Reliability Information and Testing Integration for New Product Design

by

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ABSTRACT

In the three phases of the engineering design process (conceptual design, embodiment design and detailed design), traditional reliability information is scarce. However, there are different sources of information that provide reliability inputs while designing a new product. This research considered these sources to be further analyzed: reliability information from similar existing products denominated as parents, elicited experts' opinions, initial testing and the customer voice for creating design requirements. These sources were integrated with three novels approaches to produce reliability insights in the engineering design process, all under the Design for Reliability (DFR) philosophy. Firstly, an enhanced parenting process to assess reliability was presented. Using reliability information from parents it was possible to create a failure structure (parent matrix) to be compared against the new product. Then, expert opinions were elicited to provide the effects of the new design changes (parent factor). Combining those two elements resulted in a reliability assessment in early design process. Extending this approach into the conceptual design phase, a methodology was created to obtain a graphical reliability insight of a new product's concept. The approach can be summarized by three sequential steps: functional analysis, cognitive maps and Bayesian networks. These tools integrated the available information, created a graphical representation of the concept and provided quantitative reliability assessments. Lastly, to optimize resources when product testing is viable (e.g., detailed design) a type of accelerated life testing was recommended: the accelerated degradation tests. The potