum of all degradation mechanisms. The degradation profile used in the simulation experiment only uses one degradation mechanism, which is not likely to happen in real product use. In practice the degradation profiles probably need to be measured. Many test methods and estimation methods could provide practically valid degradation profiles of the design parameters. Literature provides a wealth of test methods, like compressed time testing methods [LEW96], degradation-testing methods [TSE94], accelerated testing methods [KEC93].

The variability and degradation introduced in these design parameters will influence the performance characteristic R_T according to equation 5.9 (functional relationship). Given the functional relationship and time t, the $R_T(t)$ value may be calculated at any time t.

Assumption 3: *A functional relationship (equation 5.9) between the performance characteristic and the dominant design parameters exists and is known.*

Assumption 3 is a central assumption in the theoretical approach. However, this relationship will never be available in practice. Maybe on component level a physical model might be available, but for complex electro-mechanical products this relationship will not be found in literature. The functional relationship between the performance characteristic and the dominant design parameters has to be established by testing. Test methods that provide a way of doing this are DOE [CON01] or Taguchi [PHA89] testing methods. And even with these well-accepted testing strategies care has to be taken. One of the main problems that possibly arise is the fact that the established functional relationship is only valid for values that have been included in the tests. However, the products degrade over time, so the validity of the models over the complete lifetime of the products is even then questionable and alternative test strategies might be necessary.

Taking lower and upper specification limits of the performance characteristic into account the Time-To-Failure (TTF) of a random product realization can be estimated.

Assumption 4: *The specification limits for the performance characteristic are known.*

In practice the specification limits have to be determined. And well-known methods in literature, like stress-strength reliability methods ([JEN95], [KAP77]), even warn for the fact that the specification limits might be statistical in nature. But most reliability optimization methods use deterministic specification limits.

5.5.1 Conclusions on practical value of assumptions and preconditions of the simulation experiments

From a theoretical point of view the approach is very appealing. However, as the previous discussion shows, the practical applicability of the method is in its current form not optimal. The preconditions and assumptions are not always practically feasible. Adjustments are suggested that could make the theoretical approach for predicting and optimizing reliability of products more suitable for real industrial products. The practical value and implementation possibilities of these suggestions have to be further investigated.

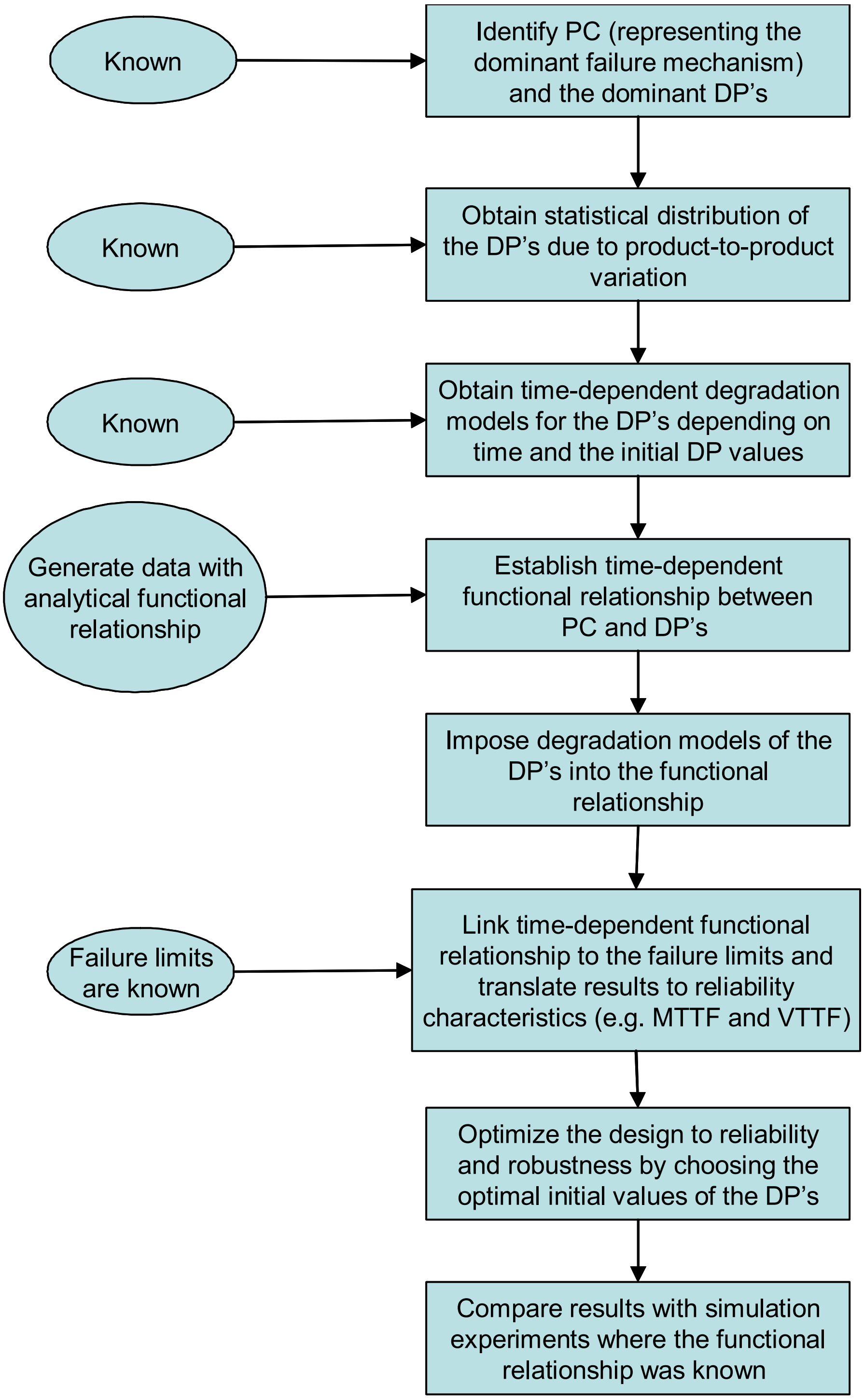


Figure 5.11: overview of steps in simulation experiment.

Next, a new computer-based simulation experiment will be presented where the assumptions are more relaxed. For this simulation experiment the same circuit design example as in simulation experiment 2 is used for this purpose. The emphasis of the simulation experiments will be on the unavailability of the functional relationship between the performance characteristic under study and the dominant design parameters. In theory, and in the simulation experiments, the functional relationship is a known analytical expression. However, since this is highly unlikely in practice, in the computer-based simulations presented in the next section it is assumed that this relationship is not available and has to be estimated for the rest of the analysis. Using the same circuit design provides the possibility to compare the optimization results of the simulations with functional relationship in analytical form with the simulations without the functional relationship in analytical form. The rest of the assumptions will be kept similar to simulation experiment 2. This means that standard design parameter degradation models for the design parameters in this problem, available in literature, are used for the tests. Design parameter variations are described through statistical distributions. Using standard design parameter degradation models, the degradation of the performance characteristics for any simulated circuit can be obtained. Given the specification limits, the time-to-failure of all the simulated circuits are traced. Hence, estimations of the MTTF and VTTF are established. Figure 5.11 gives an overview of the steps that are carried out in this simulation experiment and the assumptions that have been made for these experiments.

A designed experiment is then carried out to establish the effect of each design parameter on the MTTF and variance of the time to failure (VTTF). This information is then used in the optimization phase to select the design parameter values that maximize the MTTF and minimize the VTTF simultaneously. Finally, the results of this approach are compared to the results of the theoretical method. Details of the simulation are given in the next section.

5.6 Simulation experiment 3: Temperature Control System without functional relationship

In order to be able to compare the results of this simulation approach with the results of simulation experiment 2, the same simple temperature control system has been used in this computer-based simulation experiment. In the theoretical situation the functional relationship is available [PHA89]:

$$R_T = \frac{R_3 R_2 \left(E_z R_4 + E_0 R_1\right)}{R_1 \left(E_z R_2 + E_z R_4 - E_0 R_2\right)} \tag{5.17}$$

However, in this experiment this functional relationship in analytic form is not used. Instead, we will estimate it using simulated measurement data. Therefore, we generate data using the analytical functional relationship (eqn. 5.17). The generated data is considered as being the measured data from test experiments. The data is generated in such a way that the data could have been gathered by using a test strategy like the one proposed by Chiao and Hamada [CHI01]. For the purpose of comparison of the results of the two simulation experiments also the user-profile is included in the data generation process.

5.6.1 Details of simulation experiment 3

In this study two characteristics, as mentioned earlier, are used to quantify product reliability, namely:

→ Mean time to failure (MTTF), say μ;

→ Variance of time to failure (VTTF), say σ^2.

The goal is to identify the design parameter values that maximize the MTTF and simultaneously minimize the VTTF.

In order to meet these goals the necessary steps of the protocol of ROMDA have been followed and the results are stepwise presented below:

1. The first step is to identify the dominant time-dependent design parameters and the dominant performance characteristic describing products' behaviors over time. These have already been identified as being the four resistors R_1 to R_4, and R_T respectively.

2. Model the degradation of these dominant design parameters as a function of time and their initial values. For the problem used in this work, this information is also available. Similar degradation profiles as in the theoretical case are used to generate degradation data of the design parameters (see eqn. 5.18 for $R_i(t)$).

$$R_i(t) = R_{i0} \cdot (1 + 5 \cdot 10^{-3} \cdot t) \tag{5.18}$$

3. The time-dependent functional relationship between the design parameters and the performance characteristic is established by a regression fit using least-squares estimation to the longitudinal degradation data generated by the analytical functional relationship (eqn. 5.17). For the regression model a linear model with interaction terms is used. Data was generated for only 40 sample paths for the purpose that in practical problems it is also not possible to get thousands of samples measured. This resulted in the following time-independent regression model:

$$\begin{aligned} R_T &= 11.97 - 1.30R_1 - 0.39R_2 - 4.47R_3 - 0.15R_4 - 0.37R_1R_2 \\ &\quad + 0.09R_1R_4 + 2.08R_2R_3 - 0.24R_3R_4 \end{aligned} \tag{5.19}$$

Note that equation 5.19 is used as an empirical model that describes the behavior of the product population, while equation 5.17 describes the real behavior of the products.

The *Coefficient of Determination* (R^2) can be used to determine the amount of variability in the data explained, or accounted for by the effects of the design parameters. The design parameters reasonably explain the variation of the performance characteristics function (R^2=0.89).

4. The fourth step is to impose the stochastic time-dependent models of the design parameters into the functional relationship to obtain a time- and design parameter-dependent model for the performance characteristic. Since the regression model is fitted over the complete time domain, taking into account the degradation paths of the design parameters, the regression model is already time and parameter dependent. Therefore, the regression fit can be rewritten as:

$$\begin{aligned} R_T(t) &= 11.97 - 1.30R_1(t) - 0.39R_2(t) - 4.47R_3(t) - 0.15R_4(t) \\ &- 0.37R_1(t)R_2(t) + 0.09R_1(t)R_4(t) + 2.08R_2(t)R_3(t) \\ &- 0.24R_3(t)R_4(t) \end{aligned} \quad (5.20)$$

5. For every sampled product, the time to failure is evaluated from the above equation. The time-to-failure is the time at which this product violates at least one of the specifications of R_T. Similar specification limits as in simulation experiment 2 are used in these simulation experiments. In order to evaluate the MTTF and VTTF values of the design, 'n' values of R_1, R_2, R_3 and R_4 are randomly sampled at t=0, and thus each of these design parameter combinations constitutes a single product with a specific R_T value. Hence, all the 'n' products will give rise to 'n' different R_T values. The degradation of each of these values through time may thus be tracked through the expression given above. Hence, at any time, given the specification limits, quantities like the number of failures, time to failure, MTTF and VTTF may be evaluated or estimated.

6. A DOE test is designed. The test setup and the corresponding results for the MTTF and SDTTF are presented in table 5.6.

Table 5.6: DOE setup and results.

run	pattern	R_1	R_2	R_3	R_4	n products	MTTF	SDTTF
1	----	3.75	7.5	0.95	37.5	1000	276.06	2.7397
2	+---	4.25	7.5	0.95	37.5	1000	306.16	2.6720
3	-+--	3.75	8.5	0.95	37.5	1000	213.48	3.0534
4	++--	4.25	8.5	0.95	37.5	1000	281.74	3.0331
5	--+-	3.75	7.5	1.05	37.5	1000	209.33	2.8717
6	+-+-	4.25	7.5	1.05	37.5	1000	244.06	2.6282
7	-++-	3.75	8.5	1.05	37.5	1000	119.13	3.1033
8	+++-	4.25	8.5	1.05	37.5	1000	190.82	2.8943
9	---+	3.75	7.5	0.95	42.5	1000	273.01	2.4197
10	+--+	4.25	7.5	0.95	42.5	1000	262.64	2.1805
11	-+-+	3.75	8.5	0.95	42.5	1000	218.15	2.6590
12	++-+	4.25	8.5	0.95	42.5	1000	243.01	2.5976
13	--++	3.75	7.5	1.05	42.5	1000	234.05	2.6035
14	+-++	4.25	7.5	1.05	42.5	1000	227.45	2.2086
15	-+++	3.75	8.5	1.05	42.5	1000	153.43	2.7680
16	++++	4.25	8.5	1.05	42.5	1000	179.79	2.4923
17	a000	3.875	8.0	1.00	40.0	1000	217.37	2.6817
18	A000	4.125	8.0	1.00	40.0	1000	232.68	2.5422
19	0b00	4.0	7.75	1.00	40.0	1000	239.39	2.5536
20	0B00	4.0	8.25	1.00	40.0	1000	212.13	2.7311
21	00c0	4.0	8.0	0.975	40.0	1000	241.72	2.6101
22	00C0	4.0	8.0	1.025	40.0	1000	209.56	2.6432
23	000d	4.0	8.0	1.0	38.75	1000	227.71	2.7040
24	000D	4.0	8.0	1.0	41.25	1000	223.81	2.4928
25	0000	4.0	8.0	1.0	40.0	1000	225.96	2.6135

The regression models linking the MTTF and SDTTF to the design parameters are fitted in a similar manner as presented in step 3 in section 5.3.3. The models are:

$$\begin{aligned} MTTF &= 225.51 + 14.95R_1 - 27.08R_2 - 32.26R_3 - 3.10R_4 \\ &+ 8.96R_1R_2 + 0.83R_1R_3 - 10.66R_1R_4 - 6.89R_2R_3 + 1.73R_2R_4 \\ &+ 7.00R_3R_4 \end{aligned} \tag{5.21}$$

$$\begin{aligned} SDTTF &= 2.64 - 0.096R_1 + 0.143R_2 + 0.014R_3 - 0.192R_4 \\ &+ 0.237R_1R_2 - 0.046R_1R_3 - 0.027R_1R_4 - 0.024R_2R_3 + 0.014R_3R_4 \end{aligned} \tag{5.22}$$

The various terms of the design parameters explain the variation in the MTTF very good (R^2= 0.99). Also the variation of the SDTTF is well accounted for by the design parameters (R^2=0.99). With these models simultaneously maximizing the MTTF and minimizing the SDTTF becomes possible.

The "starting values" of the design parameters in the optimization scheme, which are the nominal design values, are given in the second column of table 5.7. This column also contains the MTTF and the SDTTF corresponding with these settings of the design parameters. The third column of table 5.7 shows the design parameter settings that realize the maximum *Overall Desirability* and thus the "optimal" trade-off in maximizing the MTTF and simultaneously minimizing the SDTTF for the practical approach.

Table 5.7: Results of Reliability Improvement (practical approach).

DP	**"Starting values"**	**"Optimal values"**
R_1 (kΩ)	4.0	4.25
R_2 (kΩ)	8.0	7.5
R_3 (kΩ)	1.0	0.95
R_4 (kΩ)	40.0	37.5
MTTF	225	307
SDTTF	13.2	14.4

The results show that it is possible to achieve an improvement of 36% in the MTTF. However, the SDTTF slightly decreases in performance.

This small decrease in the performance of the SDTTF is mainly caused by the choice of the degradation models of the design parameters. The variance of the performance characteristic is independent of the level of the mean values of the design parameters and independent of the variances of the design parameters. Hence, the variance of the performance characteristic is not affected by changes in the mean values of the design parameters. Therefore, the SDTTF, which is dependent of the variance of the performance characteristic, can, in this case, not be improved by *parameter design*. Thus, in these simulation experiments *parameter design* can only be used to improve the MTTF.

The performance of SDTTF slightly decreased using this approach of Robust Design. Hence, *tolerance design* may be a next step in improving the SDTTF. This would mean linking the SDTTF to the variation of the design parameters over time and optimize the SDTTF by reducing the variation of those design parameters that influence the SDTTF most.

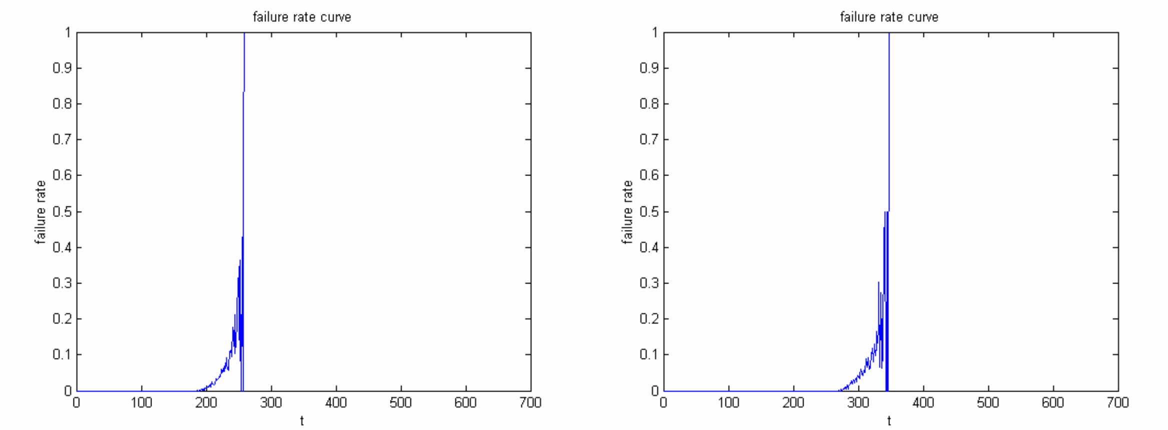


Figure 5.12:

a) *Failure rate curve: Before Reliability optimization.*

b) *Failure rate curve: After Reliability optimization.*

The results of the reliability improvement can be translated back to the failure rate curves. Figure 5.12a shows the failure rate curve of the design before the reliability optimization. A thousand products are randomly created with the nominal settings of the design parameters as given in the second column of table 5.7. Figure 5.12b represents the failure rate curve of products (also a thousand simulated products) with the design parameters set on the "optimal" values determined in the reliability optimization.

These plots clearly show the reliability improvement due to the change of settings of the design parameters. Note that the specification limits have been chosen such that customer use causes no early failures.

5.6.2 Comparison theoretical approach with practical approach

In the previous section the results for all steps of the practical protocol were presented. A clear conclusion is that the MTTF of the design is significantly improved. This was also the case in the theoretical approach. However, notice the difference in absolute values of the MTTF of both the theoretical and the practical case (see table 5.7). The absolute values in the practical approach are structurally lower. This can be explained by looking at the customer use profile that was introduced in the simulations. Figure 5.13 shows how the customer use profile influences the performance characteristic R_T. When fitting a regression model through such a user profile one can expect some problems in accuracy of the absolute values.

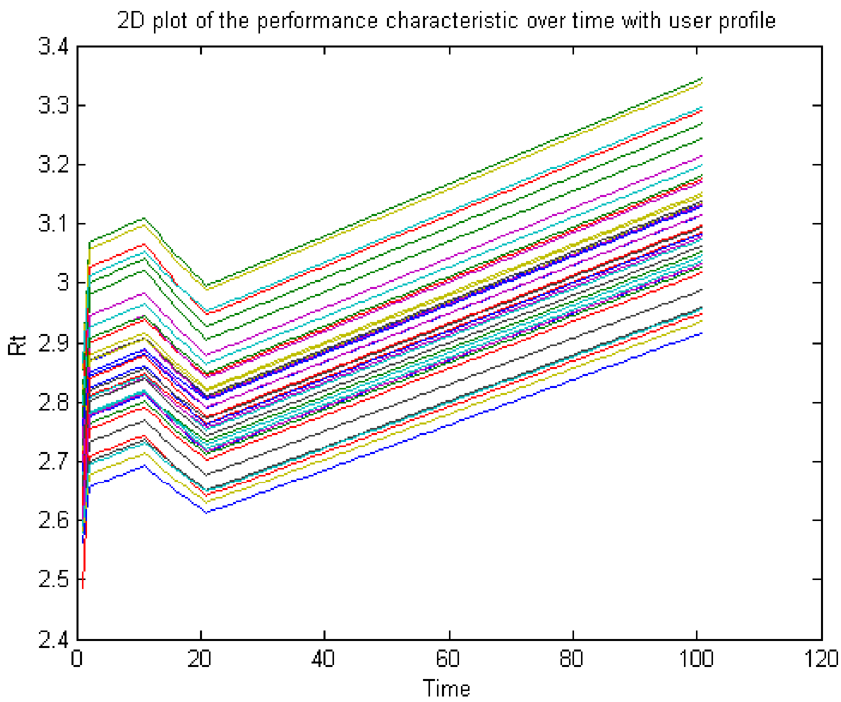


Figure 5.13: Degradation profile of the performance characteristic over time.

Another observation in the comparison of the results is that the optimal value settings differ for resistor R_4. In the theoretical approach the optimal value of R_4 is 40.6, while in the practical approach the optimal value of R_4 is 37.5. A natural question then would be how good the optimized results of the practical approach really are. In order to answer this question, the optimal values that were calculated using the practical approach, in which an approximation for the functional relationship is used, are used in the analytical functional relationship (eqn. 5.17) to see how the design would really perform. Table 5.8 shows the results of both the optimal values in terms of reliability characteristics using the theoretical approach and using the practical approach.

Table 5.8: results computer-based simulations.

Design Parameters	*Starting values*	*Theoretical optimal values*	*Practical optimal values*
R_1 (Ω)	4.0	4.25	4.25
R_2 (Ω)	8.0	7.5	7.5
R_3 (Ω)	1.0	0.95	0.95
R_4 (Ω)	40.0	40.6	37.5
MTTF	331	519	496
VTTF	31.9	28.7	35.5

With the settings that were the result of the practical approach, where the functional relationship has been estimated by a regression model, a significant improvement of the performance of the design is established. In the theoretical approach the improvement was 57%, but using the optimal settings estimated using the practical approach still gives an improvement of 50%. Notice that the performance of the VTTF increases slightly.

5.6.3 Additional analysis

Since the absolute values of the MTTF and the VTTF differ significantly between the theoretical and the practical approach, similar analyses as described above are performed, but then without the customer user profile incorporated in the analyses for both the theoretical and practical approach. The results are shown in table 5.9.

Table 5.9: results computer-based simulations without user profile.

Design Parameters	*Starting values theoretical approach*	*Theoretical optimal values*	*Practical optimal values*
R_1 (Ω)	4.0	4.25	4.25
R_2 (Ω)	8.0	7.5	7.5
R_3 (Ω)	1.0	0.95	0.95
R_4 (Ω)	40.0	42.5	42.5
MTTF	327	540	540
VTTF	29.7	37.8	37.8

The absolute values of the results using the estimated regression models are similar to the results of the simulations using the mechanistic relationship. Also the improvements are significant and are for both approaches 65%. Here the VTTF in both cases increases slightly.

5.6.4 Conclusion simulation experiment 3

The presented simulation experiments in this section clearly show the validity to use the ROMDA method when a functional relationship in analytical form is not available in literature. However, to make ROMDA useful for real industrial products all the assumptions and preconditions that are highly unlikely in practice have to be overcome.

5.7 Overall conclusions simulation experiments

This chapter starts with a simulation experiment using a simple electrical circuit design. Basically the purpose of that simulation experiment is to prove that using standard robust design optimization methods focused on time-independent performance of products does not always lead to an optimized design towards reliability characteristics.

The second simulation experiment follows the complete protocol of ROMDA introduced in chapter 4. The results of this simulation experiment are very promising. The mean time to failure (MTTF) increases with 57% and also the standard deviation of the time to failure (SDTTF) decreases slightly. However, as the analysis shows in section 5.5.1, the assumptions and preconditions used in the second simulation experiment are highly unlikely to be valid in a real industrial environment on real products.

A third simulation experiment is performed to research on the influence of these assumptions. This simulation experiment concentrates on the assumption that the functional relationship exists in an analytical form. The functional relationship is never, or at least, almost never known. The other assumptions, like the degradation profiles, are more straightforward measurements and the optimization phase is intuitively less influenced by these assumptions.

The results of the third simulation experiment also shows some very promising results; even taking into account the difficulties of modelling data with some steps in it due to the customer use profile.

However, the main conclusion that can be drawn from these experiments is that ROMDA is promising, but not yet practically applicable. In section 5.5.1 some suggestions are made on how to make ROMDA practically applicable. Chapter 6 describes ROMDA in a practically applicable protocol. This practical protocol is then tested on real industrial products to validate the value and applicability of ROMDA on real products.

6 Practical protocol ROMDA

6.1 Introduction

Chapter 4 presented the general cocepts behind ROMDA. These are demonstrated on a theoretical problem in chapter 5. The first simulation experiment shows that using robust design optimization methods based on time-independent performance does not automatically optimize a design in terms of reliability. The results of the second simulation experiment shows a substantial increase in the reliability characteristics of the simulated products. However, in these experiments some assumptions and preconditions are not realistic for real industrial products. This is pointed out in section 5.5. These assumptions and preconditions are extensively discussed in section 5.5 and an analysis of the possible consequences of these assumptions is provided. In order to research on the consequences for the simulation experiment, a new simulation experiment was conducted to quantitatively investigate the consequences for the temperature control system that was used for the second simulation experiment. The results of that simulation experiment were still very promising. However, to make ROMDA applicable for real industrial products a few adjustments need to be made in the protocol. This chapter presents these necessary adjustments to the protocol to make ROMDA practically applicable. Section 6.2 first presents the adjusted protocol in terms of goals that have to be reached after every step. The next section, section 6.3, provides a detailed discussion on all methods that have to be used to gather the necessary information per step in the protocol. In some phases in the protocol standard testing methods can be used, but in some other phases in the protocol adjustments to existing testing methods are necessary to gather the necessary information. Section 6.3 indicates methods that can be used in the protocol. When adjustments to methods are necessary, a more profound description will be provided.

6.2 Practical Protocol ROMDA

In chapter 5 a protocol for ROMDA was presented. In summary the phases in the protocol are:

1. Identify the performance characteristic representing the dominant failure mechanism and the design parameters dominantly influencing the behavior of the performance characteristic.
2. Obtain stochastic models of the degradation data of these design parameters.
3. Establish a functional relationship between the performance characteristic and the design parameters.
4. Introduce the stochastic models of the design parameters into the performance characteristic/design parameter relationship to obtain a time and design parameter dependent model for the performance characteristic under study.
5. Use this model of the performance characteristic with respect to certain chosen specification limits to obtain reliability characteristics like mean time-to-failure (MTTF) and standard deviation of the time-to-failure (SDTTF).

6. Use an optimization method, like parametric robust design, to improve or optimize these reliability characteristics simultaneously by setting the nominal values of the design parameters at suitable levels.

These phases are all very general in nature. In order to make ROMDA more practical and valid for real industrial products in their real user environment, a more detailed protocol is provided next:

Phase 1. Define objectives of the experiment/system

The objectives of the experiment should be described in detail. The following issues should be addressed:

→ Description of product/module/part function

→ Objectives in relation to reliability characteristics and performance

→ Robustness requirements (in particular with respect to user environments)

→ Environmental objectives

→ Management responsibilities

→ Financial objectives

→ List of Key Performance Indicators: KPI + translation of objectives into terms of KPI's

→ Resources needed to conduct experiment

→ Resources available to conduct experiment

→ Scheduling of experiment

Phase 2. Search/research available information

In the project maximum use should be made of all available information. Typical items to be included are:

- → Results from related previous experiments and reports
- → Measurement System Analysis (MSA) (in case this is not available, it must be performed prior to further actions)
- → Failure Mode and Effect Analysis (FMEA)
- → Design specifications of the product/module/part
- → Other formal methods (e.g. Quality Function Deployment, conceptual design etc.)
- → Warranty and field data
- → Unit-to-unit tolerance information

Phase 3. Define input factors

The input factors should have a clear connection with the dominant failure mechanisms researched in phase 2. A brainstorm should yield an initial input to output table for factors and interactions between them. For each input factor, a proper description should be made that must at least address the following issues.

- → Noise factors or design parameters
- → Type of factor (continuous, discrete, functional, time-dependent)
- → Location and variability
- → Type of control (manual or automatic)
- → Difficulty of change

→ Blocking factors, sources of trend, etc

→ Flow of inputs to outputs in measurement hierarchy

→ Link with monitoring scheme

<u>Phase 4. Obtain performance characteristic and output measurement</u>

The output measurements should have a clear connection with the FMEA of phase 2 and the KPI's and the experiment objectives:

→ Classification of output factors: continuous, discrete, functional, time-dependent

→ Measurement: sensor specification, instrumentation, on-line/off-line, laboratory, post-processing, sampling and sample rate, units of measurement

→ Full list of all variables, with all characteristics

→ Link with monitoring scheme

→ Relation of output factor to functioning product/module/part: measurement hierarchy

<u>Phase 5. Describe output analysis</u>

The experiment proposal should include a description of the analysis methods that are likely to be used. Typical methods include:

→ Regression analysis

→ ANOVA

→ Kernel methods

→ Wavelet

→ Other function data analysis methods

<u>Phase 6.   Perform initial and screening experiment</u>

→ Confirm choice of input factors, noise factors, and output factors

→ Initial experiments to check measurement, and control

→ Screening experiment to detect: statistically and practically significant factors, interactions, noise factors (confirm results of FMEA)

→ Possible use of sequential screening experiment

→ Analysis: statistical and practical significance of factors, influence of noise factors, initial modeling input factors against output factor

<u>Phase 7.   Perform limit settings experiment and design tolerance input factor level determination</u>

→ Determine failure limits of input factors and output factor

→ Determine achievable changes in input factor levels for optimization purposes

<u>Phase 8.   Perform accelerated degradation life tests (ADT)</u>

→ Choice of key input factors and output factor

→ Choice acceleration testing type (compressed-time testing, accelerated stress testing, etc.)

→ Choice of acceleration factors

→ Initial experiment to check measurement, and control

→ ADT to identify: degradation profiles input factors, degradation profiles output factor, shape degradation curves (convex, concave, linear)

→ Analysis: model degradation curves using regression analysis, ANOVA, time-series analysis, etc.

Phase 9. Perform complex experiments

→ Detailed multilevel/multi-stage experiment for key input factors/output factor

→ Experimental design: response surface design, design for non-linear models, etc.

→ Experiments over "time" to link degradation characteristics input factors to output factor

→ Influence unit-to-unit variability on output factor and degradation profiles

→ Analysis: regression, kernel methods, time series, wavelet, etc

Phase 10. Analyse data and translation to reliability characteristics

→ Translate degradation models to reliability characteristics using failure specification limits

→ Model reliability characteristics in terms of input factors

→ Analysis: regression analysis, ANOVA, etc.

Phase 11. ***Perform stochastic optimization of reliability characteristics of product/-module/part design***

→ Stochastically optimize product/module/part towards reliability and robustness

Phase 12. ***Confirmatory phase***

→ KPI for success of confirmation

→ Test of full product/module/part for interactions: success rates, false negatives, false positives etc.

The next section provides an extensive description of all phases in the protocol. When standard testing methods, analysis methods or tools are used, only a brief description is given. In cases where adjustments, or new methods, need to be used, a more in-depth description will be provided.

6.3 Extensive description of phases in protocol

Phase 1: Define objectives of the experiment

Phase 1 is the phase where the objectives of the experiment are extensively described. Firstly, decisions have to be made on more general objectives, like financial objectives, technical objectives, environmental objectives. Then issues about which products, modules, or parts provide the best opportunities for reaching the objectives have to be addressed. Next, decisions have to be made on responsibility, resources needed to conduct the experiments and resources that are available for the experiments. Also a time schedule/plan for the complete experimental plan has to be made. And finally, objectives in relation to reliability characteristics, robustness requirements, and performance requirements have to be formulated. This phase serves as a formalization of the complete experiments.

Phase 2: Search/research available information

When the experiment is formalized the next step is to gather all relevant information. But to do so, an extensive description of the product, module, or part is necessary. This way a good overview of all parts and functions is available for searching relevant information. But this information can also help with certain methods, like a FMEA, where all parts could serve as point of analysis.

When measurements have to be conducted, it is important to be sure that the measurements are correct (predictable and stable). To accomplish this, a Measurement System Analysis (MSA) in the form of a Gage R&R [MON97] has to be performed. For more details about the Gage R&R method the reader is referred to literature (e.g. Montgomery (1997) [MON97]).

Besides these calculations of the Gage R&R, X- and R-control charts are often used to check whether the measurements are stable and predictable. The R-chart of the measurements should be in control in order to guarantee predictable and stable measurements. Next to that, variations due to changes in settings between runs should be larger than the variation between the successive tests at the same level settings. In other words, variation between different settings (setting variation) should be larger than variation between replications of the same setting (test variation).

This phase is also used to perform a qualitative failure analysis by performing a FMEA. These methods can give good qualitative information about expected weak spots in the design.

Within the framework of ROMDA, the design parameters have to meet three criteria:

1. These variables must have a dominant influence on the performance characteristic.
2. The design parameters have to degrade over time, since in this research the focus is on failure behavior due to degradation effects of the dominant design parameters.
3. The measurability of the design parameters must be high enough to be able to measure the degradation paths of these design parameters reckoning with the available means (time, money, tools).

As a result of complying with the first two criteria, the performance characteristic deteriorates with respect to the specification limits under study. The last criterion assures that only measurable design parameters are selected. Selecting design parameters that are (too) difficult to measure can cause the following problems:

→ The measurement process takes long and the results are unreliable and/or inconsistent;

→ The development of a measurement tool is too challenging and this causes serious delays in the overall project progress;

→ The research results developed cannot be employed in practice because the process requires highly sophisticated measurement tools.

When important parameters cannot be measured, derivative parameters could be used to describe the behavior of the important ones.

The classical FMEA method can be quite helpful in this situation, because of its structured way of analyzing qualitative failure data. Based on this failure data, design parameters can be identified that have a dominant influence on the performance of the product/module/system (criterion 1). Although the main concept of the FMEA method is applicable in this context, some adjustments are necessary in order to comply with criteria 2 and 3.

The first adjustment to the classical FMEA [MIL87] method is the addition of the factor “time-dependence”. Since the focus of ROMDA is on failure behavior due to degradation effects of the dominant design parameters, the design parameters must change over time (criterion 2). To discriminate between degradation failure modes and time-independent, or instantaneous, failure modes, the factor time-dependence is introduced. The scale of this factor is defined as follows:

Table 6.1: Factor scale time dependence.

Time dependence	
values	**describing**
1	a time independent failure mode
2	a time dependent failure mode

Time-independent factors are included in the FMEA table for the reason that the results of the FMEA analysis may be used for other purposes within a company that require information about time-independent failure modes.

The second adjustment to the classical FMEA table is the replacement of the original factor detection by the factor measurability. The classical FMEA method has been developed for safety analysis purposes. In safety analysis, failures that are easy to detect are less harmful than failures that are difficult to detect. For the purpose of this research, detection is less critical since the main goal is the prediction and optimization of the degradation processes. Therefore, detection is replaced by a more suitable factor: measurability. This factor describes the ease of measurement of the failure modes. In case of a low measurability, it will be quite difficult to measure the related design parameters and this may cause problems later in the project. This new factor measurability complies with design parameter criterion 3. An example scale of this factor is defined is shown in table 6.2:

Table 6.2: Factor scale Measurability.

Measurability values	**describing a failure mode that**
1	is (almost) impossible to measure
2	can only be measured indirectly
3	is difficult to measure directly
4	is moderately difficult to measure directly
5	is easy to measure directly

In conformance with the classical FMEA for the new factor a 5-value scale is used. Value 1 means that the parameter cannot be measured. Measurability value 2 means that the parameter cannot be measured directly, but the parameter can be measured using a derivative parameter. An example could be magnetic induction. This factor is difficult to measure, but it could be done using related parameters late electrical current. The rest of the measurability values follow a same line of reasoning.

It is also important to notice that measurability is not included in the multiplication of the factors that result in the RPN (the priority number). The measurability has no influence on the priority of the failure modes. A failure mode that is difficult to measure is not more critical than a failure mode that is easy to measure. Therefore, the measurability factor is particularly used for stressing possible difficulties with failure modes that are difficult to measure. This factor can be used as a criterion in the process of design parameter identification for the practical feasibility of ROMDA, the selected design parameters may not be too difficult/impossible to measure (criterion 3).

The factor Criticality describes the seriousness of a certain failure mode similarly as the factor Severity does in a classical FMEA table. The scale of the Criticality factor is as follows:

Table 6.3: Factor scale Criticality.

Criticality values	**describing**
1	a Failure Mode with a very low impact
2	a Failure Mode with a low impact
3	a Failure Mode with an average impact
4	a Failure Mode with a high impact
5	a Failure Mode with a very high impact

The factor Occurrence is maintained in the multiplication that results in the RPN. The scale of this factor is as follows:

Table 6.4: Factor scale Occurrence.

Occurrence values	**describing**
1	a Failure Mode with a very low failure frequency
2	a Failure Mode with a low failure frequency
3	a Failure Mode with an average failure frequency
4	a Failure Mode with a high failure frequency
5	a Failure Mode with a very high failure frequency

These adjustments together with the classical FMEA table lead to the following format of the “adjusted FMEA table” (the data in this table is fictional).

Table 6.5: Example adjusted FMEA table.

Component name	Failure mode	Cause of Failure	Possible Effects	T	O	C	M	RPM *
Hoover motor	Over-heating	Timeclock defect Paper jam Bimetal defect Short circuit	Fire Resistance break-down					20 20 12 15
	Discolored surface	Wrong paint Light explosion	Customer rejection					8 40

[* $RPN = T \times O \times C$]

Next to FMEA information about failure behavior of a type of products, also design specifications of a product, modules or parts have to be collected. This information could prove very useful in later phases where tests have to be designed.

Also warranty and field data of previous generation products could serve as information source. Most products are derivative products of previous generation products and the failure behavior of those products could give a good insight in the weak parts of the product.

Phase 3: Define input factors

The third phase is called input factors. Input factors can be divided into design parameters and noise factors. In this phase a more in-depth study has to be performed on the design parameters and the noise factors. These design parameters and noise factors should be determined using the results of the FMEA and other information that is gathered in phase 2.

Before setting up the experiments the experimenter needs to know the properties of the factors (e.g. continuous, discrete, functional, time-dependent). In this phase also information about the nominal values and typical range of the factors should be examined. For experimental purpose it is important to know how these factors can be changed during an experiment. The type of control could be automatic or manual.

In relation with measurability that is taken into account in the FMEA, in this phase an analysis has to be made on the difficulty of changing the values of the factors that will be included in the experiment.

And for the purpose of preventive maintenance, which is one of the main objectives, measurability information can be very important. Products need to be monitored in the field to make maintenance decisions. And measurability information can help in deciding what properties have to be monitored in order to make a correct preventive maintenance decision.

Phase 4: Obtain performance characteristic and output measurement

The fourth phase in the protocol focuses on determining the performance characteristic and output measurements. The performance characteristic is the characteristic that has to be optimized to improve the time-dependent behavior of the products. Therefore, the performance characteristic has to represent the dominant failure mechanism. This makes the translation of dominant failure mechanisms to measurable physical properties (performance characteristic) essential for the success of the execution of the rest of the protocol. The dominant failure mechanisms are determined in phase 2 using methods like FMEA and will be confirmed in phase 6.

Some important issues that have to be taken into account for selecting a performance characteristic are the properties of the characteristic. Are the characteristics continuous or discrete factors, are the characteristics time-dependent degrading factors or controlled factors. These properties are closely related to the measurability of the characteristics.

One of the main objectives in the research objective is preventive maintenance. It would be ideal if it would be possible to monitor only the performance characteristic in order to judge the status of the product. However, many examples can be found where the performance characteristic can only be measured using special measurement equipment in laboratory environment. In that case the dominant design parameters can be used for monitoring purposes in order to make preventive maintenance decisions possible.

Phase 5: Describe output analysis

Phase 5 is added in the protocol for completeness. It is obvious that the results of the experiments need to be analyzed to come to conclusions. In cases where the experimenters are familiar with all the analysis methods, this step is unnecessary. However, when methods have to be used that are not yet well-understood, it might be necessary to gain knowledge of these methods before an experimenter can even setup a test (since you don't exactly know what you need to measure, how many times etc.). Or even worse, when the experimenters have no idea of what analysis methods have to be used. To give an example of data that most often needs different analysis method is sound or vibration data. This kind of information is very hard, or even impossible, to analyze using standard ANOVA or regression techniques. More sophisticated methods like wavelet analysis might be necessary for the analysis.

For this reason phase 5 has been included as a separate phase in the protocol.

Phase 6: Perform initial and screening experiments

The initial and screening experiments have a few goals. The initial experiments focus on the possibility to measure design parameters. This also includes performing a gage R&R, or a Measurement System Analysis (MSA) to check if the measurement setup is in control and the results can be reproduced.

The purpose of the screening experiment is to gather information about the significance and interactions of the design parameters and the performance characteristic that are determined in phases 1 to 4. Also the influence of the noise factors is researched in the screening experiments. Basically, the screening experiments verify the results of the phases 1 to 4 in a quantitative manner.

The initial experiments and the screening experiments can be performed using standard methods and procedures. Gage R&R can be used for the initial experiments and for the screening experiments methods like Design of Experiments (DOE) or Taguchi based experimental setup schemes can be used.

Phase 7: Perform limit settings experiment and design tolerance input factor level determination

In phase 7 the failure limits of the performance characteristic and the design parameters are determined. Both limits are determined in order to know the limits both in the parameter space and in the performance space. It is necessary to know these limits for all three main goals of this research (optimization of design towards reliability, re-use and preventive maintenance).

The second goal of phase 7 is to determine the practically possible changes of the design parameters for the purpose of optimizing the product performance towards reliability. To illustrate this point consider a car tire. The main goal of a car tire is to give grip to a car. So, one way to give more grip is by increasing the width of the car tire. However, there is a practical limit to the width of the car tire. This could be costs, fuel consumption, etc. For this reason it is important to know the practical limits of the design parameters for optimization purposes.

A method that can be used for the determination of the failure limits is to increase (or decrease) the values of the parameters until the product does not function properly anymore. When interaction could be important, a simple DOE experiment could be performed.

Phase 8: Perform accelerated Degradation life Tests (ADT)

The goal of the Accelerated Degradation life Tests (ADT) is to gather information about the time-dependent behavior of the products. To do so, the degradation behavior of both the performance characteristic and the design parameters is examined. The results of the ADT give information about how these factors degrade and the shape of the degradation profiles (convex, concave, linear). This information is necessary for setting up the experiments of the next phase (complex experiments).

A first step that has to be taken is to check whether the measurement system is in control. A Gage R&R can be used for this purpose.

A large amount of literature is available on ADT methods (see chapter 3). So, the next step is to make a decision on what acceleration testing type will be used. Examples are: compressed-time testing, accelerated stress testing, etc.

When a choice about the ADT method has been made, the acceleration factors have to be determined. Basically this is closely connected to the choice of ADT method that will be used. When a compressed-time testing method will be used, then a factor should be chosen that increases the intensity of usage of the product. For example, when testing a car tire, one could decide to let the car tire continuously run on rollers and therewith intensify the usage intensity.

Also a decision has to be made on the stopping criteria of the tests. With current highly reliable products it would be very time-consuming and costly to test products to their end-of-life. So, it is desirable to stop the tests when enough information is available to make good predictions for the rest of the life of the products.

The results of the ADT can be analyzed using methods like ANOVA, regression analysis methods, time series methods, etc.

Phase 9: Perform complex experiments

The complex experiments are conducted to establish the link between the performance characteristic and the dominant design parameters, or in other words, establish the functional relationship between the DP's and the PC.

For the complex experiments a special form of Design of Experiments (DOE's) will be introduced. Normally, a DOE is time-independent and conducted at time t = 0. The purpose of such an experiment is to optimize a process or the quality of a product. However, in this concept not the quality of the product, but the reliability is of main interest and the factor "time" is added. This gives rise to a problem, because DOE's are time-independent, while time-dependent data is necessary. C.H. Chiao and M. Hamada [CHI01] present a testing method in their paper "*Analyzing Experiments with Degradation Data for Improving Reliability and for Achieving Robust Reliability*" that would provide the necessary data. They propose a DOE settings strategy at time t = 0 and let the products degrade over time for all the different settings. This way of experimenting proved to be very versatile, but very time-consuming. Their experiments on 20 LED's took more then 12,000 hours per LED, which is 500 days of continuous testing. This becomes an even bigger problem when testing very expensive and reliable products. DOE is a very good testing method to get statistical data for the purpose of determining a functional relationship between input factors and output factors. However, DOE's are time-independent. This results in the necessity of performing various DOE's "at certain moments representing points in time". The DOE's are considered time-independent at every moment representing a point in time. This approach is fundamentally different from other lifetime tests or degradation tests. Figure 6.1 gives a systematical overview of the test setup.

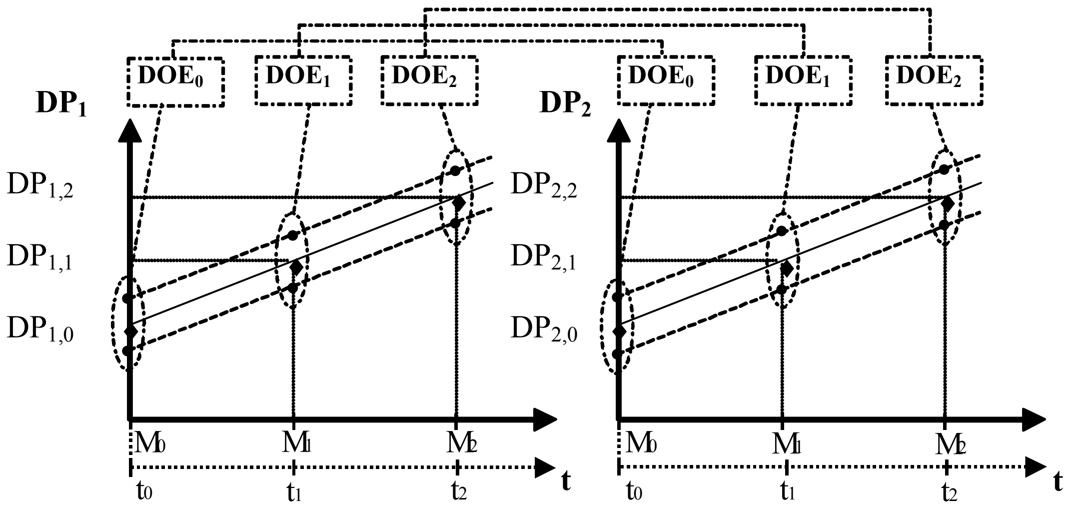


Figure 6.1: Schematic overview of time-dependent DOE's.

In figure 6.1 two design parameters can be recognized. The left figure is design parameter DP_1 and the right figure shows design parameter DP_2. The horizontal axes show the moment of testing that could be translated to real time. The vertical axes represent the values of respectively DP_1 and DP_2. M_0 in both figures represents the initial design values $DP_{1,0}$ and $DP_{2,0}$ of the design parameters. A complete DOE is designed around these initial values and the performance characteristic is measured. The DOE is performed in a normal way. But over time the values of the dominant design parameters degrade. The values of these design parameters change systematically over time. The information gathered in phase 8 provides information about the degradation of the DP's and their shapes. And phase 7 provides information about the maximum values of the DP's where the products still perform as intended. These values are just above the values $DP_{1,2}$ and $DP_{2,2}$.

Degradation can be either linear, as in the figure, or convex or concave. To take these possibilities into account, the complete range of possible values of the design parameters has to be divided in at least three parts. At a certain moment M_1 in time, DP_1 will reach level $DP_{1,1}$. The same is true for DP_2. In order to get statistical information of DP_1 and DP_2 on the performance characteristic, a complete DOE is performed with the nominal value settings $DP_{1,1}$ and $DP_{2,1}$. And again a complete DOE is done for the settings $DP_{1,2}$ and $DP_{2,2}$. When these DOE-tests are performed the following example results represented in figure 6.2 could be observed.

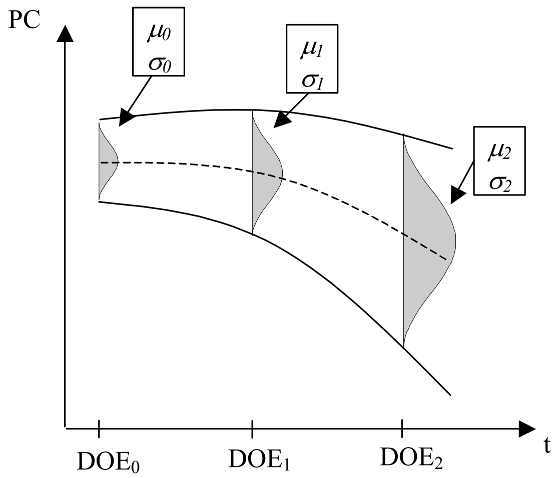


Figure 6.2: Example results of time-dependent DOE's.

At the initial settings of DP_1 and DP_2, the statistical influence on PC can be observed. In the example figure 6.2, this is a normal distribution. Such a statistical representation of PC for every setting for the DOE of DP_1 and DP_2 could be made. DOE_0 represents the initial settings and product performance of the product. DOE_1 shows how the PC would degrade over time when DP_1 and DP_2 would have degraded as figure 6.1 shows. The same accounts for DOE_2. This results in the knowledge of how the products degrade over time and its relation over the complete time span of the performance characteristic in relation to the design parameters. In equation form the model could look like:

$$\begin{aligned}
\mu_{PC}(t) &= \alpha_0 + \alpha_1\mu_{DP_1}(t) + \alpha_2\mu_{DP_2}(t) + \alpha_3\mu_{DP_1}(t)\mu_{DP_2}(t) \\
&\quad + \alpha_4\mu^2_{DP_1}(t) + \alpha_5\mu^2_{DP_2}(t) \\
\sigma^2_{PC}(t) &= \beta_0 + \beta_1\sigma^2_{DP_1}(t) + \beta_2\sigma^2_{DP_2}(t) + \beta_3\sigma^2_{DP_1DP_2}(t)
\end{aligned} \tag{6.1}$$

The levels of the three DOE's are designed in such a way that the various levels of each design parameter cover the entire range (=from initial design values to failure levels) of this parameter, where the product is still able to function properly. The values of design parameters DP_1 and DP_2 will be changed to simulate the degradation of these dominant design parameters in order to substitute time-consuming life tests. This is possible due to the fact that the chosen design parameters are time-dependent. So, by changing the value of a parameter, a certain time step is introduced. Therefore, all experiments can be performed at the same time, but the results represent the behavior of the design parameters over time.

The left-hand plot of figure 6.1 shows the degradation profile of design parameter DP_1. As shown in figure 6.1 below, this degradation model assumes that only the mean value of this distribution changes over time, while the variance remains constant. This does not have to be the case. However, real information about the degradation of the parameters should be available or should be gained by screening tests. When performing this test strategy the real degradation profiles should be used and scaled back the moment settings of the DOE's to eventually come to a valid functional relationship over time.

The measurements on times M_0, M_1 and M_2 of the three DOE's are performed at time t=0, but these measurements can be scaled back to a real time axis. Therefore, this is only possible when real degradation information is used to setup the test strategy. The values of $DP_{1,0}$ till $DP_{1,2}$ of parameter DP_1 and of $DP_{2,0}$ till $DP_{2,2}$ of parameter DP_2 represent the mean value of the distributions of both design parameters at respectively time t_0, t_1 and t_2. By varying the values of the design parameters around these mean values it is possible to determine the influence of both design parameters on the performance characteristic at each point in time. Besides, this also provides information about how variations in the design parameters, which can be seen as product-to-product variation, influence the variation in the performance characteristic over time.

The experiments presented so far do not take product-to-product variation into account. Although the variation in design parameters, introduced through the various levels of these design parameters in the DOE's, could be seen as a kind of product-to-product variation, this variation is not the real variation within a batch of products. In a DOE setup the chosen variations in the values of the parameters should be bigger than the random product-to-product variation in order to see the systematic effects, and not the random effects. But it is assumed that the functional relationship will not change due to the real product-to-product variation. It will however increase the bounds representing the variance of the performance characteristic over time. The real product-to-product variation could be measured at time $t = 0$. An estimate would result in a good approximation of the behavior of the performance characteristic over time.

When the complex experiments have been performed a time-dependent functional relationship can be formulated using standard statistical analysis methods like ANOVA and regression analysis. This model represents the dominant failure mechanisms in the form of performance characteristics and design parameters dominantly influencing the performance characteristics that were determined in phase 1 to 4. This model takes into account the noise factors that have been researched in the screening experiments in phase 6. The model is valid to the technical end-of-life of the products due to the fact that in the experiments the limits of the DP's and the PC have been determined at phase 7 and have been included in the complex experiments in phase 9. The factor time in the model is the result of the degradation tests that have been performed in phase 8. And by using the variation measurements that are included in phases 6 and 9 the statistical behavior of the product population can also be included in the model.

When this phase is finished and the models are available, it is possible to judge the status of the products at all times. And therefore, it can be concluded that with this information all necessary information for preventive maintenance decisions and re-use decisions is available. For the third main goal, which is robust reliability optimization, some more information is necessary and, therefore, the next 2 phases are a necessity for optimization purposes.

The next phase focuses on the translation of the time- and design parameter-dependent model that is available at this moment to reliability characteristics.

Phase 10: Data analysis and translation to reliability characteristics

The objective of phase 10 is to translate the time-dependent degradation models that have been developed in phase 9 to reliability characteristics. As mentioned in chapter 4, this thesis will only focus on the Mean Time To Failure (MTTF) and the Variance of Time To Failure (VTTF). When other reliability characteristics are required, this is possible with the available data. However, then it is highly possible that standard stochastic optimization methods are not sufficient and new optimization methods need to be developed. This is not the objective of this research.

For optimization purposes the models of the MTTF and the VTTF should be a function of the design parameters.

$$\begin{aligned} MTTF &= f(DP_i) \\ VTTF &= g(DP_i) \end{aligned} \tag{6.2}$$

In chapter 5 a brief description of a step-by-step approach for gathering data to formulate the MTTF and VTTF model is given. Basically, with the use of the models of phase 9 and the failure limits of phase 7 a simulation experiment can be designed in the form of a DOE. When different design parameter settings are filled in the model and a time to failure of that particular setting is registered, and this is repeated many times, quantities like MTTF and VTTF in relation with DP settings may be evaluated or estimated using data analysis methods. Section 5.6.1 gives an example of this procedure in the simulation experiments.

When these reliability models have been formulated optimization of the product design towards reliability characteristics becomes possible. This is phase 11.

Phase 11: Stochastic optimization of reliability characteristics of product/module/part design

The objective of phase 11 is the optimization of the product design towards reliability and robustness itself. Many optimization methods are available in literature. Only a brief discussion of available optimization methods was given in the literature overview in chapter 3. It is not a goal of this research to develop a new optimization method. Instead, in this thesis only a standard method, the Desirability Approach, is used for the reason that it works for this type of problems. However, when more precise optimization methods are preferred, the author refers to literature (e.g. Ermoliev and Wets (1988) [ERM88], Blischke and Murthy (2000) [BLI00], Heyman and Sobel (1984) [HEY84]).

Phase 12: Confirmatory phase

Phase 12 is the last phase and deals with the confirmation of the results to the objectives that are described in phase 1. In phase 1 an extensive description is given with all the objectives of the complete experiments in terms of reliability and robustness objectives, but also in terms of environmental and financial objectives.

The success of the project depends on the success of the experiments.

7 Case studies

7.1 Introduction

Chapter 6 provides a practical protocol of ROMDA that enables engineers to gather information for preventive maintenance decisions and re-use decisions and optimization of a product design towards reliability and robustness. The protocol consists of 12 phases. This chapter presents a case study where the 12 phases have been executed. In the case study a finisher module of a copier machine has been used as the product of research. The tests have all been executed at and in collaboration with Flextronics, the Netherlands.

This chapter also briefly presents two other case studies. The second case study deals with a paper input system of a copier machine. The tests for this case study have also been performed at Flextronics, the Netherlands. This case study shows that the most difficult, and risky, phases of the ROMDA protocol are the first four phases. If wrong decisions are taken in these phases, the rest of the tests will lead to wrong conclusions. In order to reduce these risks, a third case study has been performed at OCE, the Netherlands. This case study had the goal to reduce the risk of making wrong decisions in the phases 1 to 4.

7.2 Case Study: The Finisher Module (Flextronics)

The objective of this case study is to test the practical applicability of ROMDA to a real product. The case study is organized in such a way that it follows the phases that were presented in chapter 6.

Phase 1

The first case study deals with a finisher module. The finisher module is part of a photocopier machine or a printer (fig 7.1). Figure 7.1 shows an example of the finisher module that has been used for this case study.

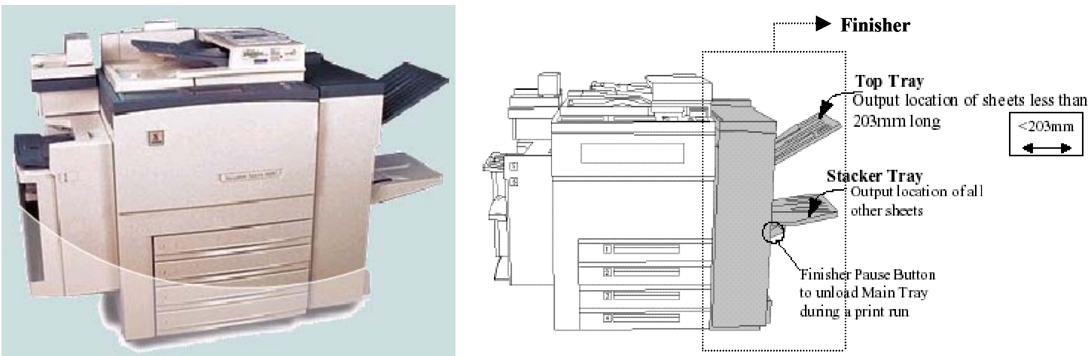


Figure 7.1: Copier machine with finisher module.

The finisher module basically has four functions. The first function is to transport the paper out of the photocopier. The second function is to select whether the paper should be collected at the top tray, where stapling is not possible, or at the main tray, where a stack of paper can be stapled. When the main tray is chosen, a tamper makes sure that the paper is accumulated in neatly piled stacks. The third function of the finisher module is to distinguish between sets of copied piles of paper. To do so, the main tray (in figure 7.1 this is called stacker tray) also has the possibility to move up and down in order to neatly collect the next sheet of paper. The fourth function of the finisher is the possibility to staple a pile of sheets. This can be done at the top corner of the paper stack or at various other places along the length of the sheets by a moving stapler. During the measurements of the tests, a so-called High Capacity Feeder (HCF) was fixated to the finisher in order to feed the finisher with sheets of 80 grams A4 paper.

The case study is performed in an on-going project subsidized by the Dutch government. The first phase is partly based on results that were already available in the project. Based on results of initial analysis of experiments conducted in an earlier stage of the project ('Main Tray Experiments' conducted on 29th and 30th May 2002 [FLE02a]) the choice was made to focus more on the nip motor. The nip motor drives the rolls mechanism to transport the paper through the finisher module. This choice to focus on the nip motor is made because that the nip motor performs one of the main functions of the finisher module. Also the results of the initial experiments [BOG02] indicated that a few design parameters, from which degradation can be explained physically, influence the performance of this stepper motor significantly. Results of these 'Main Tray Experiments' with respect to this nip motor are shown in appendix 8. Since a FMEA and screening experiments were already conducted, the dominant design parameters will be determined based on these results.

The weakest components were determined using the results of the 'Main Tray experiments. The components are respectively the stepper motor, the rolls mechanism and the Printed Wire Board Assembly (PWBA). These components and their parameters will be described in the next section and they will consequently be taken into account in the rest of the phases of the protocol.

Stepper Motor with Rolls Mechanism and PWBA

The system, which is responsible for the paper transport function through the finisher, can be divided in three parts, namely a Printing Wiring Board Assembly (PWBA), a nip motor, and the rolls mechanism.

The nip motor, a hybrid stepper motor, is powered and controlled by the PWBA. This hybrid stepper motor is an electro-mechanical rotary actuator that converts electrical energy (pulses) into shaft rotations (steps). The motor consists of multiple electrical windings wrapped in pairs (phases) around the outer stationary part of the motor (stator). Each winding is center tapped into two coils (see figure 7.2b and c).

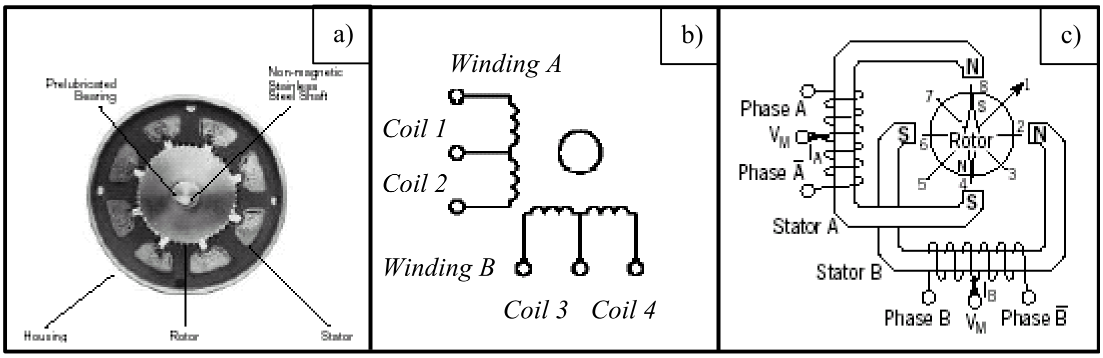


Figure 7.2: hybrid unipolar stepper motor

a) Cross-section of a hybrid unipolar stepper motor.

b) Winding diagram of a unipolar stepper motor.

c) Schematic view of stepper motor.

The inner part (rotor) consists of a magnetic disk mounted on a shaft and suspended on bearings, as can be seen in figure 7.2a. The rotor has projecting teeth, which align with the magnetic fields of the windings. When the coils are energized in sequence by direct current, the teeth follow the sequence and rotate a discrete distance necessary to re-align with the magnetic field. The number of coil combinations (phases) and the number of teeth determine the number of steps per round of the motor.

The performance of a stepper motor is highly dependent on the mechanical parameters of the load. The load is defined as what the motor drives, in this case the rolls mechanism. It is typically frictional, inertial or a combination of the two. Friction is linear to velocity. A minimum torque level is required throughout a step in order to overcome this friction (at least equal to the static friction). Increasing a frictional load lowers the top speed, lowers the acceleration and increases the positional error. A high inertial load requires a high inertial starting torque and the same would apply for braking. Increasing an inertial load will increase speed stability and increase the amount of time it takes to reach a desired speed.

The reliability of the stepper motor depends on the bearing inside the motor. The wear of this bearing will determine the deterioration of the stepper motor. Since the stepper motor in the finisher is "over-designed" and no failures in the field are known, the wear in this bearing will be small. Therefore, it is assumed that the degradation of the stepper motor itself can be neglected and under normal condition the stepper motor will not fail. However, it is possible that the motor is unable to make the next step, due to, for example, an increase in the frictional load, which results in the motor to stop. The rolls mechanism in the finisher could cause this increase of frictional load.

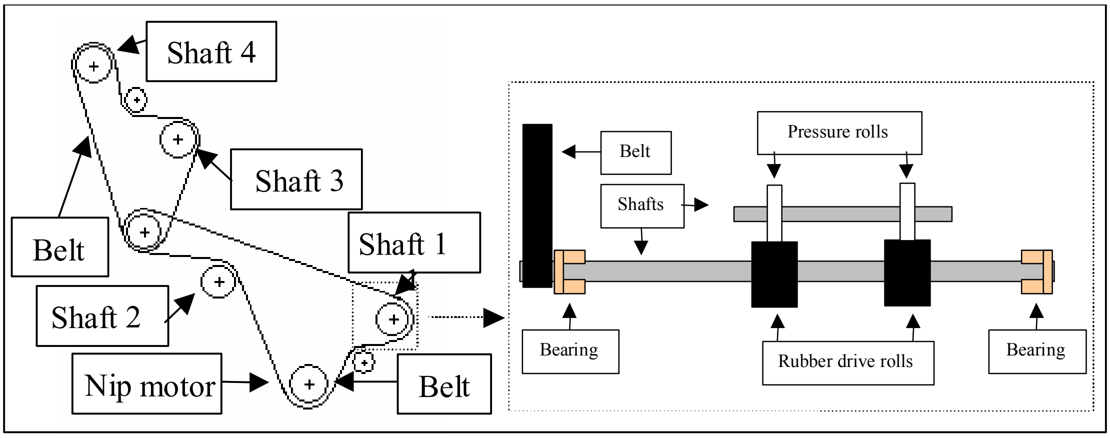


Figure 7.3: Rolls mechanism driven by stepper motor

The rolls mechanism is shown in figure 7.3. The stepper motor (nip motor) drives a belt, which is connected to four shafts. These four shafts are suspended on bronze sleeve bearings and drive the rubber nip rolls. Shaft 1 and shaft 2 transport the sheets of paper through the main tray while shaft 3 and shaft 4 do this for the top tray.

The pressure rolls make sure that no slip exists between the sheets of paper and the rubber nip rolls. Friction between the shafts and the bearings cause load. This load increases in time due to wear of the sleeve bearings. Also contamination of these parts could contribute to an increase of the load. In the next section the performance characteristic and the dominant design parameters, used in the experiments, will be defined.

Phase 2

Very few failures of the finisher module have been observed in the field. This makes the identification of the failure modes for this module very difficult and mainly based on engineering knowledge. Based on a FMEA and on past experiments conducted at Flextronics [FLE02a] the paper transport within the finisher module was selected as the function of the system that will cause most failures. Paper transport, which is provided for by the nip motor, is one of the main functions of the finisher module. In the following section the *physics of failure* of this paper transport system shall be discussed in more detail.

Previous experiments and research [EUR02] has shown that certain components within this transport system do not or hardly deteriorate with time. A conducted degradation test on the deterioration of the rubber rolls showed no significant deterioration. Likewise, degradation tests subjected to the stepper motor did not result in degradation. Also in the field there were no known failures regarding this stepper motor. These two components are therefore assumed to behave constantly over time, and therefore, not show any degradation.

The factor that was presumed to lead to failure of the system was increasing friction between shafts and bearings, leading to a higher mechanical load. This friction is caused by contamination and deterioration of the bearings.

Phase 3 and 4

Performance Characteristic

When the load on the stepper motor is increased, a change occurs in the current profile of the nip motor. The so-called c*urrent rise time* (T_pr) (figure 7.4) decreases when the load on the stepper motor increases. In the test the current has been chosen because an electronic controller controls the direct PC, which is the paper speed. This is why the current profile in the control loop is used as PC.

The physics behind this phenomenon is as follows. The nip motor is driven with a constant pulse frequency. When the load on the motor increases the speed of the steps of the motor from pole to pole decreases. However, this reduction in speed leads to less self-inductance and, therefore, leads to lesser electromagnetic force. Hence there is less force that opposes the current and this will therefore reach the current limit setting on the PWBA in a shorter time. The reduction in current rise time compensates for the slower steps of the motor, which will altogether lead to the preservation of the nominal speed of paper through the transport system.

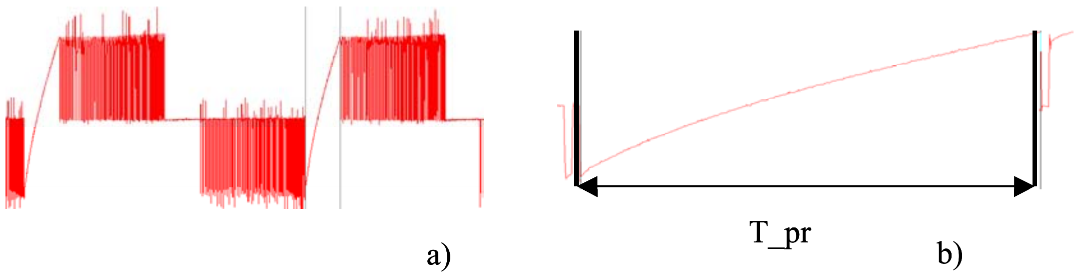


Figure 7.4: Signal of the nip motor current (a) and current rise time (b).

When the value of the load on the motor becomes too high, the stepper motor is unable to make the next step, resulting in a stagnation of the motor and hence the stagnation of the paper transport. In the degradation experiment that will be discussed in phase 8, the T_pr of only one of the four coils is measured. This is done because it reduces the variance of the measurements. The current rise time will be used as the performance characteristic. The next section will identify the dominant design parameters that influence the value of the performance characteristic.

Dominant Design Parameters

The design parameters used in these experiments have to meet two criteria. Firstly, these parameters must have dominant influence on the performance characteristic (T_pr). Secondly, these design parameters must change over time, since gradual failure or disfunction occurs as a result of degradation effects of the dominant design parameters. This again leads to changes of the performance characteristic (T_pr) with respect to the specification limits under study.

Figure 7.5: Schematic overview of relationship between PC and DP's.

Analyzing both the FMEA and experiments conducted earlier at Flextronics and taking the above criteria in consideration, the following two factors are identified as dominant design parameters:

→ The load of the rolls mechanism, T_{load} (X_1).

→ The resistance of PWBA, R_s (X_2).

The relation between the performance characteristic and the two dominant design parameters is shown schematically in figure 7.5.

A dominant failure mechanism of design parameter X_1 is the friction between the shafts and the bearings, as described in the previous section. However, no dominant failure mechanisms of design parameter X_2 have been discussed yet. An important failure mechanism of mechanically highly stressed electrical contacts is fretting corrosion, which increases contact resistance in connectors [OHR98] [HOR95].

This resistance increase results in a decrease of voltage out of the PWBA and, therefore, influences the current pulses to the nip motor. Fretting corrosion occurs in separable contacts, when the contacting surfaces are submitted to small movements relative to each other. External mechanical vibration, shock, differential thermal expansion and electrodynamics forces can induce these movements, with amplitudes at the micro- to millimeter level. The tendency of a connector to degrade by fretting depends on the contact design, on the materials used and on the environmental and electrical conditions during use. The connectors on the PWBA are indeed submitted to mechanical vibrations of the finisher module.

Phase 6 and 7

The experiments conducted on the finisher module are performed using a special software tool. This software tool controls the finisher module and the paper feeder to which the finisher module is connected.

The results of the 'Main Tray Experiments' [FLE02a] show, as mentioned before, that both the load (T_{load}) of the rolls mechanism and the resistance of the PWBA (Rs) have a dominant influence on the current rise time (T_pr) of the nip motor. This is the first criterion that the design parameters have to meet. The second criterion is that the design parameters must show degradation. In order to test if degraded values of the design parameters would indeed influence the values of the performance characteristic, a screening experiment is performed. It is impossible to wait until the design parameters reach a degraded value (approximately 6 months) and, therefore, values for the DP's are set for the experiments.

Figure 7.6: Overview experimental setup:

a) *Finisher coupled on paper feeder.*

b) *Mechanical brake subjecting the load on the nip motor.*

c) *Resistance "switch" to increase resistance of PWBA (X2).*

The load of the rolls mechanism is set on degraded values using a mechanical brake that is connected to one of the shafts of the rolls mechanism, as can be seen in figure 7.6b. The brake will increase the torque of the rolls mechanism that is driven by the nip motor. This represents a degraded load (load becomes higher due to contamination, wear of bearings and so on).

Adding resistors in series to the electrical circuit increases the resistance of the PWBA. This is shown in figure 7.6c. By making use of several 0.2 Ω resistors, the resistance can be increased stepwise.

Screening Experiments

The screening experiments are conducted to answer the following questions:

→ What is the range of the design parameters where the finisher will not fail or disfunction?

→ Are the measurements of the experiments predictable and stable?

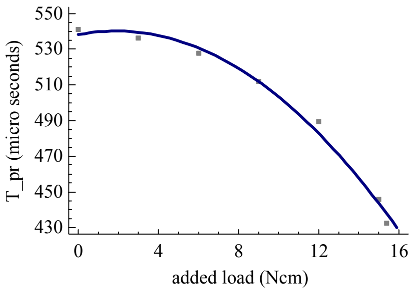
→ Is it feasible to set the design parameters at the specified levels and are these settings stable?

→ Is run-to-run variation > test-to-retest variation?

The first question can be answered by performing an experiment, in which the design parameters are increased until the finisher module is unable to function properly (e.g. nip motor stops). This test is called the limit settings experiment. In the case of the load and the resistance this test will both result in upper limits of the range of these parameters. The lower limits are the starting values of the initial design. These ranges make it possible to determine the difference between the values of the levels of the design parameters for the various runs in the Design of Experiments (DOE). If the differences between these levels are known, a Measurement System Analysis (MSA), or a gage R&R, is conducted to answer the last three questions.

Range Design Parameters

The initial values of the design parameters in the finisher module are measured under normal conditions at time $t = 0$. These values are used to determine the range of the design parameters. These values will not be used in further analysis. For all experiments where new finisher modules are analyzed, these values will be determined separately. Next to the range of the design parameters also the maximum values, or limits, of both design parameters are determined in this screening experiment.



Added load (Ncm)	Rise time (μs)
0	541,12
3	536,06
6	527,93
9	512,10
12	489,21
15	445,84
15,4	432,58

The current rise time decreases slowly with the first few added Ncm's of load. Then the decrease occurs more rapidly when a higher load is added. This implies that the rise time becomes more sensitive to load when the load increases.

Figure 7.7: The influence of DP load (X1) on the PC current rise time (Y).

First two experiments are conducted to determine the nominal value of design parameter X_1 and the maximum value of this parameter for which the finisher module is still able to function properly. In the first experiment the load on the nip motor is increased using a mechanical brake. The drive belt, which connects the nip motor with the shafts of the rolls mechanism is removed, therefore, the mechanical brake is the only load the nip motor experiences. This load is increased stepwise and at each step the current rise time (T_pr) is measured. The load is increased until the nip motor stops. Figure 7.7 shows the current rise time versus the load (T_{load}).

The maximum added value of design parameter X_1 is given in table 7.1. Next, the drive belt is reconnected and again the load of the brake is increased stepwise until the nip motor stops. However, the load now consists of the load applied by the mechanical brake and the load due to the friction in the rolls mechanism. The measured load applied by the mechanical brake is less than the load measured when the belt was disconnected. The difference between these two measurements is the nominal value (see table 7.1) of load (design parameter X_1) caused by the friction in the rolls mechanism.

Table 7.1: Limit values of design parameters X1 and X2.

factors	limits	
	minimum	maximum
X_1 (T_{load})	5.5 Ncm (nominal)	15.0 Ncm
X_2 (R_s)	0.79 Ω (nominal)	1.9 Ω

The nominal value of the resistance of the PWBA is determined using a current of 1A and measuring the voltage. The maximum value is determined by adding extra resistors in series with the PWBA until the finisher module is not able to function properly anymore. Both these values are given in table 7.1. The initial values and the limit values of the design parameters are used to design the complex experiments of phase 9.

Measurement System Analysis (MSA)

When the limits of the design parameters X_1 and X_2 are determined, it is possible to conduct the MSA experiment. The maximum extra load (X_1) that can be applied to the nip motor is 9.5 Ncm. But for the MSA a maximum extra load of 9 Ncm is used. In order to conduct the necessary experiments over the entire range of this design parameter the difference between the +1 level and –1 level is set at 2 Ncm.

The design parameter X_2 will be set at a maximum level of 1.6 Ω, because at this level of factor X_2 the finisher module still functions properly. Since resistors with a value of 0.2 Ω are readily available at Flextronics, it is chosen to set the difference of the +1 level and –1 level on 0.4 Ω. This makes it possible to include center points in the design of the main experiment.

Table 7.2 gives an example of a screening (MSA) experiment that makes it possible to answer the last three questions shown at the start of the screening experiment section. It is important that the difference between the +1 and –1 level of both design parameters is equal to the difference of the levels in the DOE of the main experiments. This way extra data is available for later analyses. In order to investigate the predictability and stability of the measurements all four runs are replicated once.

Table 7.2: Example screening experiment.

Run	***Factor***		**Response variable**
	X_1 (T_{load})	**X_2 (Rs)**	**$Y_1,Y_2,\ldots,Y_n$***
1	+1	-1	$y_{11},y_{12},\ldots y_{1n}$
2	+1	+1	$y_{21},y_{22},\ldots y_{2n}$
3	-1	+1	$y_{31},y_{32},\ldots y_{3n}$
4	-1	-1	$y_{41},y_{42},\ldots y_{4n}$

Run-to-run variation

Test-to-retest variation

Run-to-run variation > test-to-retest variation

Therefore, the screening experiment contains eight runs. This is shown in table 7.3.

Table 7.3: Design matrix Screening Experiment.

Run	**Pattern**	**X_1 (T_{load})**	**X_2 (R_s)**	**Y (T_pr)**
1	--	2.0 Ncm	0.4 Ω	y_{11}, y_{12}, y_{13}
2	+-	4.0 Ncm	0.4 Ω	y_{21}, y_{22}, y_{23}
3	-+	2.0 Ncm	0.8 Ω	y_{31}, y_{32}, y_{33}
4	++	4.0 Ncm	0.8 Ω	y_{41}, y_{42}, y_{43}
5	+-	4.0 Ncm	0.4 Ω	y_{51}, y_{52}, y_{53}
6	--	2.0 Ncm	0.4 Ω	y_{61}, y_{62}, y_{63}
7	-+	2.0 Ncm	0.8 Ω	y_{71}, y_{72}, y_{73}
8	++	4.0 Ncm	0.8 Ω	y_{81}, y_{82}, y_{83}

The R control chart for the current rise should be in control to conclude that the measurements are predictable and stable. This R control chart is shown in the right-hand side of figure 7.8. The R control chart shows that the measurements are in control.

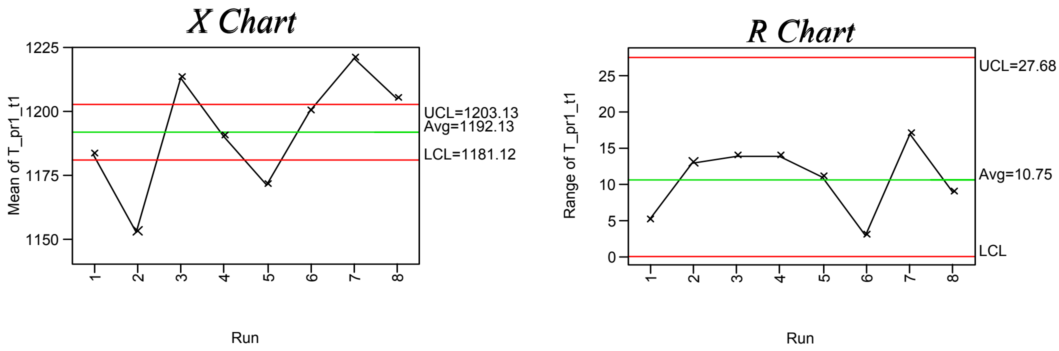


Figure 7.8: The X and R control charts for the current rise time (by run).

Although these measurements are predictable and stable, the changes in the current rise time due to the various levels of the design parameters between runs should be larger than the variation between the successive tests of each run. In terms of a $\overline{X}$ control chart this means that this chart should be out of control, otherwise the variation between tests and runs is of the same order and run-to-run variation cannot be measured. The $\overline{X}$ chart in figure 7.8 shows that the $\overline{X}$ control chart is indeed out of control. Hence it is possible to measure the run-to-run variation and thus to measure the influence of both design parameters on the performance characteristic.

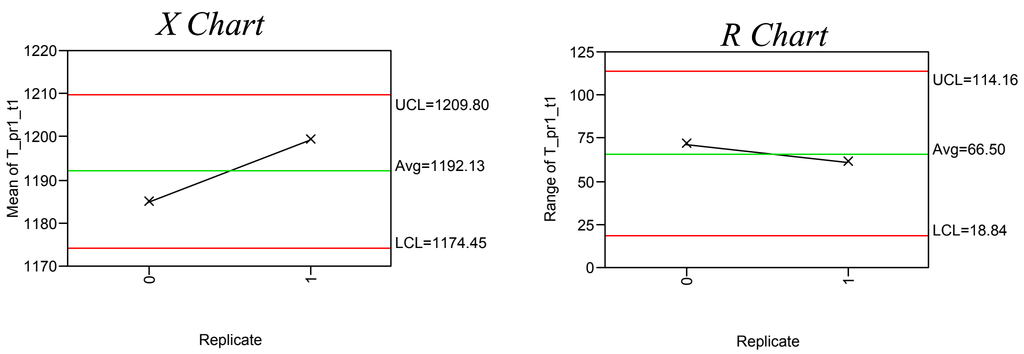


Figure 7.9: The X and R Control Charts for the current rise time (by replication).

Since the runs are replicated once, it is possible to see if it is feasible to repeat the settings of the design parameters at a specified level and to judge the stability of the measurements. The control charts, shown in figure 7.9, indicate that the settings are repeatable and stable over time.

The $\overline{X}$ chart shows that the mean of the current rise time increases slightly over time. The reason for this phenomenon is that the nip motor warms up during the first few runs. For this reason it is chosen to keep the nip motor running constantly during the experiment of phase 9. Therefore, the motor will be turned on well in advance of the main experiments.

It is also chosen to measure the current rise time (T_pr) of the first three pulses of one coil for each test in order to reduce the variability between tests. The average of these three values will be used as the performance characteristic in the main experiments. This will minimize the negative influence of accidental outliers of the current rise time on the results of the experiments.

Phase 8

The reasons for carrying out the degradation tests are as follows:

1. Check for degradation

2. Determination of the shape of the curves (linear, convex, concave)
3. Description of the degradation paths (mathematically)
4. Input for further experiments

During the test only one module was used. Naturally, it would have been better from a statistical point of view to use more than one module. Unfortunately the capacity of the research laboratory was not large enough to cope with the simultaneous execution of more than one of such a diverse module for a degradation test. In comparison to the simple systems that are usually subjected to degradation tests in literature, such as certain light sources, small components or metal parts, the finisher module is an extensive and complex system that consists of conflicting and interacting parts.

Later phases in the protocol provide the possibility to obviate the lack of statistical degradation data, the possible increase of the unit-to-unit variation cannot be compensated in later phases.

The module that has been used for the degradation test was not randomly selected, but was selected with average initial values for the PC and the DP's.

Parameters and expectations

First, a description and explanation of the factors that are measured will be given. Expectations of the time-dependent behavior of these factors is given based on models known in literature.

Paper transport

The factors that were measured for the paper transport function are the ones that are described in phases 3 and 4. These are the performance characteristic current rise time (T_pr) and its design parameters, PWBA resistance and mechanical load. The load on the system is expected to increase with time as a consequence of contamination and the friction between the sleeve bearings and the shafts (see phases 3 and 4). The resistance of the PWBA is expected to increase due to fretting corrosion of its connectors (see phases 3 and 4). Malucci [MAL03] shows in his article "*Fretting corrosion degradation, threshold behavior and contact instability*" a graph of the increase of corrosion of connectors as a result of the number of deformation cycles. This graph shows a convex increase of corrosion and, hence, of connector resistance. In other words, resistance should increase slowly in the first part of its life and then increase faster and faster due to fretting. However, in this experiment not the resistance of one connector is measured, but the total resistance of many connectors on the PWBA is measured.

Experimental set-up

The objective of the degradation test is to obtain degradation data that represents actual customer use. In other words, the results of the degradation test should provide enough information to model the degradation curves of the PC and the DP's as a function of real time, or number of device activations. In the case of the finisher module, the number of device activations represents the factor time. In total three decisions were made regarding the following features:

→ Cool down time of the bearing in the motor

→ Use of paper during acceleration

→ Times of measurements

In order to simulate normal use by customers of the finisher module, a computer program controlled the four basic functions of the finisher simulating normal customer use. During actual customer use, the module would be used off and on, but not constantly. For this reason two types of intermissions were included in the test cycle. The first was a very short intermission after every nineteen copies. This was done to make the motor start from standstill. The startup procedure of the finisher module can have negative influence on performance of the mechanical parts of the system. A second type of intermission was programmed to make the module, and especially the nip motor and the paper transport shafts cool down to room temperature. In normal use a copier is not constantly used and will therefore cool down. The bearings of the motor were cooled down using a fan. Figure 7.10 shows the cool down profile, where the x-axis is the time-axis. Based on figure 7.10 it was decided to set the cool down time in the test at 30 minutes.

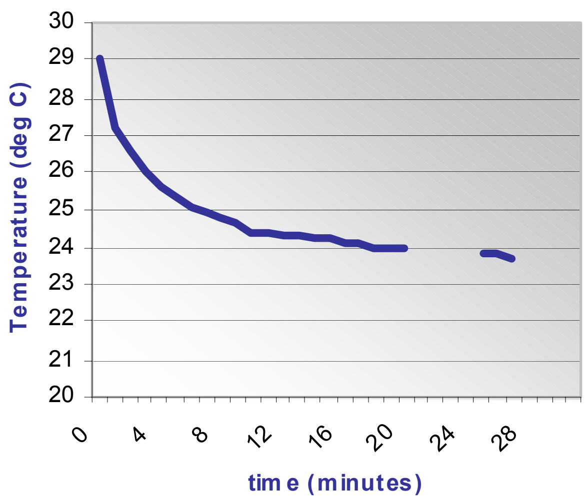


Figure 7.10: Cool down profile at motor bearing.

Due to practical limitations a second decision has been made. Due to the very large amount of paper (11.000.000 copies) that would be required to perform the degradation test, it was decided to accelerate the test without the use of paper. Initial tests [DAM04] show that the weight of paper has negligible influence on the sleeve bearings in comparison to the shafts themselves.

Figure 7.11 shows the measurement routine that has been used in the degradation test taking into account the three decisions that have been made. In practice, the measurements M were conducted every two days. When the actual measurement was performed, the finisher was loaded with A4 paper (80 grams). The produced paper sets were stapled with the normal stapler. At each measurement time the finisher was measured five times for all the factors.

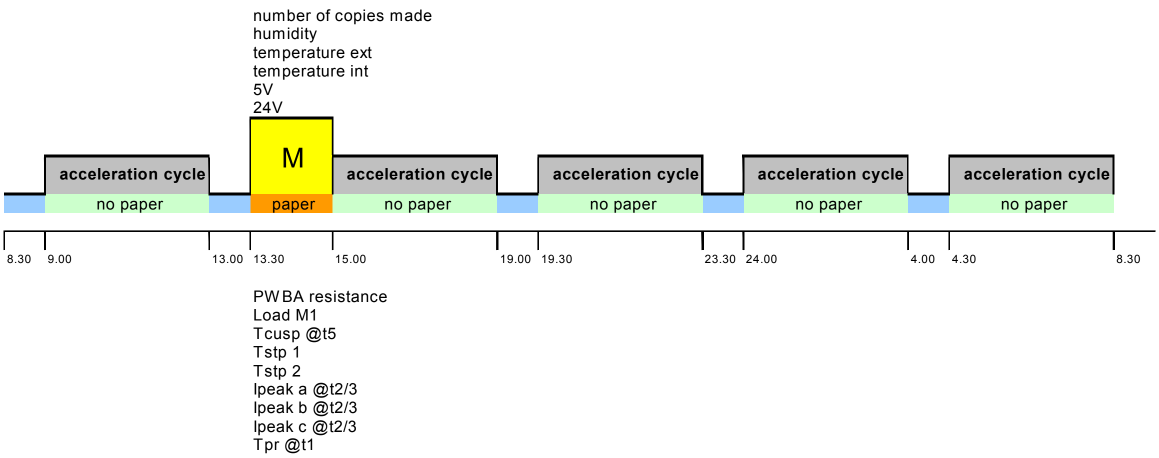


Figure 7.11: Measurement routine [DAM04].

Test results

The previous section showed that the finisher was measured approximately every two days. Five measurements were then conducted in order to deal with measurement variability. This section presents the results of the test. During the degradation test on 33 time steps measurements were performed on all selected factors. The passed lifetimes for the factors are as follows:

Measurement 33:

Number of copies made by the nip motor M1: 3.475.089 number of copies.

The following sub-sections each discuss the results of the measured factors for one of the finisher's functions. The next part of this section presents the fitted degradation functions for the different factors.

Paper transport function

The measured factors that are critical to the paper transport function were measured on a time scale of "*number of copies processed*" by the nip motor. Each factor will now be discussed separately.

Mechanical Load on the nip motor

The load on the nip motor caused by the increase of friction and contamination between de shafts and bearings of the paper transport system turned out to significantly degrade over time. Fluctuations in the results of the measurement can either be the result of movement of the system itself or be influenced by the test operator. This sometimes led to unexpected increases or drops of the load on the motor. Nevertheless the load turned out to have quite a significant increase. Figure 7.12 shows the X-bar and Range chart for this factor.

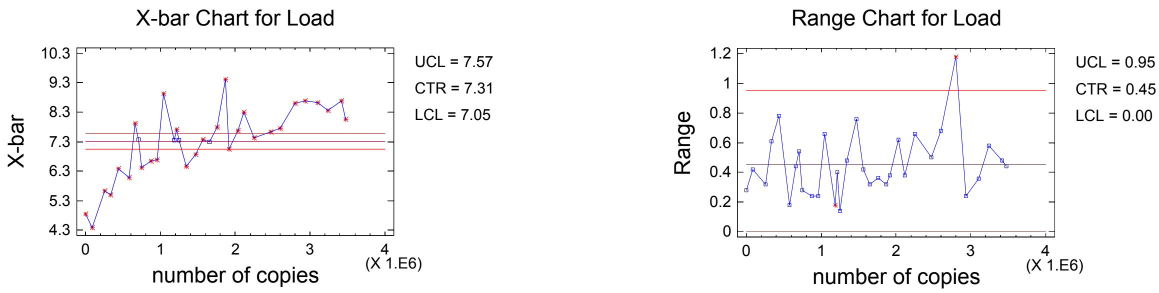


Figure 7.12: X-bar chart and Range chart for the Load.

The X-bar chart is significantly out of control. This implies that we have observed degradation. The range chart is out of control once. This out-of-control situation was due to a shaft that experienced a lot of friction with the startup of the five measurements. This friction automatically resolved during the five measurements and, therefore, led to higher differences between the obtained values. This measurement was not taken out of the dataset because its mean value corresponded to expectations. As a result of these two charts it may be concluded that it is permitted to model the change of the mechanical load on the nip motor as a function of *number of copies processed*.

Electric resistance of the PWBA

Measurement of the resistance of the PWBA suffered from many complications during the ADT. Therefore, first the actual observations are presented. Subsequently, the out-of-control situations are explained and removed from the data set. The control charts that are shown in the next figure (figure 7.13) are obtained with two measurement systems. The range chart clearly shows from which point (measurement day 26) the second measurement system is used. The two systems unfortunately lead to other measurement values as a result of a difference in equipment. In the figure below this difference is not yet compensated.

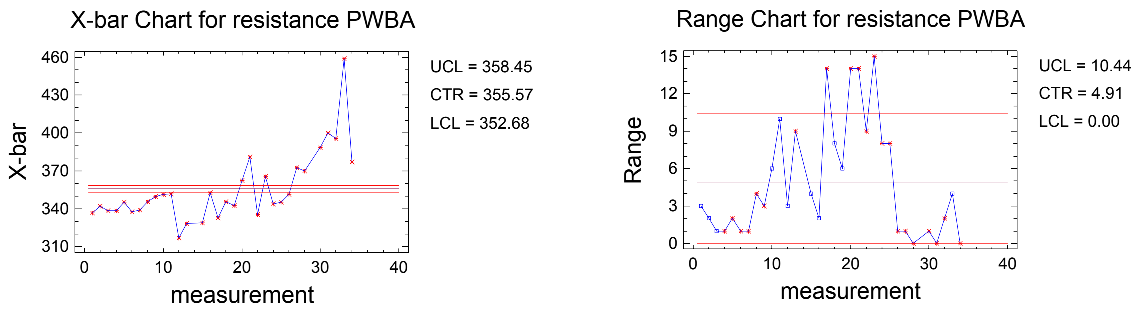


Figure 7.13: X-bar chart and Range chart for the PWBA resistance.

The reason why the measurement system was changed during the ADT was the increase of the range. Although at first hand it was expected that this increase was a result of the product's ageing, it was later found out that two of the connectors on the measurement tool (not PWBA) had aged and become unstable. The measurements that were out-of-control due to ageing of these connectors were removed from the data.

Other important observations are:

→ At measurement day 11 the orange wire on the PWBA was soldered before the fifth measurement, which led to an out-of-control range. This fifth measurement was removed.

→ A fuse change on the PWBA between measurements 11 and 12. This leads to a drop of 33 milli Ohms between measurement 11 and 12. In the following measurements 33 milli Ohms will be added to all the data after measurement 11. Therefore it is assumed that the PWBA did not degrade between measurements 11 and 12. When looking at the trend until measurement 11 this seems to be a good assumption that leads to a negligible error especially when taking into account the higher increases later on.

→ At measurement day 17 the operator altered one of the measurements in the set on purpose to see how this would affect the measurement. This measurement was removed.

→ Removing the most influential measurement in the set reduced the high variation at measurement day 20 to an in-control situation.

→ The module connector (also called interlock connector) was unplugged twice before the measurement took place. This may explain the extreme drop in resistance of the PWBA. Therefore the last measurement was removed entirely.

→ The variation in sets that was observed with the new measurement system was so small that a relatively high range (4 milli Ohms) is devoted to the way of observing by the operator. This range is almost equal to the range at the start of using measurement system one.

After applying these changes the results for the PWBA resistance over time follow the degradation path shown in figure 7.14.

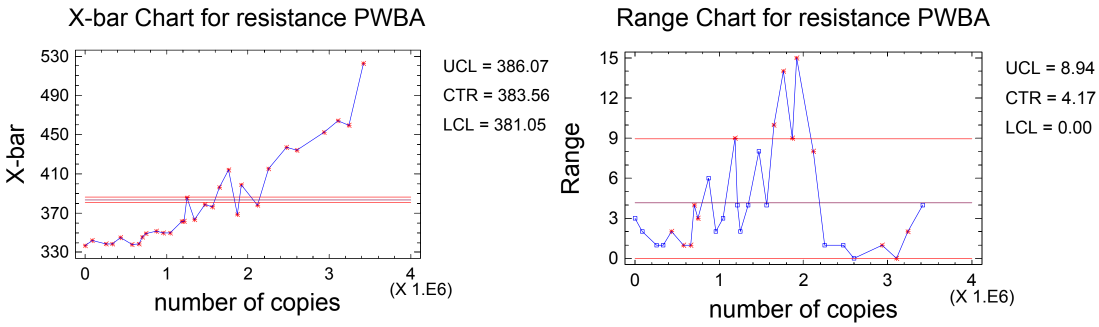


Figure 7.14: New X-bar chart and Range chart for the PWBA resistance.

Note that the range chart is still out of control for a number of measurements, but that the upper control limit for the range is lower. Given the degradation that is observed for the measurements that are in control, the ones that are out-of-control do not lead to strange values in the x-bar chart. Therefore, it is decided to model the resistance of the PWBA as a function of time.

Current rise time of the nip motor

The current rise time of the nip motor represents the performance characteristic. The 'Maintray experiments' [FLEX02a], 'Screening experiments' [FLE02b] and Van Hoorn's thesis [HOO03] substantiate these expectations. The following X-bar chart and Range chart demonstrate the behavior of the current rise time.

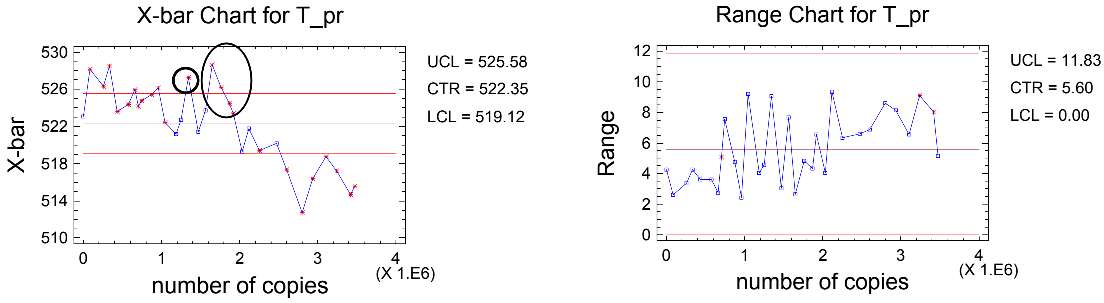


Figure 7.15: X-bar chart and Range chart for the Current rise time.

The figure clearly demonstrates that the range chart is in control. The range seems to be slowly increasing with time. This was also observed in the main experiment in 2002 [HOO03]. The out–of-control x-bar chart shows that the current rise time (T_pr) decreases with time.

The observations that are circled in figure 7.15 are unexpected high values that disturb the decreasing trend. After the first circled measurement it was found that the 5V power supply was badly regulated. Therefore, an experiment based on [BOT00] was conducted to reproduce this high value. However, this power source experiment did not fully explain the unexpected values.

The second circle involves four observations. These measurements coincide with an out-of-control situation of the solenoid. A cover of the solenoid was not correctly mounted. This led to very high values for the solenoid time and an out-of-control for its range chart.

In conclusion it may be said that the current rise time of the nip motor changes with time. According to the screening experiment its behavior is the result of the increase of the load on the motor and the increase of the resistance of the PWBA, which drives and controls the motor.

As a consequence of the analysis of the factors in this section it may be concluded, that only three factors significantly show degradation, where time may be expressed in number of times of usage of a function. These are the following factors:

Paper transport function:

→ Mechanical Load on the nip motor

→ Electric resistance of the PWBA

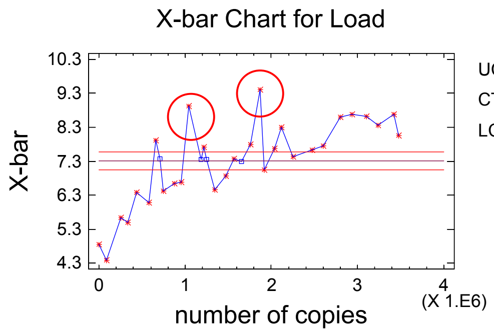
→ Current rise time of the nip motor

Degradation models DP's

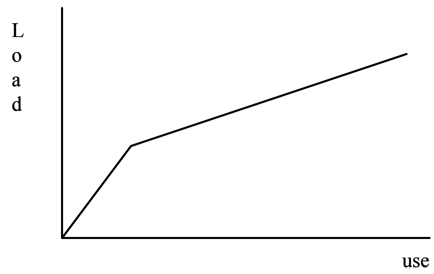
In this section the degradation models for the design parameters are established. For each factor the degradation models are separately described. The first factor to be modeled is the load of the system on the nip motor.

Mechanical Load

Literature [LAN93] states that for the increase of the mechanical load on a system two phases can be distinguished. The first phase is a phase of rapid increase until a point after which the mechanical load will increase linearly. This pattern can also be distinguished in the experimental data.



a) Observed load



b) Load according to [LAN93]

Figure 7.16: Load: reality vs theory.

In order to find the point of time where the gradient changes, the measurements 5 to 13 have been evaluated using the performance indicators **standard deviation from estimate** and **R^2 adjusted for degrees of freedom**. The first part of the curve was also assumed to be linear. Table 7.4 below shows the results of the evaluation. The first three columns focus on the first part of the curve, while the fourth, fifth and sixth column focus on the rest of the curve.

Table 7.4: Evaluation of the point for linear increase[DAM04].

Part 1	**Stdev**	**R^2 d.f.**	**Part 2**	**Stdev**	**R^2 d.f.**
1-4	0,350	57,49	5-rest	0,487	60,00
1-5	0,369	74,06	6-rest	0,490	56,48
1-6	0,384	71,18	7-rest	0,480	53,76
1-7	0,517	77,53	8-rest	0,433	63,32
1-8	0,487	82,38	9-rest	0,418	67,22
1-9	0,560	73,43	10-rest	0,423	63,31
1-10	0,600	67,10	11-rest	0,430	59,65
1-11	0,620	62,36	12-rest	0,437	55,72
1-12	0,609	64,37	13-rest	0,444	55,70

Based on this table it is chosen to model the load from measurement 9 as a linear function for the rest of its life. This leads to the lowest standard deviation for the estimate of curve part two and to the highest R^2 d.f for both parts. Hence, the model for the second part of the curve becomes:

$$Load_{9-\infty}(t) = 6{,}90 + 7{,}14 \cdot 10^{-7} \cdot t \quad (7.1)$$

where t is number of copies.

At this point the nip motor had already processed 745.541 copies. Therefore, the entire model will be:

$$Load\,(t) = 6{,}90 + 7{,}14 \cdot 10^{-7} \cdot (t - 745.541{,}5) \quad (7.2)$$

for $t \geq 745.541$ copies.

We are however interested in the load increase, because this can be used for every system. The initial load on the motor was 4,85 Ncm. This leads to the following expected growth model for the load:

$$Load\ \ increase(t) = 2{,}05 + 7{,}14 \cdot 10^{-7} \cdot (t - 745.541{,}5) \quad (7.3)$$

where *t* is the number of copies processed by the nip motor.

Electric resistance PWBA

The electric resistance of the PWBA was expected to degrade as a result of fretting and corrosion of the connectors on the PWBA and the main finisher connector (also called interlock switch). Literature was found on resistance increase of single connectors. Malucci [MAL03] states that the increase *rate* of resistance at a certain point in time is a linear function. Therefore, the actual increase is a second order function of time with no first order term. However, it cannot be simply assumed that this implies that the increase of resistance on a PWBA with multiple connectors also takes place according to this model. In order to ensure the correctness of the second order model this model was tested using Statgraphics. Statgraphics accepted the second order term in the model and rejected the first order term with a statistical fit of R^2 adjusted for degrees of freedom of 93 %.

$$R(t) = 339 + 1{,}30 \cdot 10^{-11} \cdot t^2 \tag{7.4}$$

and

$$R\ \ increase(t) = 1{,}30 \cdot 10^{-11} \cdot t^2 \tag{7.5}$$

where t is the number of copies processed by the nip motor and the resistance is in milli Ohm.

For the current rise time no degradation model will be made. This parameter is dependent on the degradation of its two design parameters.

Conclusion and discussion of phase 8

The accelerated degradation test was performed in order to capture the degradation of the design parameters and to prove that the performance characteristic changes as a result of this degradation.

Analyses resulted in the conclusion that only 3 factors show degradation. These are the mechanical load on the nip motor (DP_1), the electric resistance of the PWBA (DP_2), and the current rise time of the nip motor (PC). Literature provided information about typical degradation behavior for the two design parameters. The experimental data of the degradation test was compared with the models that literature suggested, and the results of these analyses supported the models proposed in literature.

The degradation test was conducted during a considerable period of time (approximately 3,5 months) during which the paper transport function processed almost 3,5 million copies. In this time the finisher module was subjected to several issues. This complicated the measurements and affected testing speed.

The size and complexity of the finisher also made it difficult to perform measurements. The module has several functions that interact and consequently influence these measurements. This experiment profited from the presence of past data, which made it possible to determine these measurement interactions before the test started.

The degradation of the design parameters load and PWBA resistance in combination with the observed decrease of the performance characteristic underpins the expectations of the ROMDA concept and the involved engineers. This allows for the continuation with the next experiment, which is an experiment to predict the finisher's degradation over its technical life. Here the degradation models that resulted from this chapter will be used to superimpose the degradation of the paper transport function over life on its performance characteristic.

The size and complexity of the system made it time consuming to perform a set of measurements. This in combination with the restricted number of man-hours (due to other activities) led to the decision to test only one Finisher unit. This made it impossible to incorporate the variance in degradation speeds of multiple units in the models. Therefore, it is assumed that all finisher units degrade according the degradation profile of the tested unit.

Phase 9 and 10

Main experiment

The main experiment is conducted to construct a mathematical model of the performance characteristic for the entire product population of finishers as a function of the increase of its design parameters. As the first line already states, the model should represent the entire product population. This implies that at every point in time the performance characteristic has a probability density function with a mean value and a variance. Design Of Experiments [CON01] is used in order to generate this probability density function (pdf) at a specific point in time. In this research the objective is to predict reliability, which is quality over time. Since DOE only uses experiments that are static in time the factor time needed to be added to the experiments. In order to do this three DOE's are performed at different 'points in time'. These points in time are created by artificially adding degradation to the two design-parameters load (X1) and PWBA resistance (X2). Load is added by means of the mechanical break and resistance is added by putting resistance in series with the PWBA and the main connector.

Experimental design

The design that was used for the experiments is Central Composite Design.

Time points

In this section the 'times' and settings of the center points are determined for each of the three DOE's. The objective was to predict performance over life with three DOE's. Therefore, a DOE needed to be performed at t=0 (DOE_0), in order to know the nominal values of the performance characteristic and at its expected end of life (DOE_2) to be able to make good predictions of the TTF. The other DOE, DOE_1, was consequently chosen at halfway the 'age' of the finisher to make the predictions over life as good as possible with a limited amount of testing time using only three DOE's. At each of these times the corresponding settings for the center points of the design parameters are determined [DAM04]. In the following section the + and – levels for the DOE's are determined.

DOE_0

The center point settings for the first DOE, which will be called DOE_0, are set around the nominal values of the design parameters resulting in the nominal value of the performance characteristic.

DOE_1

For DOE_1 the design parameters are set at the levels that they are expected to have halfway the 'time' of DOE_2. This is done to make the best possible predictions over life with three DOE's. Hence the expected added load and added resistance at $time_{DOE1} = \frac{1}{2} \cdot time_{DOE2} = 4539711$ copies are calculated.

Hence using equation 7.3 the added load will be:

$$Load\,(time_{DOE1}) = 6{,}90 - 4{,}85 + 7{,}14 \cdot 10^{-7} \cdot (time_{DOE1} - 745541{,}5) = 4{,}76\,Ncm$$

And using equation 5.5 the added resistance will be:

$$R(time_{DOE1}) = 1{,}30 \cdot 10^{-11} \cdot (time_{DOE1})^2 = 266{,}47\,m\Omega$$

Concluding, the level settings for DOE_1 are around the 4,76 Ncm and $266{,}47\,m\Omega$ for the nominal added load and the nominal added resistance respectively.

DOE_2

For practical reasons it was chosen to use an added break force of 8 Ncm as the highest center point for the load (X_1). According to the degradation model for the load (eq. 7.3) this amount of load increase would be observed at:

$$time_{DOE2} = 745.541{,}5 + \frac{8-(6{,}90-4{,}85)}{7{,}14 \cdot 10^{-7}} = 9.079.423 \text{ copies.}$$

The amount of 745.541 copies is the number of copies made at the beginning of the second part of the degradation function for the load. 6,90 Ncm is the expected load at this same point. During these 745.541 copies the load is expected to increase with the amount of $6{,}90 - 4{,}85 = 2{,}05\,Ncm$.

The settings for the resistance need to be calculated at the same number of copies as that that was expected for the load. Using equation 7.5 leads to the following added resistance:

$$R(time_{DOE2}) = 1{,}30 \cdot 10^{-11} \cdot (time_{DOE2})^2 = 1.065{,}9\,m\Omega$$

So the level settings for DOE_2 are around 9 Ncm and $1.065{,}9\,m\Omega$ for the nominal added load (X_1) and the nominal added resistance (X_2) respectively. Based on the calculated number of copies the levels for DOE_1 can now be set.

Now that the nominal levels for the DP's of DOE_0, DOE_1 and DOE_2 are known, the + and – settings will be determined.

Level settings

In this section the + and – level settings are determined for the DOE's. Each DOE should generate a probability distribution that represents the actual product population at that specific moment in time. Therefore a + or a – setting for a design parameter should represent the value of this design parameter for a randomly chosen other product. This is the expected deviance from the mean value, or standard deviation.

The 'Part-to-Part Experiments' that were conducted at Flextronics on the 4th and 6th of December 2002 [FLE02c] resulted in unit-to-unit data on new, refurbished and field returned Finishers. This data was obtained from five new, five field-returned and five refurbished Finishers. The data on the refurbished finishers were not used because it was not documented what types of repairs or alterations were made to these products. The standard deviations of the design parameters of the population of new finishers were calculated to be 0,39 Ncm for the load (X_1) and 12,9 $m\Omega$ for the resistance of the PWBA.

For the PWBA resistance this standard deviation is larger than the highest standard deviation of variation within sets that was observed during the measurements in the degradation test. This is a minimum requirement in order to be able to measure unit-to-unit variation and draw conclusions from the DOE's.

The values 12,9 $m\Omega$ and 0,39 Ncm are practically difficult values to use. Therefore the values of 20 $m\Omega$ and 0,40 Ncm are used in the experiments for DOE_0.

Field data was necessary in order to use realistic settings for the second and third DOE (DOE_1 and DOE_2). Although there was unit-to-unit data on field returned finishers, this data did not contain the age of the measured units. Hence it is not possible to make a good statement about the unit-to-unit variation at a specific point in time (age). Because neither Flextronics nor its customer keeps track of the number of copies that a finisher produces in the field, it can be said with certainty that there will not be any usable unit-to-unit data of field returned finishers available in the short run regarding this dilemma.

For this reason the assumption is made to assume that unit-to-unit variation does not change with time. This assumption is disputable, but it is the best possible assumption to be made. However, the dilemma of changing unit-to-unit variation over time is one that always exists in case of newly designed products, because field data will not be available for these products. This problem could naturally be resolved by degradation testing several units instead of the one unit that was used in this research.

Consequently the standard deviations between units are also used for the level settings of DOE_1 and DOE_2. This leads to the following design grid (table 7.5).

Table 7.5: Experimental design Main experiment.

	X_1 (load in Ncm)			**X_2 (resistance in Ω)**		
	-	0	+	-	0	+
DOE 0	0	0,4	0,8	0	0,02	0,04
DOE 1	4,4	4,8	5,2	0,25	0,27	0,29
DOE 2	7,6	8	8,4	1,05	1,07	1,09

Figure 7.17 presents a graphical representation of this experimental design. All three DOE's represent the expected degradation of the design parameters at a certain time.

The level settings per run are presented in appendix 9. For each combination of level settings five sets are produced. This is the same number of sets that was used in the degradation test. Note that the combinations of runs are randomized in the experiments in order to prevent that conditions in a previous situation influence the results in the next situation.

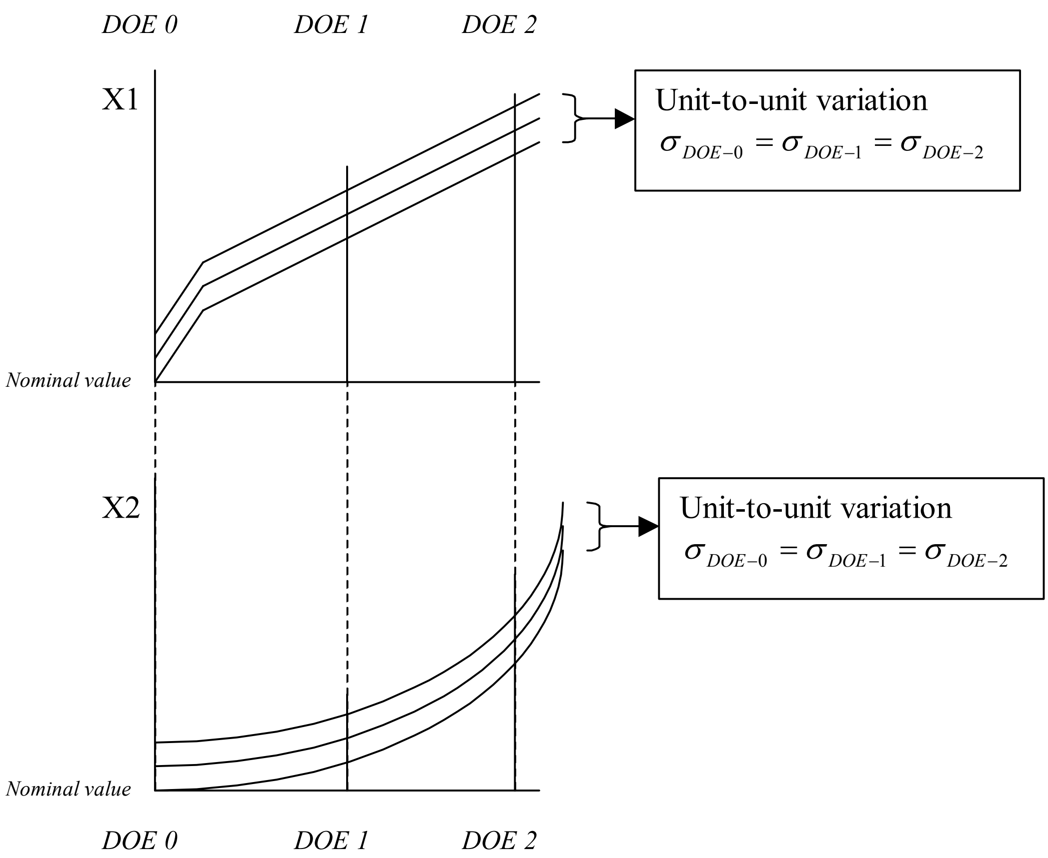


Figure 7.17: Graphical representation experimental design.

Results of Main experiment

The data that was generated in the experiment first needs to be analyzed and checked on normality. This is done by means of Shewart control charts.

Analysis of the results

This sub-section analyses the results for each DOE separately. In order for the results to be used they need to be stable and predictable. This check is performed by means of control charts (figures 7.18, 7.20 and 7.22). The reason why each DOE is considered separately is because of the expected increase in range as the design parameters increase [BOG02]. This contribution of the range of the performance characteristic in DOE 2 could then cover up a possible out-of-control situation in DOE 0 or DOE 1.

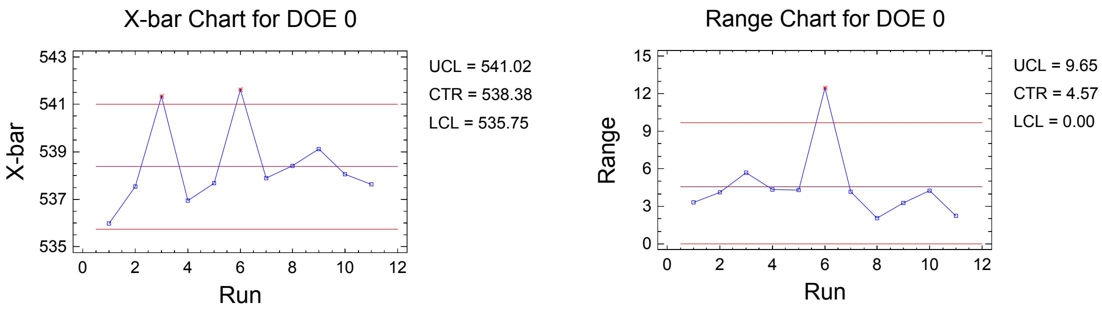


Figure 7.18: Control charts for DOE 0.

The range chart for DOE 0 shows a clear out-of-control situation at run 6. This run has combination settings Load + and Resistance -. Therefore, it is expected that this combination would lead to a mean value that is lower or equal to the mean value of DOE 0. The x-bar chart shows however a conspicuously high value for the mean value of this run. Appendix 9 shows that this high mean value and high range are caused by two of the five measurements in the set. Figure 7.19 presents two histograms with probability density plots that represent the data of DOE 0. One with the extremes of run six and one without. Removal of the two extreme values (547,63 and 548,11) brings the range back in control and leaves the observations of 535,64, 536,85 and 539,92 microseconds.

Removing these two values hardly influences the mean of the population. The mean decreases only 0,38 microseconds. The standard deviation however is affected stronger by this change and decreases from 2,68 to 1,97. This in combination with the expectation that the values would be lower or equal to average has led to the decision to leave out these two values of run six in further calculations.

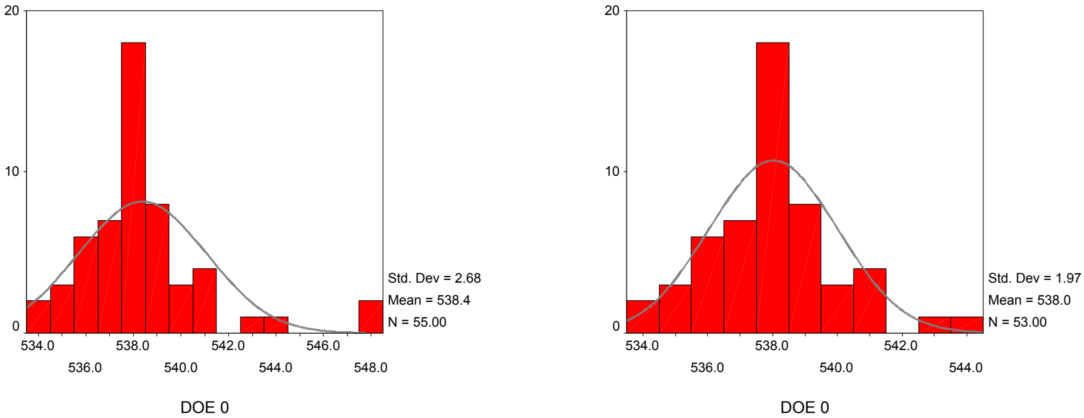


Figure 7.19: Histograms DOE 0:

a) with extremes of run 6.

b) without extremes of run 6.

The other out-of-control situation, for the x-bar chart, is the result of the level settings in the DOE. For this the standard deviations of the design parameters are used. Certain combinations of these settings may result in an observation that distinguishes itself from the rest of the measurements. This does however not imply that this observation is wrong, but that it represents a product that is significantly different from the mass.

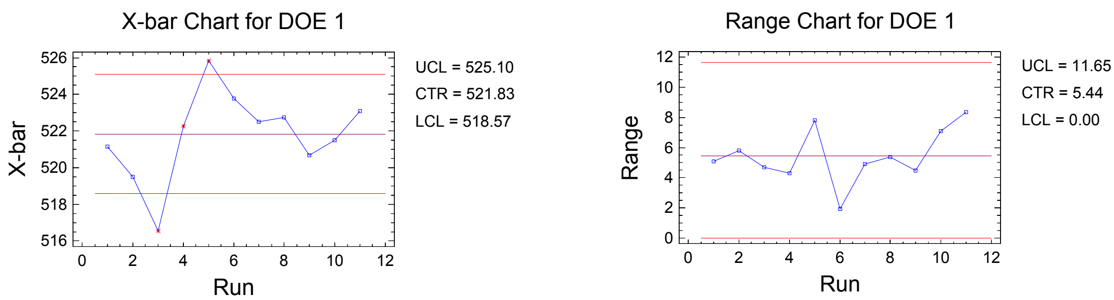


Figure 7.20: Control charts for DOE 1.

The range chart for DOE 1 shows no out-of-control situations. The explanation for the out-of-control x-bar chart can be found above. This results in the following product population (figure 7.21).

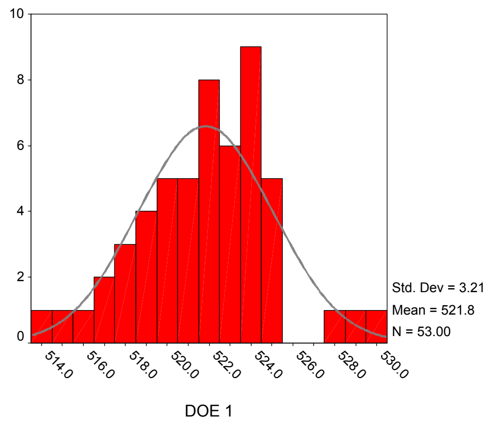


Figure 7.21: Histogram DOE 1.

Note the lower average rise time and the higher variance of the current rise time. This shows that the performance characteristic also decreases with time in this experiment.

The control charts for the last DOE, DOE 2, are as follows.

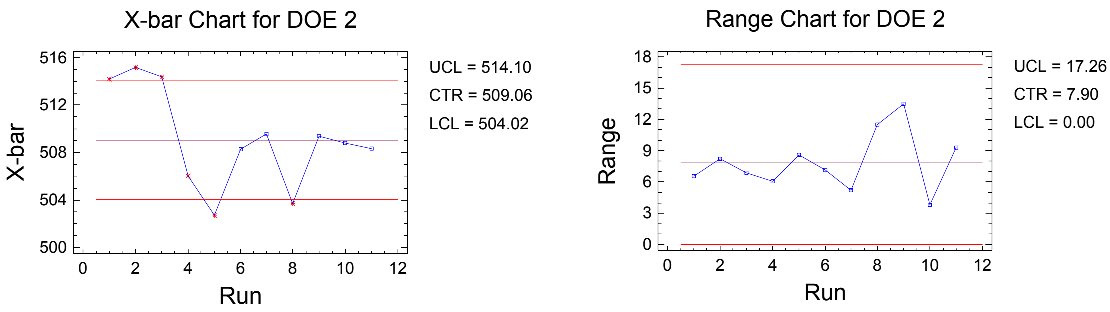


Figure 7.22: Control charts for DOE 2.

The resulting distribution of the measured values for the current rise time is presented by the histogram in figure 7.23.

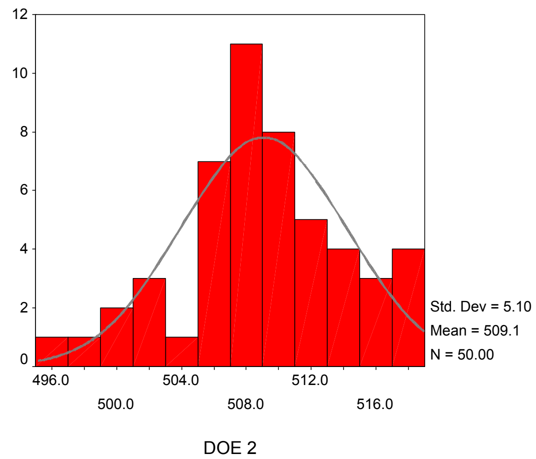


Figure 7.23: Histogram DOE 2.

Also the means and ranges between the three DOE's are checked for out-of-control situations (figure 7.24). If there is no statistical significance between the mean values of the three DOE's, the current rise time may not be modeled as a function of time and can, therefore, not be used as a performance characteristic.

The x-bar chart confirms the expectation that the means of the three DOE's are out-of-control [BOG02]. Hence it is allowed to model the 'current rise time' as a function of time and, thus, it may be used as a performance characteristic. The x-bar chart also implies that the performance characteristic changes significantly as a function of its design parameters. Although the range chart shows to be in control it can be concluded that the mean range per DOE definitely increases over time. Next it needs to be determined how the design parameters affect the performance characteristic. For this purpose Analysis Of Variance (ANOVA) is used.

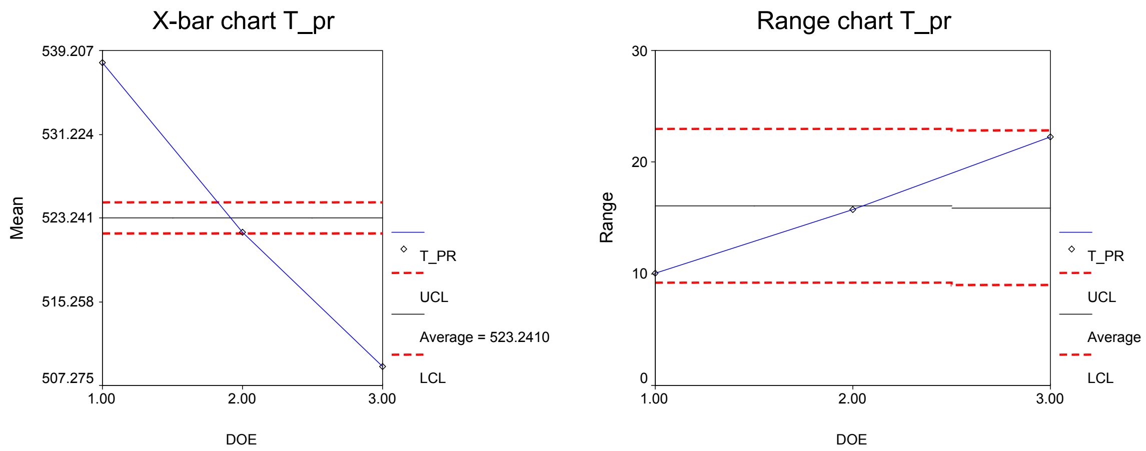


Figure 7.24: Control charts between DOE's.

Regression model

Performing the ANOVA was not a straightforward process. The three DOE's generated three datasets that were not joined by time and thus did not have consecutive values for their settings. These separate points in time made it impossible to perform ANOVA directly on the results. Therefore, the degradation functions were used to generate a large dataset for every factor over time as in [BOG02]. Next, an ANOVA is performed to relate the design parameters to the performance characteristic.

First the degradation function of the performance characteristic needed to be identified. A regression analysis was performed on the data for the current rise time that was obtained in the DOE's. This resulted in the following function of the current rise time and its variance over time:

$$\mu_Y(t) = 538{,}02 - 3{,}94 \cdot 10^{-6} \cdot t + 8{,}29 \cdot 10^{-14} \cdot t^2 \tag{7.6}$$

$$\sigma^2{}_Y(t) = 3{,}88 + 3{,}93 \cdot 10^{-7} \cdot t + 2{,}25 \cdot 10^{-13} \cdot t^2 \tag{7.7}$$

This degradation function and the degradation functions of the design parameters were used to generate large datasets for these parameters over time. The generated datasets were analyzed using ANOVA in order to determine how the design parameters influence the performance characteristic. The ANOVA table indicated that all terms that were tested were significant.

The following second-order regression model was fitted.

$$\begin{aligned} \mu_Y &= \alpha_0 + \alpha_1\mu_{X_1} + \alpha_2\mu_{X_2} + \alpha_{11}\mu_{X_1}{}^2 \\ \sigma_Y^2 &= \beta_0 + \beta_1\mu_{X_1} + \beta_2\mu_{X_2} + \beta_{11}\mu_{X_1}{}^2 \end{aligned} \tag{7.8}$$

Here μ_Y, μ_{X_1} and μ_{X_2} represent respectively the mean value of the performance characteristic and the mean values of the dominant design parameters, while σ_Y^2, $\sigma_{X_1}^2$ and $\sigma_{X_2}^2$ represent respectively the variance of the performance characteristic, and the variance of design parameters X_1 and X_2 .The coefficients α_0, α_1, α_2, α_{11}, and β_0, β_1, β_{11} and β_2 will have to be determined by means of regression.

First the regression model for the mean is determined. This is done by means of linear regression with least squares estimation (LSE). The estimation is made based on the data from the Main experiment (appendix 9). For this not the added values are used, but the real values of the design parameters. This gives a real representation of the factors that influence the nip motor. And secondly, a model with the real values is more useful in the optimization step. The regression model is as follows.

$$\mu_Y = 504{,}96 + 6{,}29\mu_{X_1} + 24{,}79\mu_{X_2} - 0{,}69\mu_{X_1}{}^2 \tag{7.9}$$

The resulting R^2 for this model is 94,75 percent.

This model represents the influence that the actual resistance and load have on the current rise time of the motor. Note that the design parameter factors are both functions of time that can be substituted into this model, making it time-dependent. Figure 7.25 represents the influences of both design parameters on the performance characteristic separately. Note that these influences are as expected.

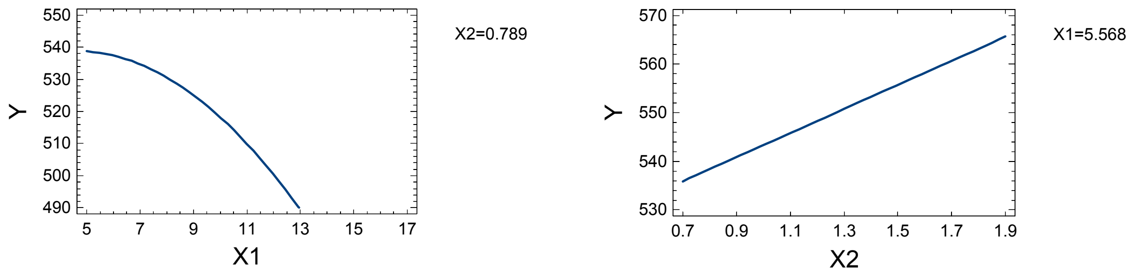


Figure 7.25: Influence of the actual DP values on the PC.

The second regression model that is determined concerns the expected variance of the performance characteristic as a function of the variances of the design parameters. This is however impossible due to a lack of information on time dependent unit-to-unit variation of the design parameters load and PWBA resistance.

Specification limits

A product will only function properly as long as it satisfies its specifications. In order to determine the product's expected lifetime a specification limit needs to be set beyond which the product does no longer function properly. The performance characteristic decreases over time and, therefore, only the Lower Specification Limit (LSL) is important. For the finisher module the LSL is:

$$LSL_{PC} = 504.28\ \mu s$$

Figure 7.26 shows the expected degradation of the performance characteristic over time with the lower specification level at which the paper transport function is expected to fail.

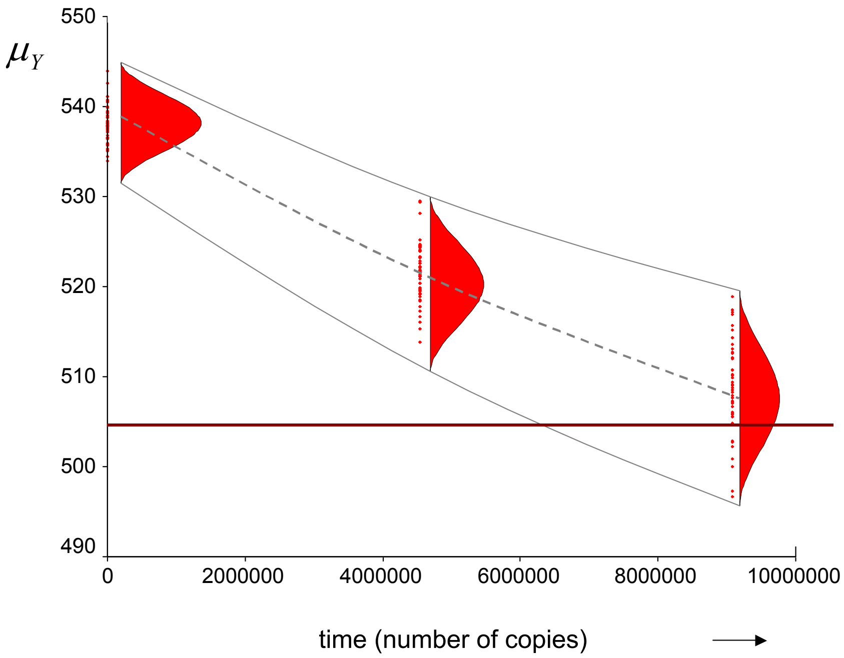


Figure 7.26: Performance characteristic as a function of time (number of copies).

The figure shows the decrease of the performance characteristic over time. Note that using the calculated specification limit would lead to the rejection of a part of the population.

Discussion

The degradation models that were constructed in the previous chapter were used in this chapter to set up an experiment to predict the behavior of the performance characteristic over life. Therefore the expected values of the design parameters were calculated at three points in time: when the product is new, halfway its life and as a close as possible near its expected end of life. These expectations of degradation were set in the system in order to model the change of the performance characteristic over time.

The experiment attempted to generate a probability distribution of the performance characteristic as a consequence of the variation in the design parameters between Finishers. Therefore unit-to-unit data on the design parameters of new Finishers were used for level setting in a design of experiments at the first time point. Unfortunately the lack of information on variation in degradation speeds between Finishers made it impossible to incorporate such variation in the other DOE's. Hence for these design parameter settings the same variation has been used.

The final point of discussion applies to the unit-to-unit variation. It is very well possible that a different Finisher module would have degraded slower or faster than the unit that was used in the ADT. This would lead to a different behavior of the performance characteristic over time and also to a change in variation. This makes it difficult to say if this function of the performance characteristic is representative for the entire Finisher population. The experiment that is described in this chapter however uses the initial unit-to-unit variation of new Finishers to model the performance characteristic for the Finisher population. Therefore the only variation that the model over time does not take into account is possible difference in degradation speeds between units. For the time being there is no data that indicates that the two design parameters deteriorate significantly faster or slower for other finisher units.

Phase 11

Design optimization

The last phase of ROMDA is the optimization step. First the performance of the present situation is determined. Next, an optimization method is applied to find the settings for the design parameters that optimize the Mean Time To Failure and minimize the variance of the Mean Time To Failure of the PC.

Present situation performance

Before calculating the optimal design parameter settings, the performance in the present situation should first be determined. In order to do this a simulation is run based on the obtained models with their variances. The degradation paths are presented in figure 7.27 and 7.28. The figures represent the simulation of a sample of 1000 Finisher modules.

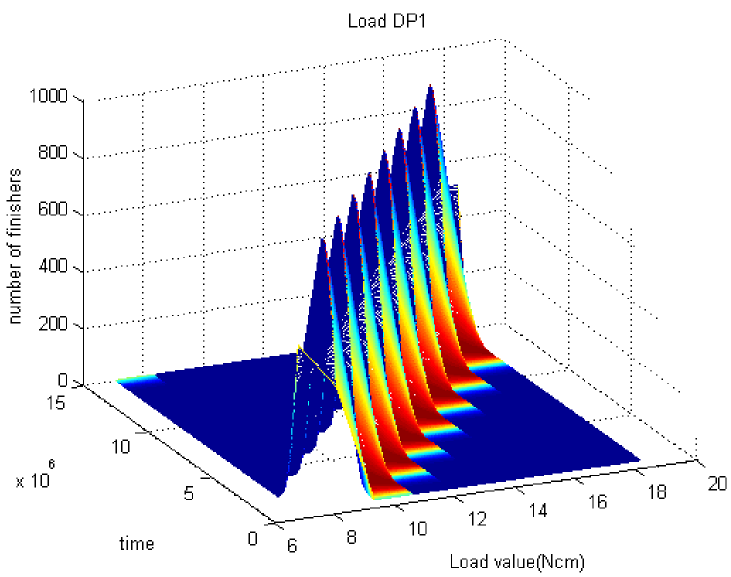


Figure 7.27: Simulated degradation path of the load.

The simulations are started at 745.541 copies. This is the lifetime from where on the load increases linear with time. These degradation paths are again superimposed on the rise time by means of equation 7.9. The resulting current rise time of the nip motor is presented in figure 7.29a. For clarity this degradation function is presented in 2D. Application of the lower specification limit of 504,28 μs leads to the failure rate curve in figure 7.29b.

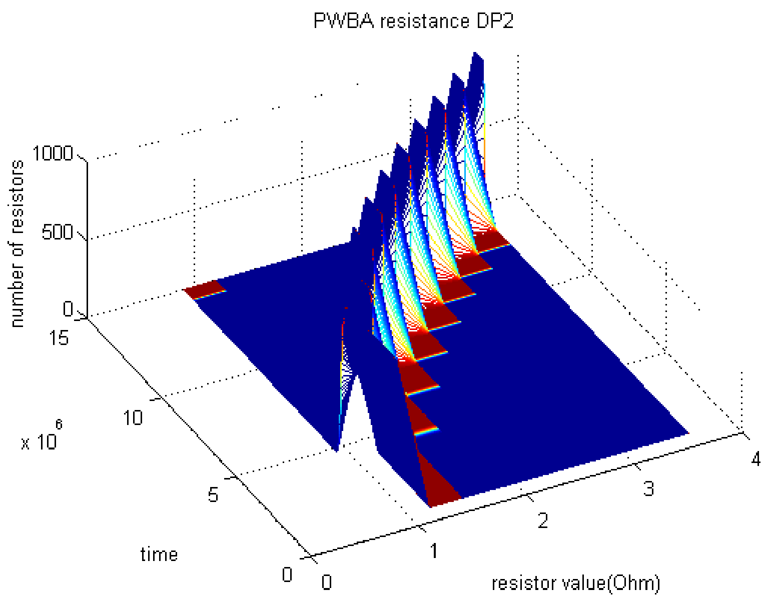
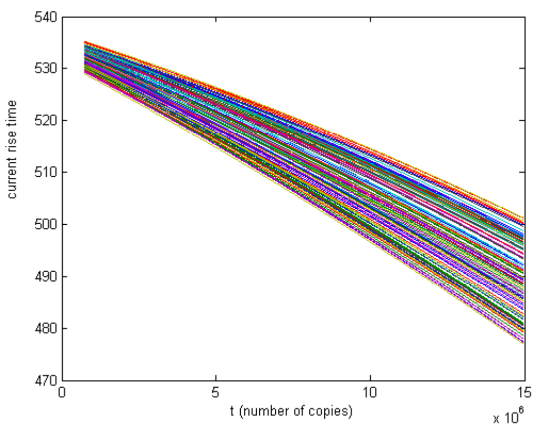
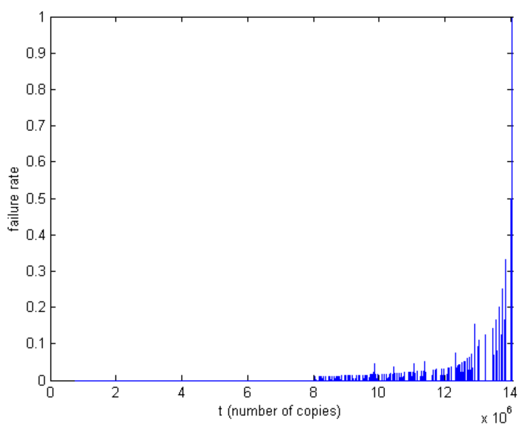


Figure 7.28: Simulated degradation path of the PWBA resistance.

The resulting current rise time also shows the increasing variance as a result of the degradation of the design parameters. This was also observed in the data of the Main experiment.



a)



b)

Figure 7.29:

a) The resulting current rise time.

b) Failure rate curve for the finisher population.

The results of the simulations show an expected MTTF of 11.215.541 copies and the log of the Standard Deviation of the TTF, log(SDTTF), is 14,48, or 1.943.498 copies. The next section will attempt to optimize the design of the Finisher module. The performance indicators that are used to compare the new with the present situation are the MTTF and the SDTTF.

Optimization of the Finisher module

In this section the Finisher module is optimized based on the performance indicators MTTF and SDTTF. The Desirability Technique by Derringer and Suich [DER80] is applied to determine the design parameter settings that lead to an optimal balance between MTTF and SDTTF. Before this method can be applied first the functions for the MTTF and SDTTF need to be established. This is done by means of a Design Of Experiments on the simulation data.

First the function for the load is interpolated to time t=0 in order to be able to optimize the initial value of the load. Therefore, the load is interpolated to time t=0 as if it were linear. The calculation is presented below. Figure 7.30 shows a graphical representation of this calculation.

$$Load\ \ increase = 7{,}14 \cdot 10^{-7} \cdot 745.541 = 0{,}53\,Ncm$$

This leads to an initial load setting of 2,05 – 0,53 = 1,52 Ncm higher. With this setting it is possible to use the linear part of this degradation model from t=0 for the optimization step.

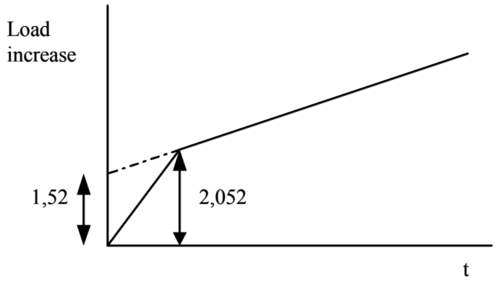


Figure 7.30: Interpolation of the degradation model.

Next, the models for the MTTF and SDTTF are constructed based on a simulated DOE. The nominal values of the design parameters are used as center points and the standard deviations that were applied in the Main experiment (0,4 Ncm and 0,02 Ω) are used as + and – settings. The DOE is constructed in order to make a model of the MTTF and SDTTF as a function of the DP's.

With this model the nominal design parameter settings can be optimized near the current settings. The DOE results are presented in table 7.6:

Table 7.6: DOE on the TTF.

run	pattern	DP_1	DP_2	MTTF	Log(SDTTF)
1	--	6,688	0,689	12.105.541	14,60
2	-+	6,688	0,889	13.615.541	14,58
3	00	7,088	0,789	11.215.541	14,48
4	0-	7,088	0,689	10.165.541	14,31
5	+-	7,488	0,689	8.354.541	14,21
6	++	7,488	0,889	9.905.541	14,30
7	0+	7,088	0,889	11.815.541	14,49
8	+0	7,488	0,789	9.245.541	14,16
9	-0	6,688	0,789	12.505.541	14,58

The following functions are established:

$$\begin{aligned} MTTF &= 1025.71 - 178{,}55 * DP_1 + 78{,}67 * DP_2 \\ \log(SDTTF) &= 5.201 - 0{,}182 * DP_1 + 0{,}041 * DP_2 \end{aligned} \qquad (7.10)$$

The model of the PC as function of its DP's is only valid for the settings interval of the Main experiment and somewhat beyond. This puts limitations to the optimization range of the design parameters. In order to optimize the design of the finisher within the practical limits of the design parameters, first the optimization intervals need to be determined. Hence the following optimization intervals were defined (input from designers):

DP1=[6.29; 7.88] and DP2=[0.63; 0.99]

Subsequently, the optimal design parameter settings are calculated using the Desirability Technique. The target value for the MTTF is set to be twenty million and the target value for the log(SDTTF) is set near zero. The coefficient r is set to be 1.

This results in the following optimal values:

DP1 = 6.29 Ncm, which corresponds to a real setting of DP1 = 6.29–1.52 = ***4.78 Ncm*** *and DP2 =* ***0.99 m*** Ω

This leads to a MTTF of 12.575.541 copies, which is 12,1 % longer than the expected 11.215.541 copies for the system that was used in the Main experiment. The log(SDTTF) is somewhat higher however. It has increased from 14,48 to 14,56, which is an actual increase from 1.943.498 copies to 2.105.366 copies.

Discussion

In conclusion it can be said that the simulated optimization step resulted in a considerable increase of the Mean Time To Failure of the Finisher module. This was accompanied by a loss in robustness of the reliability of the system's TTF.

Phase 12

The purpose of this phase is to verify the results of the experiments and analyses with products in the field. The second purpose of phase 12 is to confirm if the results of all analyses indeed optimized product performance over time, and make preventive maintenance and re-use decisions possible.

Unfortunately, this phase is not yet completed during the writing of this thesis. The finisher modules have been introduced to the market for just a short period of time. The performance of the finisher modules is monitored for verification purposes. But the results over time are not sufficient in order to verify all models. The expected time for the first results are within 1,5 years.

7.3 Case study: Paper-Feed Module (Flextronics)

For the second case study a paper-feed module of Flextronics BV has been used. The paper-feed module can be considered as a completely different product compared to the finisher module that was used in the first case study. Also in this case study the protocol described in chapter 6 has been followed. For this reason only a summary of all phases of this case study will be presented in this section. For detailed information about all phases of the protocol the reader is referred to literature [VIS04]. This section finishes with a discussion on the results of this case study.

Phase 1, 2, 3, and 4

The paper-feed module stores the blank paper sheets in paper trays and delivers these sheets on request to the first stage of the copy process.

The paper-feed module as part of the total copier is displayed in figure 7.31; the paper path inside the paper-feed module is schematically displayed in figure 7.32.

Figure 7.31 shows that the paper-feed module can be divided into three module units: the High Capacity Feeder (HCF), the paper trays, and the Manual Sheet Input (MSI). The experiments presented in this chapter are all concerned with the High Capacity Feeder module units.

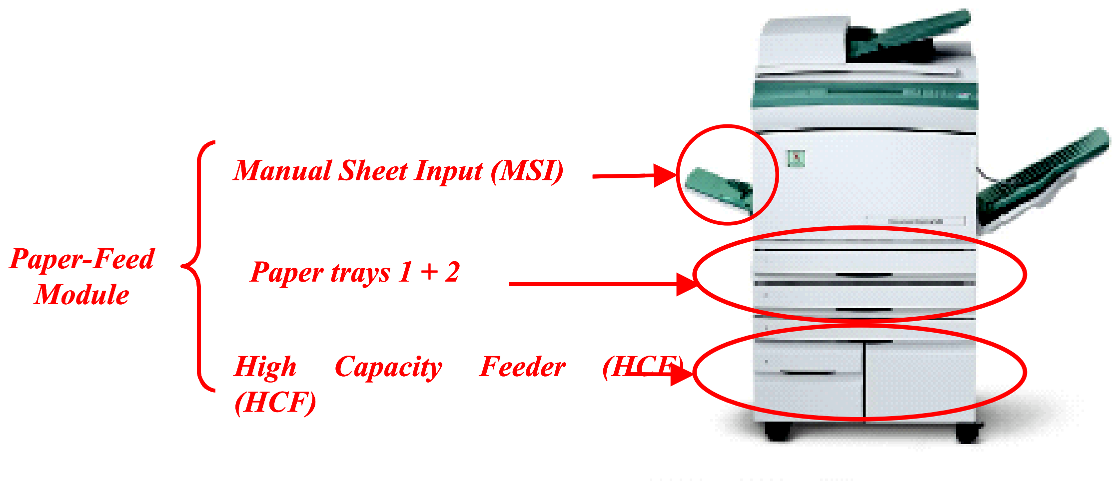


Figure 7.31: Copier with paper-feed module.

As mentioned before, not all module functionalities can be dealt with during this research project. Although the paper elevation-, grip-, and transport functions of the HCF module unit have been included in the FMEA this case study will only focus on the elevation function of the HCF.

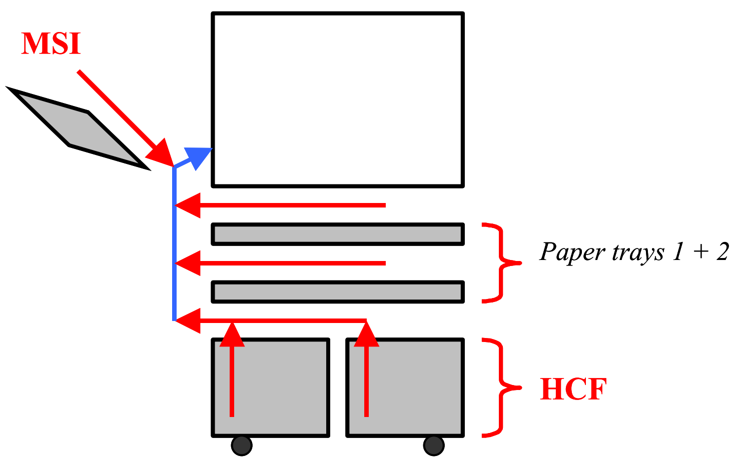


Figure 7.32: Schematic overview of paper-feed module.

According to the FMEA, the degradation of the elevation motor (1a) causes a decrease in motor speed (lowering of the number of revolutions). The more difficult rotation of the axle in the gear shaft (1k), the wear in the cable system (1b) and the resistance rise in the slide bearings of the elevator brake system (1f) contribute to a torque increase in the elevation mechanism. In other words, these failure modes make it mechanically more difficult to lift an elevator plate loaded with a certain amount of paper. Based on these results, the design parameters of the elevation function are determined. These design parameters are:

→ motor speed (number of revolutions);

→ torque in elevation mechanism.

Table 7.7: Failure mechanisms of the elevation function.

Number	Component name	Failure Modes	T	O	C	M	RPN
1a	Motor	1. decline in motor power	2	4	5		40
1k	Gear shaft	1. more difficult rotation of the axle in the shaft	2	2	3	2	12
1b	Cable system	1. cable breakage 2. pully wear	2	1	5	1	10
1i	Tray closing mechanism*	1. widening of the closure clamps	2	2	2	2	8
1f	Elevator brake system	1. resistance rise in the slide bearings	2	1	2	1	4

* *(low cost item: replaced during remanufacturing)*

The Elevation Function

The paper lift's task is to elevate the paper up to the right level at the right moment. The elevation level is determined by a paper level sensor. The paper mechanically presses this sensor when it reaches the right level. The right moment implies that the paper lift should reach the right paper level in time. If the paper lift reaches this right paper level too late, the copier will come to a standstill and an error message will be displayed. The *elevation speed* is the relevant parameter that defines whether the paper lift will reach the right paper level in time. Since the elevation distance is constant, this elevation speed can be replaced by *elevation time* (t_E). Elevation time can be defined as the time required to lift a certain amount of paper over a fixed distance. This elevation time may be considered as a good indicator of the elevation performance and will therefore be used as a performance characteristic for this function.

Identification of the Design Parameters

In order to define the dominant design parameters for the elevation function and the paper grip and transport function, a FMEA was executed for the HCF module unit.

Elevation Function Design Parameters

The performance characteristic of the elevation function was defined as the elevation time (t_E). The time dependent failure mechanisms from the FMEA concerning this elevation function are summarized in table 7.7.

The elevation function of the HCF is summarized in figure 7.33.

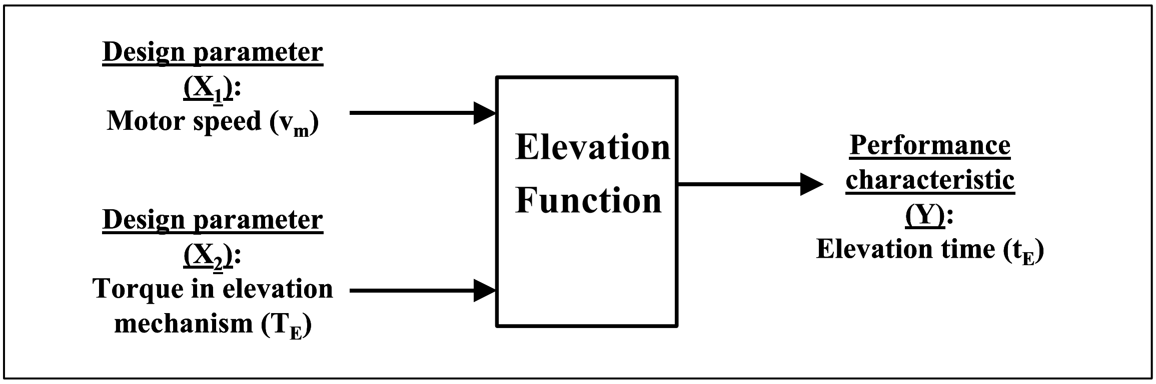


Figure 7.33: The HCF elevation function.

Phase 5, 6, and 7

Experimental Set Up

The elevation time (t_E) is measured by using the encoder wheel at the end of the motor axle. The number of revolutions of this encoder wheel corresponds with the number of revolutions of the motor (exit) axles. The encoder wheel contains 20 spokes that successively pass a sensor, see figure 7.34. As a result this sensor generates 20 electrical pulses per rotation.

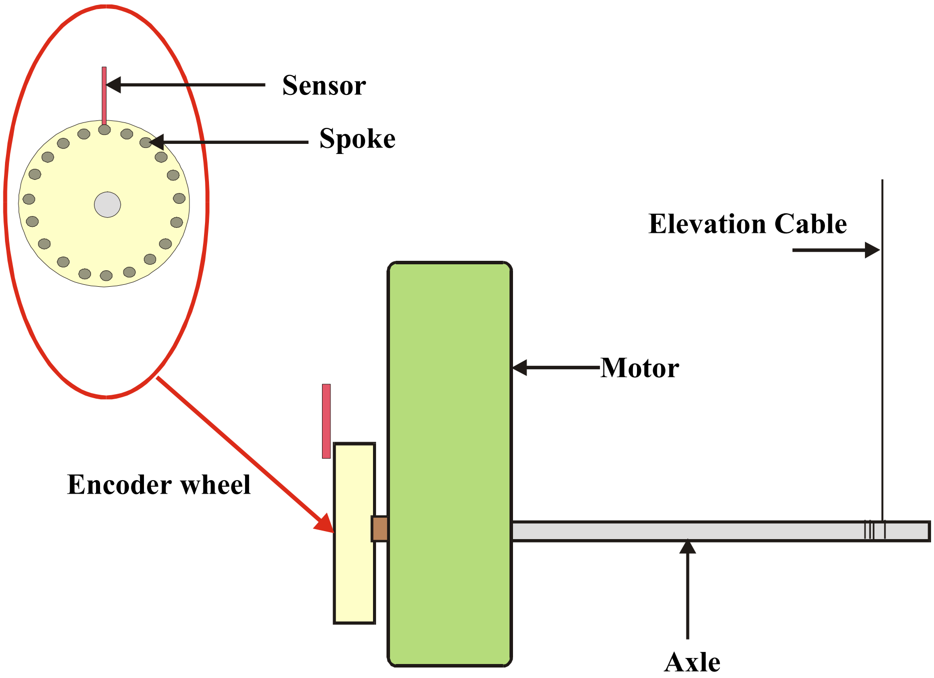


Figure 7.34: The encoder wheel.

By adding up the time between these electrical pulses, the rotation time of the axle can be calculated. Since the elevation distance is constant and one axle rotation corresponds to a fixed elevated distance, (a multiplication of) this rotation time can be used as a measure for elevation time.

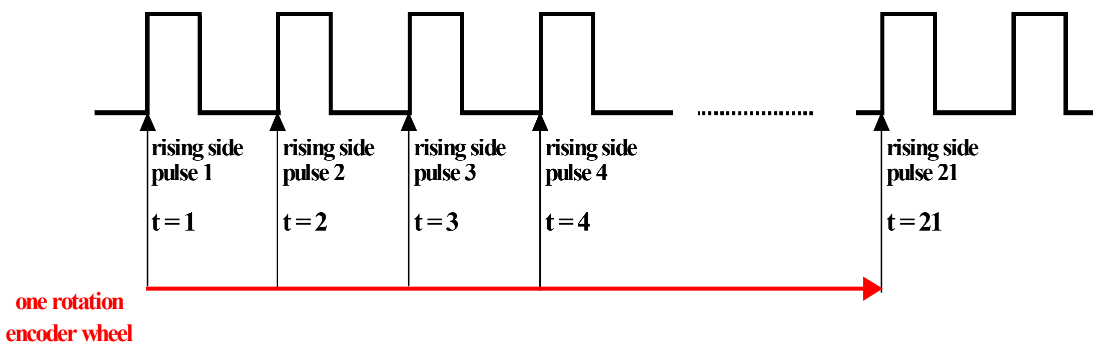


Figure 7.35: Pulses encoder wheel.

To be able to test the influence of the design parameters *motor speed (v_m)* and *torque in elevation mechanism (T_E)* on the elevation time (t_E), the values of these design parameters need to be varied. The motor speed can be varied by placing different voltages on the lift motor. A higher voltage corresponds to a higher motor speed. The torque in the elevation mechanism can be varied by placing different weights on the lift plate. A higher weight corresponds to a higher torque in the elevation mechanism. As a result, it is expected that when motor speed *decreases* and torque in elevation mechanism *increases*, elevation time will *increase.*

The ranges of the design parameter settings are described in the specifications of the HCF and the lift motor. The nominal weight on the lift plate corresponds to two packs of paper, that is 5 Kg. The minimal weight placed on the lift plate is no weight in case of an empty paper tray. The maximal weight on the lift plate corresponds to four packs of paper, that is 10 Kg. It is physically impossible to store more paper on the lift plate.

The nominal voltage placed on the lift motor is according to specification 24,5 Volt. The minimal and maximum voltage placed on this motor are consecutively 21,6 Volt and 26,2 Volt. Beyond these specification limits, the HCF is not able to function properly anymore. An overview of these ranges is given in table 7.8.

Table 7.8: Ranges of design parameters.

	limits		
	minimal	**nominal**	**maximal**
Motor speed (Tension)	21,6 V	24,5 V	26,2V
Torque in elevation mechanism (Load)	0 KG	5,0 Kg	10,0 Kg

The design factor levels in the screening experiment are determined to be the minimal, nominal and maximal levels of the design parameter (see table 7.8). This results in the following screening design:

Table 7.9: Screening Design.

Pattern	Voltage	Load
--	21,6 V	0 Kg
-0	21,6 V	5 Kg
-+	21,6 V	10 Kg
0-	24,5 V	0 Kg
00	24,5 V	5 Kg
0+	24,5 V	10 Kg
+-	26,2 V	0 Kg
+0	26,2 V	5 Kg
++	26,2 V	10 Kg

This screening design is replicated three times, resulting in 27 runs. In order to prevent systematic measurement failures in the design, the runs are completely randomized. The 27 runs could not be performed in one day. As a result, the blocking factor "day" was introduced in order to investigate the influence of the factor *day* on the elevation time measurements. These results are analyzed using X- and R- control charts and ANOVA to determine whether *motor speed (tension)* and *torque in elevation mechanism (load)* have a significant influence on the performance characteristic *elevation time.*

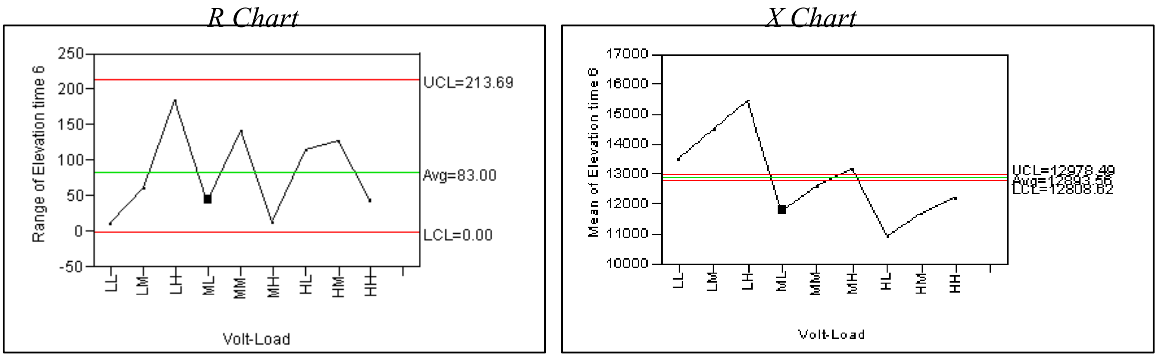


Figure 7.36: Control charts of the elevation time for the screening experiment; L=low, M=middle and H=high (Voltage or Load).

The R control chart of the screening experiment shows that the measurements are in control. In order to measure the change in performance characteristic due to the various settings of the design parameters, the X control chart should be out of control, which indicates the possibility of measuring this setting variation. As can be seen in the X chart of figure 7.36, also this criterion is met.

Figure 7.37 shows that the effect of the design parameters motor speed (voltage) and torque in elevation mechanism (load) have a P-value equal to zero. It is important to remark that the P-value of the interaction effect between voltage and load is rather low indicating a significant interaction effect.

Based on the results from this screening experiment, it can be concluded that motor speed and torque in the elevation mechanism do have a significant influence on the elevation time of the paper lift in the HCF module unit.

*** Analysis of Variance Model***
Short Output:
Call:
formula = Elevation time ~ Block + Tension + Load + (Block + Tension + Load)^2
Terms:

	Block	**Tension**	**Load**	**Block: Tension**
Sum of Squares	353	37201063	10662962	0
Deg. of Freedom	1	1	1	1
	Block: Load	**Tension: Load**	**Residuals**	
Sum of Squares	4356	389520	1911129	
Deg, of Freedom	1	1	20	

Residual standard error: 309,122

	Df	**Sum of Sq.**	**Mean Sq.**	**F Value**	**Pr(F)**
Block	1	353	353	0,0037	0,9521606
Tension	1	37201063	37201063	389,3098	0,0000000
Load	1	10662962	10662962	111,5881	0,0000000
Block: Tension	1	0	0	0,0000	0,9991593
Block: Load	1	4356	4356	0,0456	0,8330923
Tension: Load	1	389520	389520	4,0763	0,0570952
Residuals	20	1911129	95556		

Figure 7.37: The ANOVA table of the screening experiment.

Based on the FMEA results, the motor speed is expected to *decrease* over time. On the other hand, the torque in the elevation mechanism is expected to *increase* over time. As a result of these changes in design parameters, the performance characteristic elevation time is expected to *increase* over time.

Phase 8

For the execution of this degradation test, two new modules (consisting of trays and motors) are used. During the degradation test, all measurements (elevation time, motor speed and torque) are replicated three times to be able to measure the measurement variability.

For the execution of the degradation test on the elevation function, a so-called compressed-time test was selected.

At the start of the degradation test, it was uncertain how fast the module would degrade over time. Therefore, the first four days the degradation test cycle was only 3 to 4 hours long. Between these test cycles, measurements were performed. Since the execution one measurement cycle takes about three hours, two measurements per day are performed with this 3- or 4-hour cycle. After these four days, a 6-hour test cycle was started in order to unburden the people performing the measurements, as the 6-hour test interval only requires one measurement cycle per day. After eight days, a 16-hour test cycle was started followed by a 21-hour test cycle two days later. This gradual transition to longer test periods was executed in order to speed up the degradation process. Table 7.10 gives an overview of the cycles run and the (cumulative) time run during the degradation test.

Table 7.10: Degradation test cycles run.

Cycles	**Cycles Run**	**Time Run**	**Cumulative Time Run**
3/4 hour cycles	4	15 hours	15 hours
6 hour cycles	8	48 hours	63 hours
16 hour cycles	2	32 hours	95 hours
21 hour cycles	5	105 hours	200 hours

Table 7.10 indicates that the degradation test has run 200 hours, corresponding with 2,38 times a module design life. During the fifth 21-hour cycle, both modules broke down. The modules were unable to lift the required weights during the motor speed measurements and produced strong cracking sounds under normal operating conditions. At this point, it was decided to end the degradation test and to analyze the modules together with the acquired data.

Figure 7.38 gives the R and X chart of the performance characteristic *elevation time* versus the degradation test hours. The left-hand sides of the graphs describe the behavior of module 1, the right hand sides of the graphs describe the behavior of module 2. The R chart of the elevation time indicates that the elevation time measurements are stable and predictable. Only the measurement results at 200 hour are out of control for both modules. These out of control points are the result of the break down of both modules. However, the results presented in the X chart indicate that no well-defined degradation pattern can be recognized for the elevation time of both modules. No significant rise in elevation time can be established and both modules show different elevation time behaviors. These results make it impossible to model the degradation behavior of the performance characteristic *elevation time*. Based on this parameter behavior, the breakdown of the two modules cannot be predicted. These results suggest that the performance characteristic *elevation time* should be replaced by another performance characteristic that does predict the module failure behavior.

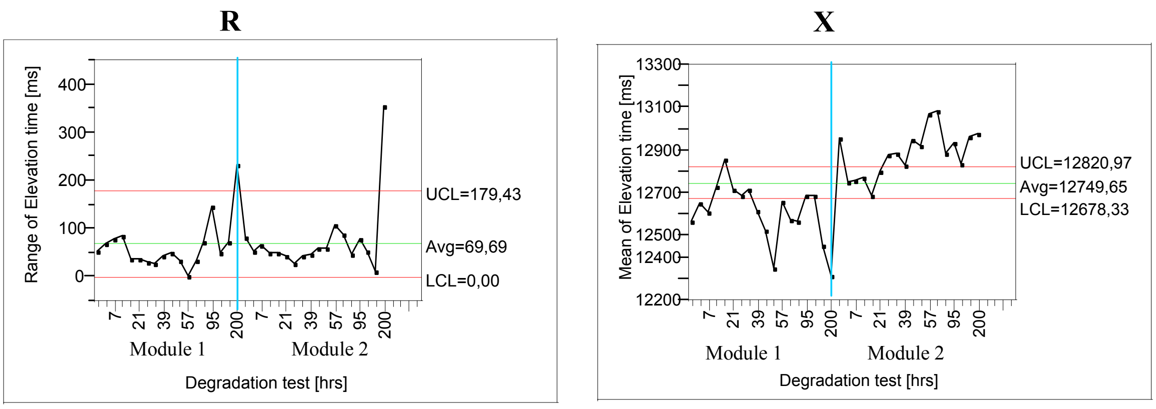


Figure 7.38: R- and X-Chart of the elevation time versus degradation test hours. For each graph applies: left side: module 1 and right side: module 2.

Figure 7.39 gives two X charts of the design parameter *motor speed* at 0 Nm load and at 0,8 Nm load versus degradation test hours. The first X chart shows a clear decrease in motor revolution time for both modules; this corresponds to an increase in motor speed. This conflicts with the expectancy of declining motor speed over time.

With hindsight, the process of carbon brush wear can explain this increase in motor speed. As a result of carbon brush wear, the contact surface of the carbon brushes increases resulting in a longer current supply to the motor. This longer current supply to the motor causes this decrease in revolution time. The second X chart shows an approximately constant motor speed over time for both modules. Only after 200 hours, as an immediate result of the module break down, motor speed drops to zero. Based on this parameter behavior, the breakdown of the two modules cannot be predicted.

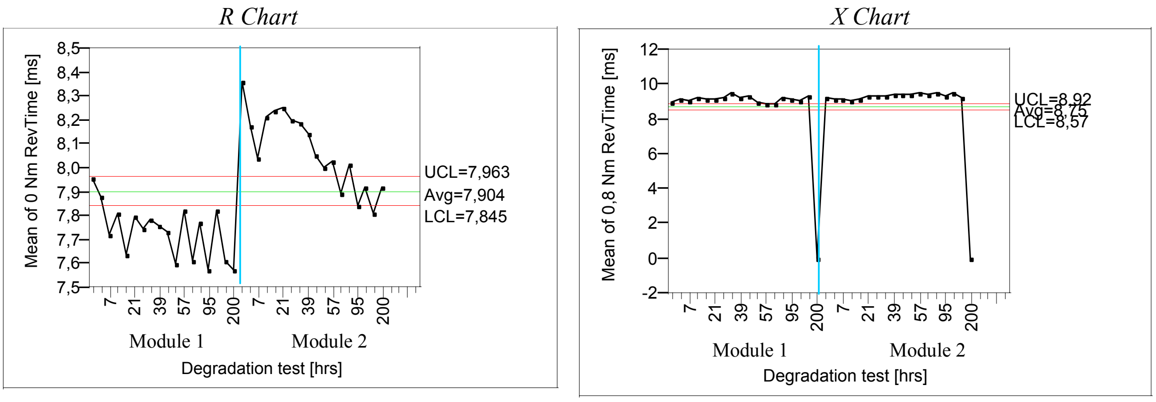


Figure 7.39: R- and X-Charts of the revolution time (at load 0 Nm and 0,8 Nm) versus degradation test hours. For each graph applies; left side: module 1 and right side: module 2.

Figure 7.40 gives two X charts of the design parameter *torque in the elevation mechanism* expressed by load and period time of the HCF. Based on the FMEA results, the HCF load was expected to increase over time, and as a result, the period time of the HCF was expected to decrease over time. The first graph shows a rather constant load level for both HCF modules. With the exception of two peaks in HCF load, which could not be technically explained afterwards. The second graph shows an erratic period time pattern over time for both modules. Although the period time strongly fluctuates over time, these results make it impossible to model the degradation behavior of the design parameter *torque in the elevation mechanism*.

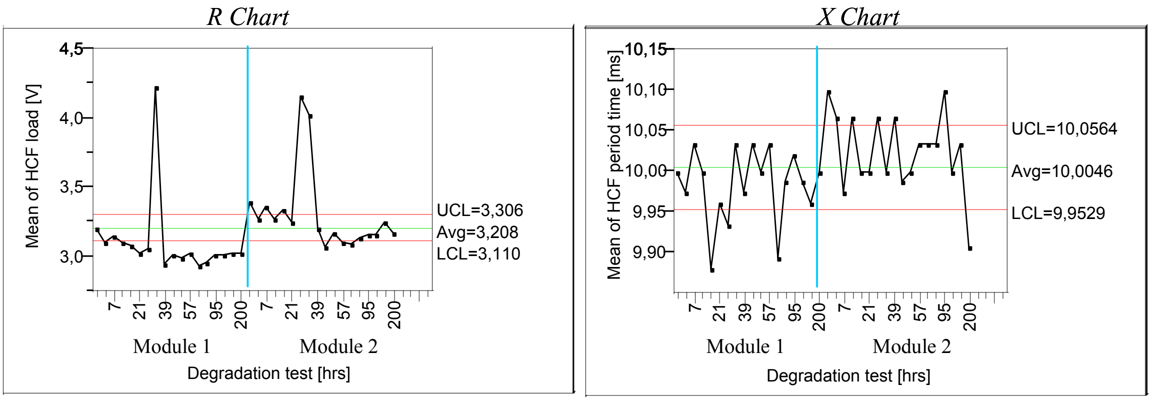


Figure 7.40: R- and X-Charts of the HCF Load and HCF period time versus Degradation test hours .For each graph applies: left side: module 1 and right side: module 2.

Since the breakdown of the modules could not be explained by the degradation of the design parameters and the behavior of the performance characteristic demonstrated no clear degradation path, further investigation was required to reveal the root cause of the module failures.

The strong cracking sounds that were produced by the modules under normal operating conditions came from the gearbox of the lift motor. On that account, it was decided to disassemble these lift motors and to investigate the several components. This investigation resulted in the detection of three defects inside the lift motor gearbox:

1. The wear down of gearwheels; as a result the constant friction between the various gearwheels, the length of the gearwheel spokes decreased. See figure 7.41a.

2. The wear down of the gearwheel axles; as a result of the rotation of the gearwheel axles in the fixation shafts, the diameter of these gearwheel axles decreased.

The wear down of the fixation shafts; as a result of the rotation of the gearwheel axles in the fixation shafts, the diameter of these fixation shafts increased. See figure 7.41b.

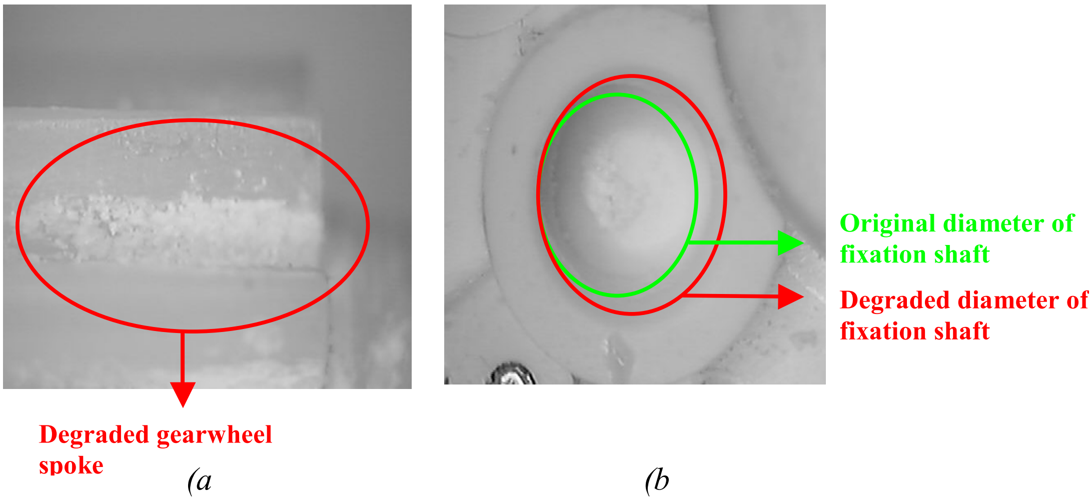


Figure 7.41: Degradation of the motor gearbox [VIS04]:

a) decrease in spoke length.

b) increase in fixation shaft diameter.

This degradation process of the lift motor’s gearbox results in a continuous increase of the play between the various gearwheels. At a certain play-level between the gearwheels, the gearwheel transmission becomes irregular due to the difference in friction at different positions of the gearwheels. Ultimately, the gearwheel transmission fails due to lack of connection between the various gearwheels. In this degradation test, this gearwheel transmission failing expressed itself as a instant failure mechanism since motor speed and elevation time does not change due to an increase in gearwheel play.

Based on these degradation test results, it can be concluded that the dominant failure mechanism was not identified in the FMEA process. The dominant failure mechanism does not find expression in the degradation behavior of the performance characteristic *elevation time* and the design parameter *motor speed.* As a result, these performance characteristic and design parameters cannot be used to describe the degradation behavior of the complete paper feed module. Using all these results from this degradation test, a new FMEA should be performed. This FMEA should identify design parameters that describe the degradation of the gearbox. Furthermore, there should be searched for a performance characteristic that describes the degradation of the paper feed module due to increases in gearwheel play. Subsequently, the screening experiments and degradation tests should be executed once more.

7.4 Case Study: Paper Input Module (OCÉ)

The purpose of the third case study differs from the first and the second case study. In the first two case studies the purpose was to prove the applicability of the protocol of ROMDA that was provided in chapter 6. The first case study was successful in this. However, the second case study was unsuccessful due to the fact that a wrong failure mechanism was identified as dominant. The consequences of focusing on less dominant failure mechanisms are a waste of money and time in terms of testing equipment and testing time. This case study focuses more on examining the possibility to reduce the risk of concentrating on wrong failure mechanisms.

7.4.1 Literature

The problem that is sketched above is not unique. It is a commonly discussed problem in literature in relation with quality and reliability studies ([LU02], [PET03]).

Literature also suggests a solution by using service and engineering data to substantiate conclusions that could be drawn from a FMEA. But for the information to be useful it should meet certain criteria. These criteria are ([BRO04], [LU02]):

1. Define the goal of the information exchange;
2. Determine the type of information required for the goal;
3. Evaluate the quality of the available information:
    a. Level of detail
    b. Deployment of information in an organization
    c. Timeliness
4. Determine the uncertainty of information.

The first and second criteria are used to determine the service information demand for ROMDA. The third criterion deals with the quality of the available information. And the fourth criteria focuses on the difference between the information need and the available information, which is defined as the uncertainty of information [LU02]

After evaluating the first and second criteria for ROMDA it can be said that:

1. The goal of the information can be defined as: the determination of the dominant failure mechanism and the root-causes of this failure.
2. The type of information can be split in the need for statistical information, which is defined as: 'The quantitative information about the frequency of product failures, meant for statements about (sub-) populations of products' [PET03] and the need for engineering information: 'the information that is necessary in order to be able to detect the root-cause of a product failure' [PET03]. Statistical information for ROMDA is necessary since statements about the

dominance of failures and about the dominance of causes are required. Also engineering information is required for ROMDA this information could help to identify the root-causes of the dominant failure.

3. The third criterion focuses on the quality of information. Three criteria define the quality of information.

a) The level of detail the information provides.

Several requirements are given by [BRO00] to estimate the level of detail. The first requirement is that the data should provide sufficient information to prioritize further actions. This requirement is covered in the process of Océ since information is collected that identifies the frequency of errors, the data dumps, and the customer complaints are registered. The combination of these should be able to prioritize further improvement actions. The second requirement is coped with in the field feedback system of Océ by making the service product specialist part of the project team and responsible for this requirement. The third requirement of the level of detail of information is that the data should enable to identify the root-cause of a problem. This is solved in the service information process of Océ by making use of the Technical Service Manual (TSM) software. However the root-causes of errors or complaints from customers are only identified with this software. Hence, the service-technician uses the software to solve the problem but the information remains qualitative. The TSM could be described as a database of the fault trees of all the errors described for a product. And each error has several root-causes. Each root-cause of an error is identified by selecting the fault tree that corresponds to the error, followed by several questions that lead to the root of the fault tree. These solutions to the errors are unfortunately not made quantitative. Hence, the TSM is able to narrow the focus to a few root-causes for a particular error, however it is not able to give a quantitative estimation of the root-causes of a failure.

b) The deployment of the information to the relevant people in the organization.

One of the purposes of the SPM department is providing field feedback to the R&D department. At the R&D department both types of actors as defined in [BRO00] are informed about the situation in the field. Hence, corrective actions as well as pro-active actions will be started if necessary.

c) The time it requires to obtain and deploy the information.

It was already noticed that this criterion was of less importance given the purpose of this thesis. However, it should be clear that by including the service product specialist in a project team a direct information flow of field feedback is created. Furthermore there is made use of Internet and email tooling and therefore a direct update of the field performances of products can be taken.

The last criterion deals with the uncertainty of the information that is gathered about a product.

4. The uncertainty of the information.

The uncertainty of the information required for ROMDA can be defined as the difference between the information needed and the information provided [LU02]. The information should provide enough information to determine the dominant failure mechanism and the root-causes of this failure mechanism. In other words, this information should be able to provide a quantitative estimation of the dominant failure mechanism. For the root-causes of the dominant failure mechanism a qualitative estimation can be given of a few potential root-causes. For this purpose a fault tree relating failure mechanisms to root-causes can help to determine the level of uncertainty of the information.

7.4.2 Setup case study

For the purpose of testing the possibility of using service data to reduce the uncertainty of focusing on non-dominant failure mechanisms the approach is used to independently perform a FMEA and in parallel analyze service data. A few designers have independently performed a FMEA on the module under study. Next to that service engineers analyzed the service data for the module under study. Figure 7.42 shows a schematically overview of the setup of this case study.

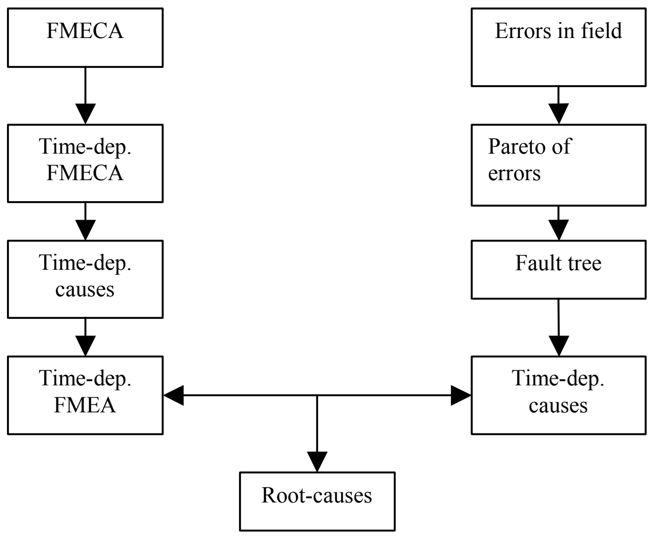


Figure 7.42: Process to root-cause identification.

At the end of both independent paths of analyses, the results are compared [LAM04]. The results of both paths of analyses show similar results and, therefore, it can be concluded that the uncertainty of focusing on the wrong failure mechanism is reduced. For details of the analysis the reader is referred to Lamers [LAM04].

Literature study together with the results of the case study lead to the following conclusions:

→ Service information can give a quantitative estimation of the dominant failure, if sufficient statistical information is available. Furthermore, when the engineering information is also able to provide quantitative information, estimations can be made about the dominance of the root-causes of failures. Therefore, by using service information a quantitative motivation can be made for the determination of the performance characteristic and the critical design parameters.

→ Furthermore, the service information can validate the screening experiment. Hence, by using this information the first phases of the protocol can be done more decisively and the probability of repeating these phases will be decreased. Therefore the use of this information can contribute to a faster execution of ROMDA.

→ A restriction for using service data is that it can only be used for a derivative product development processes as defined in [LU02]. These development processes should be able to provide relevant service information from predecessors.

7.5 Overall conclusions case studies

Three case studies have been presented in this chapter. The first case study followed the complete ROMDA protocol. This case study demonstrated that the protocol is practically applicable.

The intention of the second case study was to follow the complete protocol again and see if it could work for different problems. This case study resulted in the conclusion that the first phases of ROMDA are crucial for the success of the end result. For this purpose a third case study was initiated to research the possibilities of reducing the high risks of focusing on non-dominant failure mechanisms. Suggestions have been presented in the third case study.

With the results of the three case studies together, it can be concluded that ROMDA has a potential to become a method that can be used to meet the objectives of the three design requirements. More research is necessary to prove the real value of ROMDA and to research to area of application with corresponding boundaries.

8 Conclusions and recommendations for further research

8.1 Introduction

The goal of the research presented in this thesis was to develop one method that can provide a solution for multiple objectives. For this purpose many steps have been taken leading to ROMDA. These steps include literature research, analysis and testing of available methods in literature, combining and adjusting available methods, and develop completely new testing strategies. This chapter is organized as follows. Section 8.2 provides a short overview of the contents of chapters 1 to 7. In Section 8.3 the major research findings with respect to the research problem defined in chapter 1 are summarized. Recommendations for further research are given in section 8.4.

8.2 Overview of the research

Chapter one starts by discussing the fact that companies put a lot of effort in satisfying the following three design requirements:

→ Optimization of product design towards robust reliability

→ Providing information enabling decisions on re-use of systems or sub-systems

→ Providing information necessary for optimal preventive maintenance decisions

This leads to the following research question of this thesis:

Is it possible to develop a method that provides the possibility to tackle the three design requirements in an effective way without loss of quality of the solution?

In order to be able to answer this research question a few steps have been taken. The first important step was to set boundaries for the research area. In summary the most important research boundaries are:

→ This research emphasizes on gradual, or degraded, complete and partial extended failures of phase 2 and phase 4 of the roller-coaster curve.

→ This research took into account three causes of variability (unit-to-unit variability, variability due to operating conditions and environmental variations, and variability due to product degradation)

The next important step was to analyze methods existing in literature. Chapter 3 presents an extensive overview of available methods in literature and discusses the suitability of these methods in answering the research question. The discussions demonstrate that very useful concepts and ideas are presented in literature, but that not one single available method is able to provide a solution for the three design requirements simultaneously. Table 3.2 summarizes the results of the literature analysis.

Chapter 4 presents the theoretical framework for the developed method called ROMDA. Based on computer-based simulation experiments it was demonstrated (chapter 5) that it is possible to provide a solution for the three design requirements using one method. However, a critical analysis of the theoretical approach showed that the results of the theoretical framework could not be directly translated to a practically applicable method. For this reason chapter 6 presents a practical protocol of ROMDA. For this practical protocol all suggestions of the discussions of chapter 5 are taken into account.

The practical protocol of ROMDA is tested by means of three case studies performed at two different companies. The purpose of the third case study differs from the first and the second case study. In the first two case studies the purpose was to prove the applicability of the protocol of ROMDA that was provided in chapter 6. The first case study was successful in this. However, the second case study was unsuccessful due to the fact that a wrong failure mechanism was identified as dominant. The consequences of focusing on less dominant failure mechanisms are a waste of money and time in terms of testing equipment and testing time. The third case study focused more on examining the possibility to reduce the risk of concentrating on wrong failure mechanisms. Suggestions have been given and initially tested. The suggested approach could indeed lead to less uncertainty, and therefore less risk, in focusing on non-dominant failure mechanisms.

8.3 Contributions of research

The first contribution that can be identified in this research is the introduction of ROMDA that offers the possibility to provide a solution for the three design requirements that have been discussed in this thesis. It has been researched as to what the commonalities are between the three design requirements and if it was possible to use that information for the development of a single method fulfilling the research objective. Literature research (chapter 4) showed that not one single method in literature could be found that suited the objective.

In terms of literature, one important observation is that quality (or time-independent) related methods focus on the influence of design parameters on the performance of a class of products. In these methods the factor time is not considered. In maintenance related methods, however, almost no attention has been given to design parameters. Those methods focus more on statistical failure data or they focus more on monitoring output parameters that indicate the status of a product in terms of performance. Reliability related methods can be categorized in a few types of approaches. Some focus on statistical failure data, some focus on stress-strength characteristics, and some focus on degradation profiles of the performance characteristics of a group of products. However, none of them consider the combination of degradation of a product in terms of design parameters and degradation of the performance characteristic. When doing so, it can result in major advantages. This is thouroughly explained in section 2.2 and 4.3. In section 2.2 it is explained that using time-dependent design parameters can provide a better optimization in terms of yield, but then over time. This was explained with the use of the book of Spence and Soin [SPE88]. Section 4.3 discusses the advantages of having the extra information on the degradation profiles of the design parameters. One of the advantages is the fact that design parameters are physical parameters and usually easier to measure than a performance characteristic. In terms of preventive maintenance and re-use, it is most often easier, faster and cheaper to measure (or monitor) physical parameters online in a product than to measure a performance characteristic.

The above-two mention contributions are more concept-based. The first contribution is the development of one single method that provides a solution for three design requirements. The second conceptual contribution is to use time-dependent design parameter information leading to some major advantages. Next to these more conceptual contributions, some more method-based contributions are discussed in the thesis. These are:

→ the adjusted FMEA approach, including the suggestion to use service and engineering data parallel to the FMEA analysis

→ the time-dependent design of experiments

→ the presentation of a practical step-by-step protocol that can serve as a tool for engineers to find a solution for the three design requirements.

The first point helps to identify the important time-dependent failure mechanisms. And including the extra service and engineering data can reduce the risk of focusing on non-dominant failure mechanisms.

The time-dependent DOE can provide a method to reduce costly and time-inefficient degradation tests, while still collecting statistical degradation information that can be used for modeling and predicting the behaviour of a class of products over time.

And finally, the last point serves as a tool for engineers to collect all information that is necessary to solve for the three design requirements using only one method.

8.4 Conclusions

The research question can be divided in three parts. The first part of the research question deals with the possibility to tackle the three design requirements using one method. This part of the research question can be answered positively. Chapters 4 to 7 demonstrate the fact that the gathered information of all phases of ROMDA provide enough information to tackle the three design requirements. However, the answers to the second and third part of the research question are less evident. The second and third part of the research question describe two conditions that a new method has to satisfy. These two conditions are respectively the effectiveness of the method, and the quality of the solution of the method.

Quality of solution

With respect to the quality of the solution it is important to understand that it is very difficult to compare ROMDA with other methods. ROMDA is a very complete method in terms of practicality. ROMDA starts with the identification of dominant failure mechanisms and collects degradation data that can be translated to failure behaviour of a group of products. Most methods in literature focus on a specific phase or objective. These methods make assumptions on earlier phases, or use input data of other methods. An example is that most other methods assume to know the dominant failure mechanisms and start at that point. These methods are also many times tested on small, simple, and cheap products. With these products it is cheap to test many samples in a thorough manner and still fully understand what physically happens. Therefore, it is not impossible that those methods run into major problems when testing on big, complex, and expensive products, where only a few products are available for testing and life tests take a very considerable time. For these reasons it is very difficult to compare the quality of solution of other methods with ROMDA.

The analyses of the simulation experiments together with the analyses of the results of the case studies lead to the conclusion that the quality of the solution of ROMDA can be assumed to be similar, or maybe even better than the quality of other methods available in literature. Although it is difficult to prove this, it is obvious that ROMDA uses the strengths of many methods and combines these into one method. By combining the strengths of many different methods, the weaknesses of those individual methods are most often solved, or at least reduced. Consider, for example, robust design related methods. These methods obviously have their strengths. However, these methods are time-independent and only focus on the quality of a product design, and not on the reliability. Another example could be the statistical failure analysis related methods. These methods consider failure times of a complete population of products. However, these methods do not incorporate information of how, and why, products fail. Degradation related methods do take this extra information into account. ROMDA takes all these strengths into account. This was demonstrated in chapter 4. Therefore, it is argued that the quality of the solution of ROMDA is similar, or even better than the quality of the solution of other methods available in literature.

Another advantage of ROMDA is the fact that the practical protocol has a generic structure. When new methods become available in literature dealing with specific problems, like regression modeling, determination of the dominant failure mechanisms (like FMEA), optimized test strategies, etc., these could be incorporated in the protocol guaranteeing good quality of the solution.

Effectiveness solution method

Also the effectiveness of ROMDA is difficult to test and, therefore, to compare with other available methods. At a first glance, it may seem that ROMDA takes much more time and effort to be executed. However, when considering a similar argument as in the discussion on the quality of the solution, most methods in literature focus on certain aspects of the protocol and, therefore, have to make many assumptions to execute their methods, like the dominant failure mechanisms. But to compare the effectiveness of other methods with ROMDA, this assumption obviously has big consequences for the outcome.

Assume that methods in literature also need to establish a well-motivated starting point for the test procedures. And take into account that currently the three design requirements are tackled at different phases in the product lifecycle using different methods. This may already lead to a faster execution time of ROMDA than executing three different methods in different product lifecycle phases. Even though initially ROMDA needs to put some extra effort due to the fact that it also has to collect data for design requirement that becomes important later in the product lifecycle, it is still more efficient than performing three methods with overlapping areas of interest.

Also note that ROMDA has not been executed optimally in the case studies. For the case studies the choice was made to take the least risk in the degradation testing phase. This resulted in choosing compressed time testing strategies instead of the generally faster accelerated degradation testing strategy. This point of attention already suggests that the protocol of ROMDA should be optimized itself.

In summary it could be concluded that it is possible to develop a method that can be used to tackle the three design requirements using just one method in an effective way without loss of quality of the solution. It is important to mention that in the current state of the ROMDA method it would only be wise to use it in professional products where all three design requirements play an important role (e.g. the copier machine, a car, etc.). Although ROMDA is developed in such a way that some phases could be left out to make the process a lot faster, this has not been investigated. In order to explain this point, consider a consumer product like a mobile phone. For such a product re-use and preventive maintenance are totally unnecessary, because almost nobody uses a mobile phone longer than 3 years. However, it is still a challenge to design the product in the cheapest possible way. When this is the only goal, many phases can be left out of the protocol, making it much faster. Basically the protocol almost reduces to well-known methods from literature. This makes the generalization potential of ROMDA very high. But it has not been investigated how ROMDA could be used in different types of products.

This then leads to the recommendations for further research.

8.5 Recommendations for further research

The recommendations for further research are divided into two parts. One part discusses opportunities for further research from a theoretical point of view, while the other part discusses the practical opportunities for further research.

Recommendation from a theoretical point of view

The goal of this research was to investigate the possibility to develop one method that can tackle all three design requirements simultaneously. For the purpose of testing ROMDA some assumptions have been made. The consequences of these assumptions should be researched. Three of these assumptions were:

→ Throughout this research in the statistical analysis normal distributions have been used. The normal distribution might not always be the best choice to represent certain data. Using other statistical distribution in the analyses can result in more complex statistical modeling and optimization problems. This should therefore be investigated in more detail.

→ Reliability of a population of products can be expressed in many different reliability characteristics. In this research only the Mean Time To Failure (MTTF) and the Variance of the Time To Failure (VTTF) (or Standard Deviation of the Time To Failure (SDTTF)) have been used. Although these characteristics can be considered as reliability characteristics, it does not always suffice in reliability analyses to only use these simple characteristics. The characterization of reliability is therefore a point of interest for further research.

→ Modeling of statistical data and longitudinal data has been done using simple regression modeling techniques. For the purpose of testing if ROMDA could work, this sufficed. However, to make the analyses more rigid and reliable, other modeling methods, and the consequences of these modeling techniques, have to be researched. This could eventually lead to more precise and more reliable models. This can consequently improve the quality of the solution of ROMDA.

One phase slows down the execution time of ROMDA is the degradation testing phase. This phase could be seen as the bottleneck in terms of effectiveness of the method. Literature suggests using accelerated degradation testing strategies instead of compressed time testing strategies. To improve the effectiveness of

ROMDA it has to be researched if, and how, accelerated degradation testing strategies could be implemented.

And finally, more research effort should be put in researching possibilities of reducing the risk of focusing on non-dominant failure mechanisms. Most methods in literature leave out this issue. However, the second case study showed that the risk of focusing on non-dominant failure mechanisms is not negligible. In the third case study it is suggested to use service data to reduce the uncertainty of the results of the first few phases. But if this approach is the only possible approach, or if other possible approaches could be used, this should be further investigated. This could improve ROMDA substantially.

Recommendation from a practical point of view

To start with the last remark of the conclusions, it should be researched for what type of products ROMDA could be used and could be beneficial. This would lead to more insight in the boundaries of application of the ROMDA method. In theory the protocol could be used for many different product groups and categories, but it would not always be beneficial to use it.

In this research the case studies have performed on products that were available for other project purposes. But in order to make implementation of the ROMDA method possible in a product development process (PDP), it is crucial to understand when in the PDP the ROMDA method should be performed. This has not been studied in this thesis. For practical implementation possibilities this point need to be researched.

References

[ABR83] Abraham, B., and Ledolter, J., *Statistical Methods for Forecasting*, John Wiley & Sons, Inc., 1983

[AHM97] Ahmed, A.N., Soliman, A.A., and Khider, S.E., *Preservation Results for Ordered Random Variables, with Applications to Reliability Theory*, Microelectronic Reliability, Vol. 37, No. 2, 277-287, 1997

[AHS03] Ahsan, T., and Bischof, C.S., *Stability of Mold Compounds for Lead (Pb)-Free Electronics*, Third International Conference on Lead Free Electronic Components and Assemblies, 123-126, San Jose, 2003

[BAR65] Barlow, R.E., and Proschan, F., *Mathematical Theory of Reliability*, John Wiley & Sons, Inc., New York, London, Sydney, 1965

[BEL00] Belavic, D., e.a., *An Investigation of the ageing behaviour of Thick-Film Resistors*, IMAPS Conference Poland, 2000

[BHA74] Bhattacharyya, G.K., and Johnson, R.A., *Stress-strength models for system reliability*, Madison: University of Wisconsin, 1974

[BHO00] Bhote, K.R., and Bhote, A.K., *World Class Quality: Using Design of Experiments to make it happen*, 2nd edition, Amacom, New York, 2000

[BIC77] Bickel, P.J., and Doksum, K.A., *Mathematical Statistics*, Holden-day, Inc., Oakland, CA, 1977

[BIE02] Bierbaum, R.L., Brown, T.D., and Kerschen, T.J., *Model-Based Reliability Analysis*, IEEE Transactions on Reliability, Vol. 51, No. 2, 133-140, 2002

[BLA94] Blache, K.M., and Shrivastava, A.B., *Defining failure of manufacturing machinery and equipment*, Proceedings Annual Reliability and Maintainability Symposium, 69-75, 1994

[BLI00] Blischke, R.W., and Murthy, P.D.N., *Reliability Modeling, Prediction, and Optimization*, John Wiley & Sons, New York, Inc., 2000

[BLI03] Blischke, R.W., and Murthy, P.D.N., *Case Studies in Reliability and Maintenance*, John Wiley & Sons, New York, Inc., 2003

[BOG85] Bogdanoff, J.L., and Kozin, F., *Probability Models of Cumulative Damage*, John Wiley & Sons, Inc., New York, 1985

[BOG02] Bogaard, J.A. van den , Hoorn, M.H.C., *A method for Signature Analysis*, EET project report, Technische Universiteit Eindhoven, 2002

[BOG03] Bogaard, J.A. v.d., e.a., *A Method for Reliability Optimization through Degradation Analysis and Robust Design*, RAMS proceedings, 2003

[BOT00] Bothe, K.R., Bothe, A.K., *World class quality: using design of experiments to make it happen*, Amacom, New York, 2000

[BRA79] Branum, J.D., *Selection and Evaluation of Environmental Screening Tests for Trident I (C4) Electronic Black Boxes*, Proceedings of the IES National Conference and Workshop on Environmental Stress Screening of Electronic Hardware, 1979

[BRO92a] Brombacher, A.C., Van Geest, D.C.L., Arendsen, R., Van Steenwijk, J.A., and Herrmann, O.E., "Simulation, a Tool for Designing-in Reliability", in *Proceedings of ESREF Conference*, (Schwäbisch-Gmünd, Germany), 201-209, 1992

[BRO92b] Brombacher, A.C., *Reliability by Design*, John Wiley & Sons, Chichester, 1992

[BRO99] Brombacher, A.C., *MIR: Covering Non-Technical Aspects of IEC61508 Reliability Certification*, Reliability Engineering and System Safety, Elsevier, 1999

[BRO00] Brombacher, A.C., *Designing Reliable Products in a Cost and Time driven Market: a conflict or a challenge*, Technische Universiteit Eindhoven, 2000

[BRO01A] Brombacher, A.C., *and de Graef, MR., Anticiperen op trends*, a chapter in the book "Betrouwbaarheid van technische systemen – anticiperen op trends" edited by M.R. de Graef, Stichting Toekomstbeeld der Techniek, Den Haag, 2001

[BRO01] Brombacher, A.C., e.a., *Bedrijfszekerheid van technische systemen bij veranderende bedrijfsprocessen*, Bedrijfskunde, Tijdschrift voor modern management **2**:49-59, 2001

[BRO04] Brombacher, A.C., Sander, P.C., Sonnemans, P.J.M., Rouvroye, J.L., *Managing product reliability in business processes 'under pressure'*, Reliability Engineering and Safety Systems, 2004

[BT87] *Handbook of Reliability Data for Components used in Telecommunications Systems*, Issue 4, British Telecom, 1987

[BUS90] *Cost of non-quality*, Business Week, April 30, 1990

[CAN75] Canfield, R.V., and Borgman, L.E., *Some distributions of time to failure for reliability applications*, Technometrics, vol. 17, 263-268, 1975

[CAN86] Canfield R. V., *Cost Optimization of Periodic Preventive Maintenance*, IEEE Transactions on Reliability, Vol.35, No.1, 1986

[CAS02] Casella, G., and Berger, R.L., *Statistical Inference (Second edition)*, Duxberry, Pacific Grove, CA, 2002

[CHA99] Chan, V., and Meeker, W.Q., *A Failure-Time Model for Infant-Mortality and Wearout Failure Modes*, IEEE Transactions on Reliability, Vol. 48, No. 4, 377-387, 1999

[CHA00] Chang, D.S., *Optimal Burn-In Decision for Products with an Unimodal Failure Rate Function*, European Journal of Operational Research, 126, 534-540, 2000

[CHA01] Chaudhuri, G., Hu, K., and Afshar, N., *A New Approach to System Reliability*, IEEE Transactions on Reliability, Vol. 50, No. 1, 75-84, 2001

[CHI01] Chiao, C.H., and Hamada, M., *Analyzing Experiments with Degradation Data for Improving Reliability and for Achieving Robust Reliability*, Quality and Reliability Engineering International, 17, 333-344, 2001

[CHI96] Chick, S.E., and Mendel, M.B., *An Engineering Basis for Statistical Lifetime Models with an Application to Tribology*, IEEE Transactions on Reliability, Vol. 45, No. 2, 208-215, 1996

[CHI99] Chinnam, R.B., *On-line Reliability Estimation of Individual Components, Using Degradation Signals*, IEEE Transactions on Reliability, Vol. 48, No. 4, 403-412, 1999

[CHI02] Chinnam, R.B., *On-line Reliability Estimation for Individual Components using Statistical Degradation Signal Models*, Quality and Reliability Engineering International, 18, 53-73, 2002

[CHO02] Choi, K.C., and Zhou, X., *Large Sample Properties of Mixture Models with Covariates for Competing Risks*, Journal of Multivariate Analysis, 82, 331-366, 2002

[CHR86] Christensen, P.T., and Murotsu, Y., *Application of structural system reliability theory*, Springer, Berlin, 1986

[CON01] Condra, L.W., *Reliability Improvement with Design of Experiments*, second edition, Marcel Dekker, Inc., New York, 2001

[COX84] Cox, D.R., and Oakes, D., *Analysis of Survival Data – Monographs on Statistics and Applied Probability*, Chapman and Hall Ltd, London, 1984

[COX00] Cox, D.R., and Reid, N., *The theory of the Design of Experiments*, Chapman and Hall/CRC, London, 2000

[CRE97] Creveling, C.M., *Tolerance Design: A Handbook for Developing Optimal Specifications*, Addison-Wesley, Amsterdam, 1997

[CRO91] Crowder, M.J., Kimber, A.C., Smith, R.L., and Sweeting, T.J., *Statistical Analysis of Reliability Data*, Chapman & Hall/CRCL, London, 1991

[DAM04] Damen, M.A., *A practical implementation of ROMDA – A method for reliability prediction and optimization through degradation analysis*, master thesis, Technische Universiteit Eindhoven, 2004

[DAS91] Dasgupta, A., and Pecht, M., (1991). "Material failure mechanisms and damage models," *IEEE Transactions on Reliability*; **40**: 531-536.

[DEH89] Edited by Dehnad, K., *Quality Control, Robust Design, and the Taguchi Method*, Wadsworth & Brooks/Cole Advanced Books & Software Pacific Grove, California, 1989

[DEN98] Denson, W., *The History of Reliability Prediction*, IEEE Transactions on Reliability, Vol. 47, No. 3-SP, 321-328, 1998

[DER80] Derringer, G., Suich, R., *Simultaneous Optimization of Several Response Variables*, Journal of Quality Technology, Vol.12, No.4, 214-219, 1980

[DIB04] Di Bucchianico, A., Figarella, T., Hulsken, G., Jansen, M.H., Wynn, H.P., *A Multi-scale Approach to Functional Signature Analysis for Product End-of-life Management*, Quality and Reliability Engineering International, Volume 20, Issue 5, 433-456, 2004

[DIS68] Disney, R.L., Sheth, N.J., and Lipson, C., *The Determination of the Probability of Failure by Stress/Strength Interference Theory*, Proceedings of Annual Symposium on Reliability, 417-422, 1968

[DOD99] Dodson, B., Nolan, D., *Reliability Engineering Handbook*, New York : Marcel Dekker, 1999

[EBE97] Ebeling, Charles E., *An Introduction to Reliability and Maintainability Engineering*, McGraw-Hill, New York, 1997

[EDG79] Edgerton Jr, D., and Quart, I., *Hughes Aircraft Company Stress Screening Studies*, Proceedings of the IES National Conference and Workshop on Environmental Stress Screening of Electronic Hardware, 1979

[ELS96] Elsayed, E.A., (1996). *Reliability Engineering*, Addison Wesley

[ERM88] Ermoliev, Y., and Wets, R.J.B., *Numerical Techniques for Stochastic Optimization*, Springer, Berlin, 1988

[ESC98] Meeker, W.Q., Escobar, L.A., Lu*, C. J., Accelerated Degradation Tests: Modelling and Analysis*, Technometrics*,* vol. 40, pp. 89-99, 1998

[EUR02] Eurandom, *Survival experiment nip motor*, EET project report, 2002

[FEI96] Feinberg, A.A., and Widom, A., *Connecting Parametric Aging to Catastrophic Failure Through Thermodynamics*, IEEE Transactions on Reliability, Vol. 45, No. 1, 28-33, 1996

[FIS12] Fisher, R.A., *On an absolute criterion for fitting frequency curves*, Messenger of Mathematics¸ Vol. 41, 155-160

[FLE02a] Flextronics International Europe, *Main Tray Experiments*, Internal report, 2002

[FLE02b] Flextronics International Europe, *Screening Experiments*, Internal report, 2002

[FLE02c] Flextronics International Europe, *Part-to-part experiments*, Internal report, 2002

[FRI97] Frigon, N.L., Mathews, D., *Practical guide to experimental design,* John Wiley & Sons Inc., 1997

[GAR88] Garvin, D.A., *Managing Quality,* The Free Press, New York, 1988

[GEN87] Geniaux, B., *E.S.S. at Assembly Level-Actual Results-Optimization Method*, Proceedings of the IES Annual Technical Meeting, 1987

[GER00] Gertsbakh, I. B., *Reliability Theory with Applications to Preventive Maintenance*, Springer, Berlin, 2000

[GER02] Gerling, W.H., Preussger, A., and Wulfert, F.W., *Reliability Qualification of Semiconductor Devices Based on Physics-Of-Failure and Risk and Opportunity Assessment*, Quality and Reliability Engineering International, 18, 81-98, 2002

[GLA80] Glaser, R.E., *Bathtub and related failure rate characterizations*, J. Am. Stat. Assoc., vol 75, 667-672, 1980

[GOH93] Goh, T.N., *Taguchi Methods: Some Technical, Cultural and Pedagogical Perspectives*, Quality and Reliability Engineering International, Vol.9, 185-202, 1993

[GOL63] Goldberg, M.F., and Vaccaro, J., *Physics of Failure in Electronics*, Cleaver-Hume Press, 1963

[GRA01] Edited by Graef, M.R. de*., Betrouwbaarheid van technische systemen - Anticiperen op trends*, Stichting Toekomstbeeld der Techniek, Den Haag, 2001

[GRO94] Groot, A.D. de, *Methodologie: Grondslagen van het onderzoek en denken in de gedragswetenschappen*, Koninklijke Bibliotheek, Den Haag, 1994 (In Dutch)

[HAM95] Hamada, M., *Using Statistically Designed Experiments to Improve Reliability and to Achieve Robust Reliability*, IEEE Transactions on Reliability, Vol. 44, No. 2, 206-215, 1995

[HEC87] Hecht, H., and Fiorentio, E., *Reliability Assessment of Spacecraft Electronics*, Proceedings of the Annual Reliability and Maintainability Symposium, 1985

[HEN81] Henley, E.J., and Kumamoto, H., *Reliability Engineering and Risk Assessment*, Prentice-Hall, Englewood Cliffs, NJ, 1981

[HEY84] Heyman, D.P., and Sobel, M.J., *Stochastic Optimization*, McGraw-Hill, London, 1984

[HOA03] Edited by Hoang Pham, *Handbook of Reliability Engineering*, Springer, Berlin, 2003

[HOO03] Hoorn, M.C.H van, *An Evaluation of a Concept for Reliability Prediction and Optimization through Degradation Analysis and Robust Design*, Master thesis, Technische Universiteit Eindhoven, 2003

[HUL03] Hulsken, G, Brombacher, A.C., Bogaard, J.A. van den, Wynn, H.P., Di Bucchianico, A., Peeters, B., Theunissen, T., and Shangguan, D., *End-of-Life Management of Electronics Products Through Functional Signature Analysis*, Proceedings of APEX, 2004

[HUN96] Hunt, T.M., *Condition monitoring of mechanical and hydraulic plant: a concise introduction and guide*, Chapman & Hall, London, 1996

[JEN82] Jensen, F., and Petersen, N.E., *Burn-In*, John Wiley & Sons, Chichester, 1982

[JEN95] Jensen, F., *Electronic Component Reliability: Fundamentals, Modelling, Evaluation, and Assurance,* John Wiley & Sons, Inc., 1995

[JOH70] Johnson, N.L, and Kotz, S., *Continuous Univariate Distributions*, Vols. 1 and 2. Houghton Mifflin, Boston, Massachusetts, 1970

[JON99] Jones, J., and Hayes, J., *A Comparison of Electronic-Reliability Prediction Models*, IEEE Transactions on Reliability, Vol. 48, No. 2, 127-134, 1999

[JON01] Jones, J., and Hayes, J., *Estimation of System Reliability Using a "Non-Constant Failure Rate" Model*, IEEE Transactions on Reliability, Vol. 50, No. 3, 286-288, 2001

[KAP77] Kapur, K.C., and Lamberson, L.R., *Reliability in engineering Design*, John Wiley & Sons, Inc., 1977

[KEC93] Kececioglu, D.B., *Reliability and Life Testing handbook*, Prentice-Hall, Englewood Cliffs, 1993-1994

[KEC94] Kececioglu, D.B., *Reliability and Life Testing handbook Volume 2*, Prentice-Hall, Englewood Cliffs, 1994

[KUM96] Kumar, D., and Westberg, U., *Proportional Hazards Modeling of Time-Dependent Covariates Using Linear Regression: A Case Study*, IEEE Transactions on Reliability, Vol. 45, No. 3, 386-392, 1996

[KUM00] Kumar, D.U., Crocker, J., Knezevic, J., El-Haram, M., *Reliability, Maintenance and Logistic Support – A Life Cycle Approach*, Kluwer Academic Publishers, Boston, 2000

[KZA79] Kzaley, J.G., *AN/UYK-20 Computer Production Reliability Test*, Proceedings of the Annual Reliability And Maintainability Symposium, 1979

[KNE97] Knezevic, J., *Systems Maintainability*, Kluwer Academic Publ., 1997

[KRA88] Kragel'skii, I.V., Mikhin, M.N., Spektor, M., Dunaevsky, V.V., *Handbook of friction units of machines*, ASME Press, New York, 1988

[LAM99] Lambert, A.J.D., *Optimal disassembly sequence generation for combined material recycling and part reuse*, Assembly and task planning (ISATP '99): proceedings of the 1999 international symposium, 146-151, 1999

[LAM04] Lamers, G.J.C., *An evaluation of using service data for ROMDA*, Master thesis, Technische Universiteit Eindhoven, 2004

[LAN93] Landheer, D., De Gee, A.W.J., *Dynamische contactverschijnselen*, Technische Universiteit Eindhoven, 1993

[LAW82] Lawless, J.F., *Statistical Models and Methods for Lifetime Data*, Johan Wiley & Sons, Inc., 1982

[LEE95] Leemis, L.M., *Reliability – Probabilistic Models and Statistical Methods*, Prentice-Hall, Englewood Cliffs, New Jersey, 1995

[LEE96] Leeuw, A.C.J. de, *Bedrijfskundige Methodologie: Management van onderzoek*, Van Gorcum, Assen, 1996 (In Dutch)

[LEG96] Legat V., A. H. Zaludova, V. Cervenka and V. Jurca., *Contribution to Optimization of Preventive Replacement*, Reliability Engineering and System Safety 51, 259-266, 1996

[LEW87] Lewis, E.E., *Introduction to Reliability Engineering*, John Wiley & Sons, New York, 1987

[LEW94] Lewis, E.E., and Chen, H., *Load-Capacity interference and the Bathtub curve*, 1994

[LEW96] Lewis, E.E., *Introduction to Reliability Engineering (2^{nd})*, John Wiley & Sons Inc., 1996

[LIN00] Lin, T.Y., and Yak, A.S., *Reliability by Robust Design for Optical Alignment in a CD Pickup*, IEEE Transactions on Mechatronics, Vol. 5, No. 4, 386-393, 2000

[LU93] Lu, C.J, and Meeker, W.Q., *Using degradation measures to estimate a Time-to-failure distribution*, Technometrics, Vol. 35, No. 2, 1993

[LU95] Lu, D.J., Meeker, W.Q., and Escobar, L.A., *A comparison of degradation and failure-time analysis methods of estimation a time-to-failure distribution*, Department of Statistics, Iowa State University, 1995

[LU02] Lu, Y., *Analysing reliability problems in concurrent fast product development*, PhD-thesis, Technische Universiteit Eindhoven, Eindhoven, 2002

[MAL03] Malucci, R.D., *Fretting corrosion degradation, threshold behavior and contact instability*, Electrical Contacts. Proceedings of the Forty-Ninth IEEE Holm Conference, 2003

[MAN74] Mann, N.R., Schafer, R.E., and Singpurwalla, N.D., *Methods for Statistical Analysis of Reliability and Life Data*, John Wiley & Sons, Inc., 1974

[MCS02] McSorley, E.O., Lu, J.C., and Li, C.S., *Performance of Parameter-Estimates in Step-Stress Accelerated Life-Tests With Various Sample-Sizes*, IEEE Transactions on Reliability, Vol. 51, No. 3, 271-277, 2002

[MEE93] Meeker, W.Q., and Escobar, L.A., *A review of recent research and current issues in accelerated testing*, International Statistical Review; **61**: 147-168, 1993

[MEE95a] Meeker, W.Q., and Hamada, M., *Statistical Tools for the Rapid Development & Evaluation of High-Reliability Products*, IEEE Transactions on Reliability, Vol. 44, No. 2, 187-198, 1995

[MEE95b] Meeker, W.Q., and LuValle, M.J., *An Accelerated Life Test Model Based on Reliability Kinetics*, Technometrics, Vol. 37, No. 2, 133-146, 1995

[MEE98a] Meeker, W.Q., and Escobar, L.A., *Statistical Methods for Reliability Data*, John Wiley & Sons, Inc., New York, 1998

[MEE98b] Meeker, W.Q., Escobar, L.A., and Lu, C.J., *Accelerated Degradation Tests: Modeling and Analysis*, Technometrics, Vol 40, No. 2, 89-99, 1998

[MEE98c] Meeker, W.Q., and Escobar, L.A., *Pitfalls of Accelerated Testing*, IEEE Transactions on Reliability, Vol. 47, No. 2, 114-118, 1998

[MEY87] Meyers, R., and Randazzo, E., *Analytical Spares Screening Evaluation Technique (ASSET)*, Proceedings of the Annual Reliability and Maintainability Symposium, 1987

[MIL61] Milligan, G.W., *Semiconductor Failures vs Removals*, a chapter in the book “Semiconductor Reliability”, edited by J.E. Shwop and H.J. Sullivan, published by AC Book Co., 1961

[MIL65] *Military standardization handbook Reliability Prediction of Electronic Equipment MIL-HDBK-217E*, United States Department of Defense, 1987

[MIL87] *Military handbook Reliability Prediction of Electronic Equipment MIL-HDBK-217A*, United States Department of Defense, 1965

[MON99] Montgomery, D.C., and Runger, G.C., *Applied statistics and probability for engineers*, 2nd edition, John Wiley and Sons, New York, 1999

[MUR02] Murthy, D.N.P, and Djamaludin, I., *New Product Warranty: A Literature Review*, International Journal of Production Economics, 79, 231-260, 2002

[MYU03] Myung, I. J., *Tutorial on maximum likelihood estimation*, Journal of Mathematical Psychology, Vol. 47, 90-100, 2003

[NAI02] Nair, J.H., and Sabnis, S.V., *A Reliability Test-Plan for Series Systems With Components Having Stochastic Failure Rates*, IEEE Transactions on Reliability, Vol. 51, No. 1, 17-22, 2002

[NEL73] Nelson, C.R., *Applied Time Series Analysis for Managerial Forecasting*, Holden-Day, Inc., San Francisco, 1973

[NEL82] Nelson, W., *Applied Life Data Analysis*, John Wiley & Sons, Inc., New York, 1982

[NEL90] Nelson, W., *Accelerated testing: statistical models, test plans, and data analysis*, Wiley-Interscience, Chichester, 1990

[OGA03] Ogasawara, H., *Correlations among Maximum Likelihood and Weighted/Unweighted Least Squares Estimators in Factor Analysis*, Behaviormetrika, Vol. 30, No. 1, 63-86, 2003

[ORM02] Ormon, S.W., Cassady, C.R., and Greenwood, A.G., *Reliability Prediction Models to Support Conceptual Design*, IEEE Transactions on Reliability, Vol. 51, No. 2, 151-157, 2002

[OSA02] Osaki, S., *Stochastic Models in Reliability and Maintenance*, Springer, Berlin, 2002

[PAI95] Painton, L., and Campbell, J., *Genetic Algorithms in Optimization of System Reliability*, IEEE Transactions on Reliability, Vol. 44, No. 2, 172-178, 1995

[PAR96] Park, S.H., *Robust Design and Analysis for Quality Engineering*, Chapman & Hall, London, 1996

[PAR97] Parkinson, D.B., *Robust Design by Variability Optimization*, Quality and Reliability Engineering International, Vol. 13, 97-102, 1997

[PEC68] Peck, D.S., *Semiconductor Device Life and System Removal Rates*, Proceedings of the Annual Symposium on Reliability, 1968

[PEC95] Pecht, Michael (ed.), *The Product Reliability, Maintainability, and Supportability Handbook*, CRC Press, New York, ISBN 0-8493-9457-0, 1995

[PHA89] Phadke, M.S., *Quality Engineering using Robust Design*, Prentice Hall International, London, 1989

[RAO92] Rao, S.S., *Reliability Based Design*, McGraw-Hill, Inc., New York, 1992

[RAO96] Edited by Rao, B.K.N., *Handbook of Condition Monitoring*, Elsevier Science, Kidlington, 1996

[ROY01] Roy, D., and Dasgupta, T., *A Descretizing Approach for Evaluating Reliability of Complex Systems Under Stress-Strength Model*, IEEE Transactions on Reliability, Vol. 50, No. 2, 145-150, 2001

[SPA99] Spanos, A., *Probability theory and statistical inference*, Cambridge University Press, Cambridge, UK, 1999

[SPE88] Spence, R., and Singh Soin, R., *Tolerance Design of Electronic Circuits*, Addison Wesley, 1988

[STR86] Strien, P.J. van, *Praktijk als wetenschap*, Van Gorcum, Assen, 1986

[TAG76] Taguchi, G. and Wu, Y., *Introduction to Off-line Quality Control*, Central Japan Quality Control Association, Nagara, 1976

[TAN95] Tang, L.C., and Chang, D.S., *Reliability Prediction Using Nondestructive Accelerated-Degradation Data: Case Study on Power Supplies*, IEEE Transactions on Reliability, Vol. 44, No. 4, 562-566, 1995

[TAN96] Tang, L.C., Sun, Y.S., Goh, T.N., and Ong, H.L., *Analysis of Step-Stress Accelerated-Life-Test Data: A New Approach*, IEEE Transactions on Reliability, Vol. 45, No. 1, 69-74, 1996

[TSE94] Tseng, S.T., Hamada, M.S., and Chiao, C.H., *Using Degradation Data from a Fractional Factorial Experiment to Improve Fluorescent Lamp Reliability*, Research Report no. RR-94-05, The Institute for the Improvement in Quality and Productivity, University of Waterloo, Waterloo, Ontario, Canada, 1994

[TYO97] Tyoskin, O.I., and Sonkina, T., *Parametric Reliability-Prediction Based On Small Samples*, IEEE Transactions on Reliability, Vol. 46, No. 3, 394-399, 1997

[VER99] Verschuren, P., and Doorewaard, H., *Designing a Research Project*, Lemma, Utrecht, 1999

[VIE88] Viertl, R., *Statistical methods in accelerated life testing*, Vandenhoeck & Ruprecht, Goettingen, 1988

[VIS04] Visser, I.M. de, *A practical application of a concept for reliability prediction and optimization through degradation analysis and robust design*, Master thesis, Technische Universiteit Eindhoven, 2004

[WAN02] Wang, K.S., Hsu, F.S., and Liu, P.P., *Modeling the bathtub shape hazard rate function in terms of reliability*, Reliability Engineering & System Safety 75, 397-406, 2002

[WEE02] Directive 2002/95/EC of the European Parliament and Council on waste electrical and electronic equipment (WEEE), 2002

[WHE92] Wheelwright, S.C. and Clark, K.B., *Revolutionizing product development: Quantum leaps in speed, efficiency and quality*, Free Press, 1992

[WIL94] Williams, J.H., Davies, A., and Drake, P.R., *Condition-based maintenance and machine diagnostics*, Chapman & Hall, London, 1994

[WOL99] Wolstenholme, L.C., *Reliability Modeling – A Statistical Approach*, Chapman & Hall/CRC, Boca Raton, Florida, 1999

[WON88] Wong, K.L., and Lindstrom, D.L., *Off The Bathtub onto The Roller-Coaster Curve*, Proceedings Annual Reliability and Maintainability Symposium, IEEE, 1988

[WON90] Wong, K.L., *Demonstrating Reliability and Reliability growth with Environmental Stress Screening Data*, 1990

[WON95] Wong, K.L., *A New Framework For Part Failure-Rate Prediction Models*, IEEE Transactions on Reliability, Vol. 44, No. 1, 139-146, 1995

[WU00a] Wu, S.J., and Tsai, T.R., *Estimation of Time-to-Failure Distribution Derived from a Degradation Model Using Fuzzy Clustering*, Quality and Reliability Engineering International, 16, 261-267, 2000

[WU00b] Wu, Y., and Wu, A., *Taguchi Methods for Robust Design*, ASME Press, New York, 2000

[WU02] Wu, S.J., and Chang, C.T., *Optimal Design of Degradation Tests in Presence of Cost Constraints*, Reliability Engineering and System Safety, 76, 109-115, 2002

[YAN98] Yang, K., and Yang, G., *Robust Reliability Design Using Environmental Stress Testing*, Quality and Reliability Engineering, 14, 409-416, 1998

[YAN02] Yang, G., Yang, K., *Accelerated degradation-tests with tightened critical values*, IEEE Transactions on Reliability, Volume 51, issue: 4, 463–468, 2002

[ZHA02] Zhang, C., Chuckpaiwong, I., Liang, S.Y., and Seth, B.B., *Mechanical Component Lifetime Estimation Based on Accelerated Life Testing with Singularity Extrapolation*, Mechanical System and Signal Processing, 16(4), 705-718, 2002

Appendix 1 Preliminaries to reliability analysis

Let a single lifetime variable T be a nonnegative random variable representing the lifetimes of individuals in some population. Usually T is assumed to be continuous, which is what will be assumed in this part.

All functions, unless stated otherwise, are defined over the interval $[0,\infty)$. Let $f(t)$ denote the probability density function (PDF) of T and let the distribution function be

$$F(t) = \Pr(T \le t) = \int_0^t f(\tau)d\tau \tag{A1.1}$$

The probability of an individual surviving till time t is given by the reliability function

$$R(t) = \Pr(T \ge t) = \int_t^\infty f(\tau)d\tau \tag{A1.2}$$

When lifetimes of manufactured items are involved, $R(t)$ is referred to as the reliability function. Without interference, e.g. maintenance, $R(t)$ is a monotone decreasing continuous function with $R(0)=1$ and $R(\infty)=\lim_{t\to\infty} R(t)=0$.

Another useful concept having to do with lifetime distributions is the hazard function, or failure rate, $h(t)$, defined as

$$h(t) = \lim_{\Delta t\to 0} \frac{\Pr(t \le T + \Delta t | T \ge t)}{\Delta t} = \frac{f(t)}{R(t)} \tag{A1.3}$$

The hazard function specifies the instantaneous rate of death or failure at time $t + \Delta t$, given that the individual survives up till *t*. And $h(t)\Delta t$ is the approximate probability of death in $[t, t + \Delta t)$, given survival up till *t*.

The hazard function *h(t)* for a continuous lifetime distribution possesses the properties

$$h(t) \geq 0, \qquad \int_0^\infty h(t)dt = \infty \tag{A1.4}$$

The functions *f(t)*, *F(t)*, *R(t)*, and *h(t)* give mathematically equivalent specifications of the distribution of *T*.

For some purposes it is also useful to define the cumulative hazard function

$$H(t) = \int_0^t h(\tau)d\tau\ , \ \ t \geq 0 \tag{A1.5}$$

H(t) has the following characteristics

$$H(0) = 0, \qquad \lim_{t\to\infty} H(t) = \infty\ , \quad H(t) \text{ is nondecreasing.} \tag{A1.6}$$

The matrix in table A1.1 from Leemis [LEE95] shows that any of the other lifetime distribution representations (given by the columns) can be found if one of the representations (given by the rows) is known.

Table A1.1: Lifetime distribution representation relationships.

	f(t)	*R(t)*	*h(t)*	*H(t)*
f(t)	-	$\int_t^\infty f(\tau)d\tau$	$\dfrac{f(t)}{\int_t^\infty f(\tau)d\tau}$	$-\log\left[\int_t^\infty f(\tau)d\tau\right]$
R(t)	$-R'(t)$	-	$\dfrac{-R'(t)}{R(t)}$	$-\log R(t)$
h(t)	$h(t)e^{-\int_0^t h(\tau)d\tau}$	$e^{-\int_0^t h(\tau)d\tau}$	-	$\int_0^t h(\tau)d\tau$
H(t)	$H'(t)e^{-H(t)}$	$e^{-H(t)}$	$H'(t)$	-

Appendix 2 Form validation

Approximate Solution: Response as a general function of multiple random variables.

$$PC = g(DP_1, DP_2, \cdots, DP_n) \tag{A2.1}$$

This function could be non-linear. If the mean and variance of each DP_i are known, but the distribution is unknown, the approximate mean and variance of PC can be estimated.

Expanding the function $g(DP_1, DP_2, \cdots, DP_n)$ in a Taylor series about the mean values $\mu_{DP_1}, \mu_{DP_2}, \cdots, \mu_{DP_n}$ one obtains,

$$\begin{aligned} PC &= g(\mu_{DP_1}, \mu_{DP_2}, \cdots, \mu_{DP_n}) + \sum_{i=1}^{n}(DP_i - \mu_{DP_i})\frac{\partial g}{\partial DP_i} \\ &+ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(DP_i - \mu_{DP_i})(DP_j - \mu_{DP_j})\frac{\partial^2 g}{\partial DP_i \partial DP_j} + higher order terms \end{aligned} \tag{A2.2}$$

where the derivatives are evaluated at the mean values of the *DP_i's*.

Truncating the series at the linear terms, the first-order approximation mean of PC, denoted as $E(PC^{|})$, can be obtained as:

$$E(PC^{|}) \approx g(\mu_{DP_1}, \mu_{DP_2}, \cdots, \mu_{DP_n}) \tag{A2.3}$$

which indicates that the first-order mean of PC is approximated by the value of the function evaluated at the mean values of the *DP_i's*. The first-order variance of PC, denoted as $VAR(PC^{|})$, can be shown as:

$$VAR(PC^{I}) \approx \sum_{i=1}^{n} \frac{\partial g}{\partial DP_i} VAR\left(DP_i\right) + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial g}{\partial DP_i}\frac{\partial g}{\partial DP_j} COV\left(DP_i, DP_j\right) \tag{A2.4}$$

or

$$VAR(PC^{I}) \approx \sum_{i=1}^{n} E_i^2 VAR\left(DP_i\right) + \sum_{i=1}^{n}\sum_{j=1}^{n} E_i E_j COV\left(DP_i, DP_j\right) \tag{A2.5}$$

or

$$VAR(PC^{I}) \approx \sum_{i=1}^{n}\sum_{j=1}^{n} E_i E_j COV\left(DP_i, DP_j\right), \tag{A2.6}$$

where E_i and E_j are constants and are the values of the partial derivatives $\frac{\partial g}{\partial DP_i}$ and $\frac{\partial g}{\partial DP_j}$, respectively, evaluated at the mean values of the *DP_i's*.

If the *DP_i's* are not correlated, then equation (A.6) reduces to

$$VAR(PC^{I}) \approx \sum_{i=1}^{n} E_i^2 VAR(DP_i) \tag{A2.7}$$

The coefficients E_i can be interpreted as amplification factors for the uncertainties in each of the corresponding random variables *DP_i's*. In general, these amplification factors will show the importance of the variables involved in the formulation. This type of probabilistic approach will also help to identify primary and secondary variables in problems where a large number of variables are involved.

This approximation of the mean and variance of PC can be improved by including the higher-order terms in the Taylor series expansion of $g(DP_1, DP_2, \cdots, DP_n)$. If DP_i and DP_j are not correlated, the second-order mean of PC, denoted as $E(PC^{II})$, can be shown to be:

$$E(PC^{\|}) \approx g(\mu_{DP_i}, \mu_{DP_2}, \cdots, \mu_{DP_n}) + \frac{1}{2}\sum_{i=1}^{n}\frac{\partial^2 g}{\partial DP_i^2} VAR(DP_i) \qquad \text{(A2.8)}$$

Again, the partial derivatives are evaluated at the mean values of all DP_i*'s*. To estimate the second-order variance of PC, the information on the third and fourth moments of the DP_i*'s* must be available. However, in most cases this information will not be available. The use of the second-order mean and the first-order variance is considered adequate for most practical engineering applications.

Appendix 3 Simulation experiments: "simple model"

This appendix shows the results of the simulation experiments of the "Simple Model", as discussed in section 4.2.3. In these simulation experiments the Monte Carlo method is used to simulate 1000 products of a certain nominal design. The design parameters R_1 and R_2 can be set at various levels between 0 Ω and 10 Ω. Both design parameters R_1 and R_2 are subjected to variability and degradation. The input voltage V_{in} is constant and 10 Volts during each run of the screening simulation experiments. The degradation models of R_1 and R_2 are:

$$\begin{aligned} R_1(t) &= R_{10}(1+5\cdot 10^{-3}\cdot t) \\ R_2(t) &= R_{20}(1+5\cdot 10^{-4}\cdot t) \end{aligned} \tag{A3.1}$$

Figure B.1 shows failure rate curves where R_1=R_2.

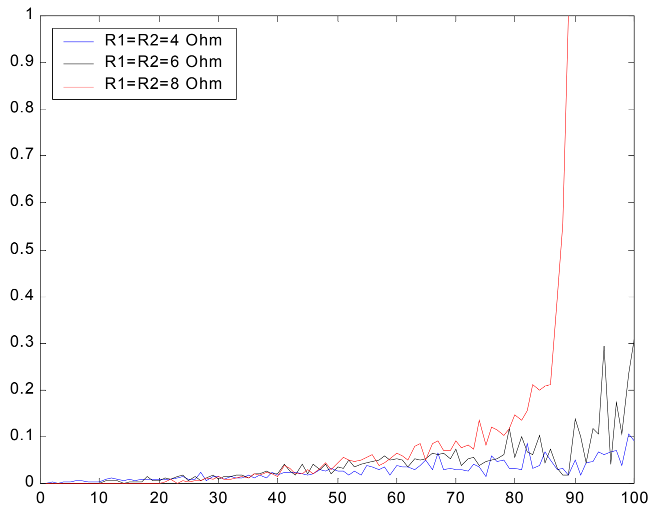


Figure A3.1: Failure rate curves for various levels of R_1=R_2

R_1 is uniformly distributed (σ=0.3 Ω).

R_2 is uniformly distributed (σ=0.3 Ω).

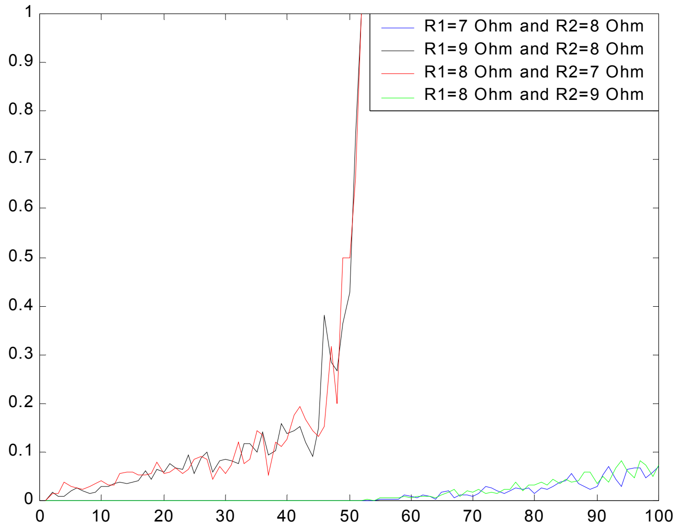


Figure A3.2: Failure rate curves for various levels of $R_1 \neq R_2$

R_1 is uniformly distributed (σ=0.3 Ω).

R_2 is uniformly distributed (σ=0.33 Ω)

Appendix 4 Design matrix "simulation experiments"

This Appendix contains the design matrix and the results of the MTTF and the natural logarithm of the SDTTF of the approach to predict and improve Reliability through *parameter design*. The design matrix and the results of both reliability characteristics are used to obtain the regression models of equation (5.17) and (5.18).

Table A4.1: Design matrix and results MTTF and SDTTF.

run	pattern	R_1	R_2	R_3	R_4	n products	MTTF	ln of SDTTF
1	----	3.75	7.5	0.95	37.5	30	375.04	3.485
2	+---	4.25	7.5	0.95	37.5	30	495.30	3.648
3	-+--	3.75	8.5	0.95	37.5	30	240.34	3.504
4	++--	4.25	8.5	0.95	37.5	30	337.90	3.611
5	--+-	3.75	7.5	1.05	37.5	30	270.69	3.434
6	+-+-	4.25	7.5	1.05	37.5	30	376.42	3.559
7	-++-	3.75	8.5	1.05	37.5	30	149.75	3.164
8	+++-	4.25	8.5	1.05	37.5	30	234.87	3.572
9	---+	3.75	7.5	0.95	42.5	30	410.74	3.462
10	+--+	4.25	7.5	0.95	42.5	30	535.55	3.651
11	-+-+	3.75	8.5	0.95	42.5	30	261.69	3.452
12	++-+	4.25	8.5	0.95	42.5	30	370.86	3.416
13	--++	3.75	7.5	1.05	42.5	30	304.80	3.418
14	+-++	4.25	7.5	1.05	42.5	30	414.54	3.446
15	-+++	3.75	8.5	1.05	42.5	30	177.98	3.477
16	++++	4.25	8.5	1.05	42.5	30	268.83	3.229
17	a000	3.875	8.0	1.00	40.0	30	303.92	3.582
18	A000	4.125	8.0	1.00	40.0	30	348.02	3.258
19	0b00	4.0	7.75	1.00	40.0	30	355.51	3.463
20	0B00	4.0	8.25	1.00	40.0	30	285.02	3.222
21	00c0	4.0	8.0	0.975	40.0	30	355.39	3.531
22	00C0	4.0	8.0	1.025	40.0	30	300.30	3.462
23	000d	4.0	8.0	1.0	38.75	30	321.24	3.497
24	000D	4.0	8.0	1.0	41.25	30	343.63	3.639
25	0000	4.0	8.0	1.0	40.0	30	331.35	3.462

Appendix 5 Results validation test

This appendix contains the results of the validation test of the regression models for the MTTF and the SDTTF of equations (5.17) and (5.18). Tables A5.1 and A5.2 show the levels of the design parameters for each run and the results for the MTTF and the ln(SDTTF) of respectively the computer simulation experiments and the regression models. In the last column the error is tabulated.

Table A5.1: Results validation test for MTTF.

run	R_1	R_2	R_3	R_4	MTTF simulation	MTTF regression	MTTF error
1	3.87	7.51	0.98	39.40	386.00	362.27	23.73
2	4.05	8.39	1.03	41.42	262.37	253.17	9.20
3	3.99	7.70	1.01	40.90	349.03	357.57	-8.54
4	4.20	7.80	0.99	39.81	402.43	405.45	-3.02
5	4.13	8.16	1.02	40.34	312.43	309.99	2.44
6	3.98	7.78	1.00	41.47	362.53	368.09	-5.56
7	3.76	7.97	0.99	37.80	269.77	294.28	-24.49
8	4.16	7.56	1.02	40.51	413.10	388.61	24.49
9	3.97	8.49	1.01	37.75	227.10	224.66	2.44
10	4.06	8.08	1.03	39.58	293.70	294.23	-0.53
11	4.15	7.92	1.05	39.03	326.93	312.03	14.90
12	4.21	8.02	1.00	41.87	384.73	394.10	-9.37
13	4.12	7.83	1.04	37.58	316.77	336.02	-19.25
14	3.84	7.93	0.97	41.34	342.47	348.82	-6.35
15	3.95	7.73	1.04	42.35	335.90	342.58	-6.68
16	4.22	8.08	0.98	42.45	407.23	421.60	-14.37
17	4.21	8.26	0.98	41.44	355.97	363.54	-7.57
18	3.96	8.03	1.04	39.69	266.77	271.97	-5.20
19	4.20	8.14	1.02	39.99	343.50	324.65	18.85
20	3.78	7.71	0.96	38.57	354.77	350.23	4.54

Table A5.2: Results validation test for SDTTF.

run	R_1	R_2	R_3	R_4	ln(SDTTF) simulation	ln(SDTTF) regression	ln(SDTTF) error
1	3.87	7.51	0.98	39.40	3.53	3.11	0.42
2	4.05	8.39	1.03	41.42	3.33	3.25	0.08
3	3.99	7.70	1.01	40.90	3.14	3.37	-0.23
4	4.20	7.80	0.99	39.81	3.45	3.45	0.00
5	4.13	8.16	1.02	40.34	3.28	3.39	-0.11
6	3.98	7.78	1.00	41.47	3.41	3.54	-0.13
7	3.76	7.97	0.99	37.80	3.22	3.76	-0.54
8	4.16	7.56	1.02	40.51	3.76	3.16	0.60
9	3.97	8.49	1.01	37.75	3.21	3.35	-0.14
10	4.06	8.08	1.03	39.58	3.41	3.43	-0.02
11	4.15	7.92	1.05	39.03	3.58	3.51	0.07
12	4.21	8.02	1.00	41.87	3.31	3.69	-0.38
13	4.12	7.83	1.04	37.58	3.50	3.87	-0.37
14	3.84	7.93	0.97	41.34	3.50	3.61	-0.11
15	3.95	7.73	1.04	42.35	3.13	3.69	-0.56
16	4.22	8.08	0.98	42.45	3.71	3.86	-0.15
17	4.21	8.26	0.98	41.44	3.41	3.48	-0.07
18	3.96	8.03	1.04	39.69	3.24	3.41	-0.17
19	4.20	8.14	1.02	39.99	3.86	3.41	0.45
20	3.78	7.71	0.96	38.57	3.42	3.49	-0.07

Appendix 6 Validation models simulation experiment 3

The models expressed in eqn 5.14 and 5.15 are validated to check if they predict the MTTF and the SDTTF without any systematic errors. The error of the prediction is defined as the difference between the value of the simulation experiments (observed value) and the predicted value of the models according to eqn 5.14 and 5.15. The error should be a random variable with mean zero. The validation test consists of 20 runs each with 30 products, with randomly selected settings of the design parameters. These tests are conducted and both the MTTF and the SDTTF are determined with use of the simulation experiment. Also the models of eqn 5.14 and 5.15 are used to predict the MTTF and the SDTTF.

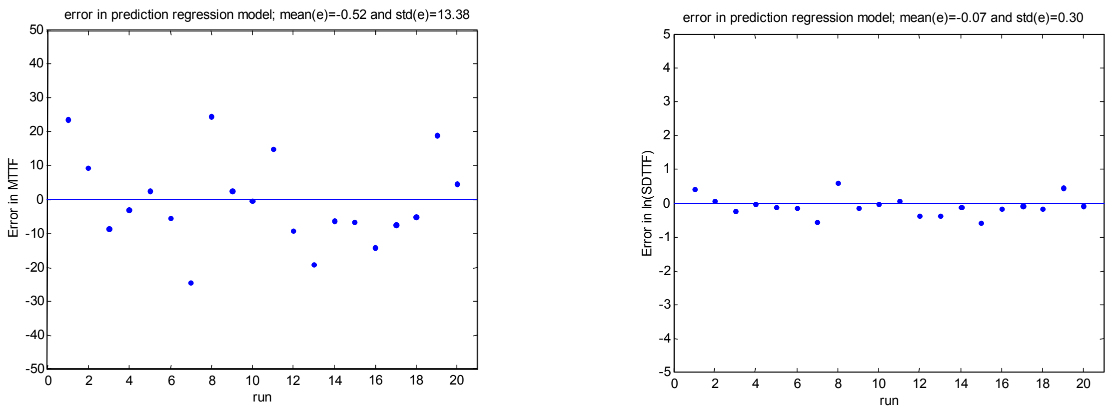


Figure A6.5: Error in MTTF and SDTTF.

Figure A6.5 shows both the error in the prediction of the MTTF and the error in the prediction of the SDTTF for each run of the validation test. Both plots show that the mean value of the error terms is approximately zero and that these error terms are randomly distributed around this mean value. Hence, it can be concluded that the predictions of the MTTF and the SDTTF contain no systematic errors.

Appendix 7 The desirability approach

The *Desirability Approach* is a method that assigns a "score" to a set of responses and chooses parameter settings that maximize this score. For each response $Y_i(x)$, a desirability function $d_i(Y_i)$ assigns numbers between 0 and 1 to possible values of Y_i, with $d_i(Y_i)=0$ representing a completely undesirable value of Y_i and $d_i(Y_i)=1$ representing a completely desirable or ideal response value.

The two individual desirabilities are then combined using the geometric mean, which gives the *Overall Desirability D* [DER80]:

$$D = (d_1(Y_1) \times d_2(Y_2))^{1/2} \tag{A7.1}$$

with $d_1(Y_1)$ the desirability function of the MTTF and $d_2(Y_2)$ the desirability function of the SDTTF. This *Overall Desirability* has to be maximized with respect to the controllable design parameters.

Depending on whether a particular response is to be maximized or minimized, different desirability functions can be used. The desirability functions used here, are proposed by Derringer and Suich [DER80]. The desirability function for maximizing a response, in this case the MTTF (Y_1), is defined as:

$$d_1(Y_1) = \begin{cases} 0 & if \quad Y_1 < L_1 \\ \left(\dfrac{Y_1 - L_1}{T_1 - L_1}\right) & if \ L_1 \le Y_1 \le T_1 \\ 1.0 & if \quad Y_1 > T_1 \end{cases} \tag{A7.2}$$

with L_1 the lower value and T_1 the target value that are desired for the MTTF.

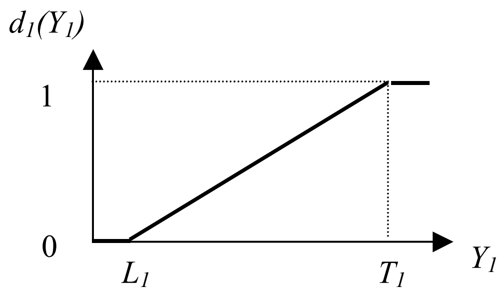


Figure A7.1: Desirability function for MTTF.

The desirability function provided for minimizing a response, the SDTTF (Y_2), is of the form:

$$d_2(Y_2) = \begin{cases} 1.0 & \text{if} \quad Y_2 \le T_2 \\ \left(\dfrac{Y_2 - U_2}{T_2 - U_2} \right) & \text{if } T_2 < Y_2 \le U_2 \\ 0 & \text{if} \quad Y_2 > U_2 \end{cases} \tag{A7.3}$$

with U_2 the upper value and T_2 the target value which are intended for the standard deviation of the time-to-failure.

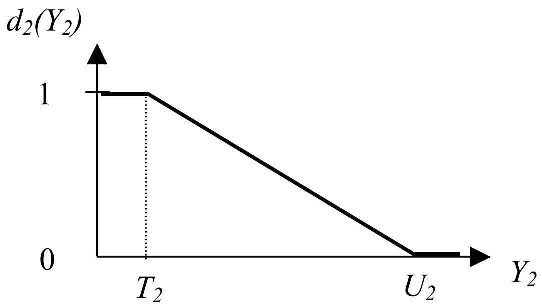


Figure A7.2: Desirability function for SDTTF.

In order to maximize the *Overall Desirability*, levels for the upper, lower and target values have to be chosen. The levels of these values are given in table A7.1.

Table A7.1: Values of the desirability functions.

	Lower value MTTF: L_1	**Target value MTTF: T_1**	**Target value SDTTF: T_2**	**Upper value SDTTF: U_2**
Levels	20	600	0	40

The lower value L_1 of the MTTF is chosen to be 20 because this approach only makes use of data starting from time t_{20} while the target value T_1 is set on 600. This level is chosen after studying the results of the simulation experiments, which show that the MTTF will not exceed this value. The target value T_2 of the SDTTF is obviously zero in order to minimize this characteristic. Again the upper value U_2 is chosen after studying the simulation experiments and is set on the level of 40 as shown above in table A7.1.

The two desirability functions and the upper, lower, and target values are used to determine the *Overall Desirability* for every combination of the MTTF and the SDTTF obtained by setting the design parameters on different levels. Next, a sequential optimization is used to find design parameter settings that result in the maximum *Overall Desirability*. Figure A7.3 shows an example of a sequential optimization for two design parameters.

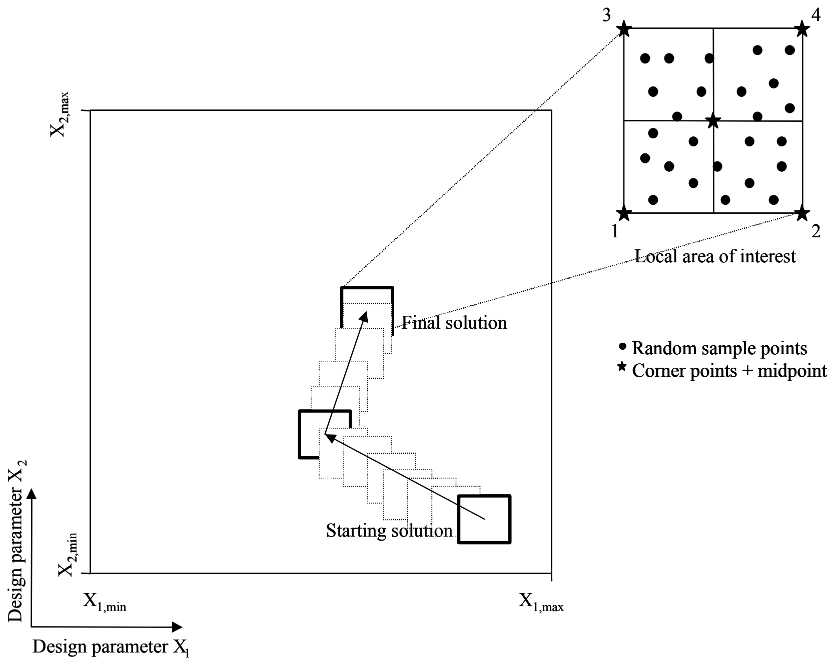


Figure A7.3: Sequential optimization approach [BIS01].

In every optimization step, a random sample of 100 products within a local area of interest (see figure 5.10) is used to determine the "optimal" setting of the design parameters for that particular optimization step. The entire design region in which the optimization takes place is equal to the region used in the Design of Experiments (table 5.4). The "optimal" setting of the design parameters in each subsequent local area of interest is used to center a new region for sampling in the next sequential optimization step, until no further improvement of the *Overall Desirability* is observed. This will ultimately lead to the optimal setting of the design parameters, which provides the maximum *Overall Desirability*.

Appendix 8 ”Main tray experiments”

This appendix contains the results of the ‘Main Tray Experiments’ conducted on the 29th and the 30th of May 2002 at Flextronics.

The results (below) show that three factors have dominant influence on the current rise time, namely the voltage of the PWBA (U24), load of the rolls mechanism (Motor load) and the resistance of the PWBA (PwbaRs). Since the voltage of the PWBA (U24) is rather constant and dependent of the resistance on the PWBA, it is chosen to exclude this factor in these experiments.

The influence of load on the current rise time is shown in the current profiles on the left-hand side. An increase in the load will result in a decrease of the current rise time.

Effect Screening T_pr1_t1

The parameter estimates are not correlated.
The parameter estimates have equal variances.

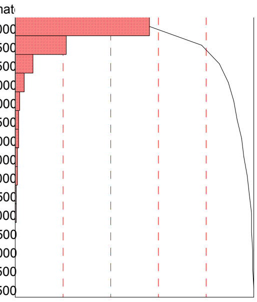
	Lenth PSE
t-Test Scale	0.06375
Coded Scale	0.0159375

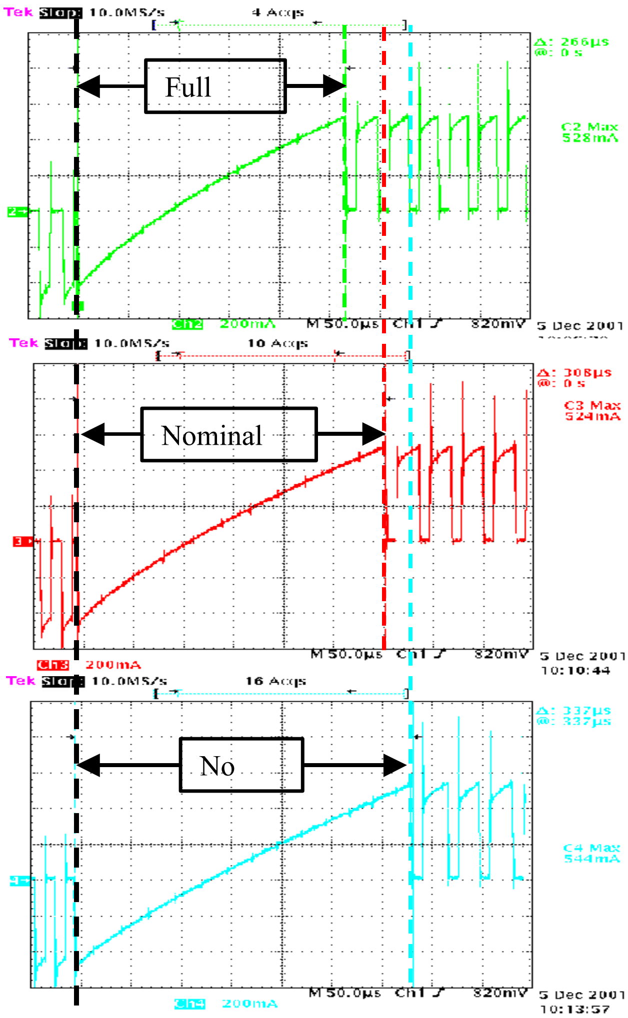
Parameter Estimate Population

Term	Origina	Orthog Codec	Orthog t-Test	Prob>|t|
Intercept	5.03625	5.03625	316.0000	<.0001
U24v(22,26)	-0.55500	-0.55500	-34.8235	<.0001
	-0.01250	-0.01250	-0.7843	0.4451
MotorLoad(0,6.5)	-0.21375	-0.21375	-13.4118	<.0001
PwbaRs(0,0.75)	-0.07375	-0.07375	-4.6275	0.0003
	0.00250	0.00250	0.1569	0.8774
	-0.01250	-0.01250	-0.7843	0.4451
	-0.01625	-0.01625	-1.0196	0.3241
	0.00875	0.00875	0.5490	0.5911
	-0.00125	-0.00125	-0.0784	0.9385
U24v(22,26)*MotorLoad(0,6.5)	0.03750	0.03750	2.3529	0.0327
U24v(22,26)*PwbaRs(0,0.75)	0.02250	0.02250	1.4118	0.1784
	-0.00125	-0.00125	-0.0784	0.9385
	0.00375	0.00375	0.2353	0.8172
	0.01500	0.01500	0.9412	0.3615
	-0.00750	-0.00750	-0.4706	0.6447

Pareto Plot of Transformed Estimates

Term	Orthog Estimat
U24v(22,26)	-0.5550000
MotorLoad(0,6.5)	-0.2137500
PwbaRs(0,0.75)	-0.0737500
U24v(22,26)*MotorLoad(0,6.5)	0.0375000
U24v(22,26)*PwbaRs(0,0.75)	0.0225000
U5v(4.5,5.5)	-0.0162500
U24v(22,26)*U5v(4.5,5.5)	0.0150000
BeltTension(1.08,2.16)	-0.0125000
SetSize(5,50)	-0.0125000
Day[1]	0.0087500
U24v(22,26)*Day[1]	-0.0075000
U24v(22,26)*BeltTension(1.08,2.16)	0.0037500
PwbaTemp(28,60)	0.0025000
U24v(22,26)*SetSize(5,50)	-0.0012500
U24v(22,26)*PwbaTemp(28,60)	-0.0012500





Current rise time = f(load):
No load: Current rise time=337µs

Nominal Load: Current rise time =308µs

Full Load: Current rise time =266µs

Total Δ current rise time at no/full load=71µs.

Appendix 9 Main experiments

D.O.E. 0	File number	RUN	Set	Pattern	Extra load (Ncm)	Extra resistance	T amb	Humidity	Supply 24V	Supply 5V	Current Rise time	Current Rise time	Current Rise time	Mean rise time
	0	1	1	--	0 Ncm	0 Ω	23	48	24	5	531.2	541	533.41	535.203
	1	1	2				23	48	24	5	539.48	535.17	538.62	537.757
	2	1	3				23	48	24	5	535.78	534.61	532.95	534.447
	3	1	4				23	48	24	5	535.16	533.38	541.25	536.597
	4	1	5				23	48	24	5	540.15	536.35	531.29	535.93
	5	2	1	-+	0 Ncm	0,04 Ω	23	48	24	5	534.76	539.59	539.36	537.903
	6	2	2				23	48	24	5	542.89	535.86	537.37	538.707
	7	2	3				23	48	24	5	534.23	544.99	538.95	539.39
	8	2	4				23	48	24	5	542.22	525.17	538.36	535.25
	9	2	5				23	48	24	5	532.88	538.98	537.55	536.47
	10	3	1	00	0,4Ncm	0,02 Ω	23	48	24	5	543.96	544.32	543.63	543.97
	11	3	2				23	48	24	5	541.75	535.39	545.11	540.75
	12	3	3				23	48	24	5	541.8	542.91	543	542.57
	13	3	4				23	48	24	5	541.93	537.27	535.61	538.27
	14	3	5				23	48	24	5	546.18	540.17	537.03	541.127
	15	4	1	0-	0,4Ncm	0 Ω	23	48	24	5	541.46	531.39	540.59	537.813
	16	4	2				23	48	24	5	540.92	536.95	536.97	538.28
	17	4	3				23	48	24	5	544.2	532.97	532.34	536.503
	18	4	4				23	48	24	5	537.76	539.57	537.24	538.19
	19	4	5				23	48	24	5	530.81	537.34	533.65	533.933
	20	5	1	00	0,4Ncm	0,02 Ω	23	48	24	5	539.91	533.62	533.71	535.747
	21	5	2				23	48	24	5	535.23	538.38	544.14	539.25
	22	5	3				23	48	24	5	541.23	537.06	539.78	539.357
	23	5	4				23	48	24	5	532.37	540.82	532.05	535.08
	24	5	5				23	48	24	5	537.62	541.91	537.35	538.96
	25	6	1	+-	0,8Ncm	0 Ω	23	48	24	5	537.85	533.11	535.96	535.64
	26	6	2				23	48	24	5	539.07	534.28	537.2	536.85
	27	6	3				23	48	24	5	538.93	541.91	538.91	539.917
	28	6	4				23	48	24	5	547.36	544.5	551.02	547.627
	29	6	5				23	48	24	5	544.25	551.97	548.1	548.107
	30	7	1	++	0,8Ncm	0,04 Ω	23	48	24	5	539.3	542.27	533.62	538.397
	31	7	2				23	48	24	5	537.74	543.06	539.24	540.013
	32	7	3				23	48	24	5	538.43	543.4	531.69	537.84
	33	7	4				23	48	24	5	536.14	537.07	538.72	537.31
	34	7	5				23	48	24	5	536.74	532.75	538.02	535.837
	35	8	1	0+	0,4Ncm	0,04 Ω	23	48	24	5	538.39	540.19	535.91	538.163
	36	8	2				23	48	24	5	538.45	538.85	537.05	538.117
	37	8	3				23	48	24	5	541.04	535.36	540.1	538.833
	38	8	4				23	48	24	5	541.04	540.25	537.19	539.493
	39	8	5				23	48	24	5	532.05	540.98	539.27	537.433
	40	9	1	00	0,4Ncm	0,02 Ω	23	48	24	5	538.27	537.68	537.91	537.953
	41	9	2				23	48	24	5	541.3	543.3	536.8	540.467
	48	9	3				23	48	24	5	541.46	542.62	539.1	541.06
	49	9	4				23	48	24	5	534.72	541.71	538.68	538.37
	50	9	5				23	48	24	5	532.86	541.96	538.53	537.783
	51	10	1	+0	0,8Ncm	0,02 Ω	23	48	24	5	540.89	535.53	537.44	537.953
	52	10	2				23	48	24	5	537.86	539.48	534.05	537.13
	53	10	3				23	48	24	5	535.13	538.28	535.83	536.413
	54	10	4				23	48	24	5	544.48	536.06	541.44	540.66
	55	10	5				23	48	24	5	534.91	542.19	537.15	538.083
	56	11	1	-0	0 Ncm	0,02 Ω	23	48	24	5	537.42	537.53	534.74	536.563
	57	11	2				23	48	24	5	543.43	538.4	534.51	538.78
	58	11	3				23	48	24	5	536.99	539.85	535.95	537.597
	59	11	4				23	48	24	5	538.25	535.5	539.03	537.593
	60	11	5				23	48	24	5	536.78	535.19	540.77	537.58

D.O.E.1	File number	RUN	Set	Pattern	Extra load (Ncm)	Extra resistence	T amb	Humidity	Supply 24V	Supply 5V	Current Rise time	Current Rise time	Current Rise time	Mean rise time
	0	1	1	--	4,4 Ncm	0,25 Ω	22	48	24	5	526.31	526.2	519.41	523.9867
	1	1	2				22	48	24	5				no trigger
	2	1	3				22	48	24	5	524.12	515.3	517.28	518.8933
	3	1	4				22	48	24	5	519.24	516.4	522.85	519.4967
	4	1	5				22	48	24	5	523.01	522	521.71	522.2233
	5	2	1	0-	4,8 Ncm	0,25 Ω	22	48	24	5	518.07	511.6	518.37	516.0067
	6	2	2				22	48	24	5	530.46	515.9	519.13	521.8233
	7	2	3				22	48	24	5	516.24	521.7	519.31	519.0767
	8	2	4				22	48	24	5	521	523.8	518.49	521.11
	9	2	5				22	48	24	5				no trigger
	10	3	1	+-	5,2 Ncm	0,25 Ω	22	48	24	5	516.20	516.63	512.97	515.27
	11	3	2				22	48	24	5	518.00	518.75	518.71	518.49
	12	3	3				22	48	24	5	520.55	519.06	515.75	518.45
	13	3	4				22	48	24	5	518.56	518.53	512.89	516.66
	14	3	5				22	48	24	5	515.29	510.33	515.72	513.78
	15	4	1	0+	4,8 Ncm	0,29 Ω	22	48	24	5	522.18	525.35	526.36	524.63
	16	4	2				22	48	24	5	521.23	523.93	526.52	523.89
	17	4	3				22	48	24	5	520.38	512.77	527.82	520.32
	18	4	4				22	48	24	5	526.41	522.64	515.86	521.64
	19	4	5				22	48	24	5	516.89	521.18	524.46	520.84
	20	5	1	-+	4,4 Ncm	0,29 Ω	22	48	24	5	532.00	525.76	530.56	529.44
	21	5	2				22	48	24	5	518.14	528.74	525.01	523.96
	22	5	3				22	48	24	5	529.38	519.29	525.06	524.58
	23	5	4				22	48	24	5	518.33	529.31	517.47	521.70
	24	5	5				22	48	24	5	521.96	538.75	527.81	529.51
	25	6	1	-0	4,4 Ncm	0,27 Ω	22	48	24	5	518.72	530.55	523.13	524.13
	26	6	2				22	48	24	5	523.79	519.19	530.21	524.40
	27	6	3				22	48	24	5	531.78	518.13	519.55	523.15
	28	6	4				22	48	24	5	524.44	524.29	519.22	522.65
	29	6	5				22	48	24	5	521.83	531.17	520.70	524.57
	30	7	1	00	4,8 Ncm	0,27 Ω	22	48	24	5	519.61	528.01	521.00	522.87
	31	7	2				22	48	24	5	525.90	526.09	521.32	524.44
	32	7	3				22	48	24	5	526.13	526.15	521.15	524.48
	33	7	4				22	48	24	5	525.28	518.26	519.78	521.11
	34	7	5				22	48	24	5	518.66	519.40	520.69	519.58
	35	8	1	00	4,8 Ncm	0,27 Ω	22	48	24	5	523.90	523.35	520.51	522.59
	36	8	2				22	48	24	5	524.15	528.52	521.20	524.62
	37	8	3				22	48	24	5	518.38	527.71	523.57	523.22
	38	8	4				22	48	24	5	523.41	524.53	524.01	523.98
	39	8	5				22	48	24	5	513.03	527.50	517.26	519.26
	40	9	1	+0	5,2 Ncm	0,27 Ω	22	48	24	5	528.08	525.44	513.26	522.26
	41	9	2				22	48	24	5	524.72	520.85	519.53	521.70
	42	9	3				22	48	24	5	521.90	518.57	524.86	521.78
	43	9	4				22	48	24	5	508.80	514.81	529.69	517.77
	44	9	5				22	48	24	5	516.27	515.56	527.82	519.88
	45	10	1	++	5,2 Ncm	0,29 Ω	22	48	24	5	522.68	524.61	522.83	523.37
	46	10	2				22	48	24	5	518.80	518.60	526.52	521.31
	47	10	3				22	48	24	5	525.71	520.59	517.41	521.24
	48	10	4				22	48	24	5	527.86	517.98	527.12	524.32
	49	10	5				22	48	24	5	513.75	523.90	514.08	517.24
	50	11	1	00	4,8 Ncm	0,27 Ω	22	48	24	5	518.94	519.87	520.40	519.74
	51	11	2				22	48	24	5	524.95	515.81	520.37	520.38
	52	11	3				22	48	24	5	529.99	523.83	530.45	528.09
	53	11	4				22	48	24	5	521.71	530.65	523.26	525.21
	54	11	5				22	48	24	5	520.05	526.66	519.61	522.11

D.O.E.2	File number	RUN	Set	Pattern	Extra load (Ncm)	Extra resistence	T amb	Humidity	Supply 24V	Supply 5V	Current Rise time	Current Rise time	Current Rise time	Mean rise time
	0	1	1	--	7,6 Ncm	1,05 Ω	23	49	24	5				no trigger
	1	1	2				23	49	24	5	508.33	515.59	519.23	514.38
	2	1	3				23	49	24	5				no trigger
	3	1	4				23	49	24	5	501.96	515.14	515.29	510.80
	4	1	5				23	49	24	5	520.92	514.34	516.84	517.37
	5	2	1	-+	7,6 Ncm	1,09 Ω	23	49	24	5	511.03	516.21	504.86	510.70
	6	2	2				23	49	24	5	517.33	524.37	515.11	518.94
	7	2	3				23	49	24	5	516.64	521.86	506.88	515.13
	8	2	4				23	49	24	5	511.68	521.39	507.81	513.63
	9	2	5				23	49	24	5	522.64	513.93	515.77	517.45
	10	3	1	-0	7,6 Ncm	1,07 Ω	23	49	24	5	509.46	517.48	520.04	515.66
	11	3	2				23	49	24	5	513.41	525.83	512.10	517.11
	12	3	3				23	49	24	5	516.84	510.19	503.60	510.21
	13	3	4				23	49	24	5	516.83	511.77	522.20	516.93
	14	3	5				23	49	24	5	512.93	516.96	506.22	512.04
	15	4	1	0-	8 Ncm	1,05 Ω	23	49	24	5	505.81	508.40	512.21	508.81
	16	4	2				23	49	24	5	503.58	503.02	501.60	502.73
	17	4	3				23	49	24	5	495.36	514.64	509.99	506.66
	18	4	4				23	49	24	5	507.05	517.80	493.48	506.11
	19	4	5				23	49	24	5	499.40	513.21	504.83	505.81
	20	5	1	+0	8,4 Ncm	1,07 Ω	23	49	24	5	502.87	509.00	502.64	504.84
	21	5	2				23	49	24	5	505.17	495.70	515.69	505.52
	22	5	3				23	49	24	5	499.47	500.21	492.33	497.34
	23	5	4				23	49	24	5	489.94	513.79	496.16	499.96
	24	5	5				23	49	24	5	509.42	498.96	509.48	505.95
	25	6	1	00	8 Ncm	1,07 Ω	23	49	24	5	506.38	509.83	505.47	507.23
	26	6	2				23	49	24	5	497.86	511.29	508.23	505.79
	27	6	3				23	49	24	5	514.27	506.12	496.37	505.59
	28	6	4				23	49	24	5	518.98	512.69	498.75	510.14
	29	6	5				23	49	24	5	512.35	512.62	513.17	512.71
	30	7	1	0+	8 Ncm	1,09 Ω	23	49	24	5	515.84	526.86	496.65	513.12
	31	7	2				23	49	24	5	517.65	497.65	513.00	509.43
	32	7	3				23	49	24	5	517.65	501.11	506.64	508.47
	33	7	4				23	49	24	5	512.18	508.52	502.99	507.90
	34	7	5				23	49	24	5	516.91	501.82	508.19	508.97
	35	8	1	+-	8,4 Ncm	1,05 Ω	23	49	24	5	503.75	510.83	508.48	507.69
	36	8	2				23	49	24	5	501.11	507.19	498.36	502.22
	37	8	3				23	49	24	5	500.86	487.96	501.30	496.71
	38	8	4				23	49	24	5	505.29	509.37	509.97	508.21
	39	8	5				23	49	24	5				no trigger
	40	9	1	00	8 Ncm	1,07 Ω	23	49	24	5	516.80	524.09	502.09	514.33
	41	9	2				23	49	24	5	502.30	500.77	499.39	500.82
	42	9	3				23	49	24	5	516.82	510.73	510.38	512.64
	43	9	4				23	49	24	5	509.89	499.01	512.69	507.20
	44	9	5				23	49	24	5	510.27	513.19	512.43	511.96
	45	10	1	++	8,4 Ncm	1,09 Ω	23	49	24	5				no trigger
	46	10	2				23	49	24	5	514.95	515.05	502.39	510.80
	47	10	3				23	49	24	5				no trigger
	48	10	4				23	49	24	5	514.64	515.31	495.68	508.54
	49	10	5				23	49	24	5	509.01	502.68	509.30	507.00
	50	11	1	00	8 Ncm	1,07 Ω	23	49	24	5	505.68	499.31	503.35	502.78
	51	11	2				23	49	24	5	517.65	511.50	507.08	512.08
	52	11	3				23	49	24	5	502.37	517.68	507.21	509.09
	53	11	4				23	49	24	5	504.56	515.13	509.97	509.89
	54	11	5				23	49	24	5	503.83	514.66	504.60	507.70

Curriculum Vitae

Johan van den Bogaard was born in Helmond, the Netherlands, on 26 November 1975. In 2000 he received his Masters degree in Mechanical Engineering from the Technische Universiteit Eindhoven. The topic of his graduation project was on robustness analysis on cd-players performed at Philips Optical Storage in Singapore.

In april 2000 he started his joint-Ph.D. work at both the sub-department Quality and Reliability Engineering of the department of Technology Management, Technische Universiteit Eindhoven, the Netherlands and the Mechanical Engineering department at the National University of Singapore.The research was performed in co-operation with various companies (Xerox, Flextronics, OCÉ, PT&E) and various research institutes (Design Technology Institute (DTI), Eurandom).

Since April 2005 he is working as RAMS consultant at the engineering company Holland Railconsult. On a daily base, he is involved in helping the Dutch Railway companies to implement safety lifecycle management activities.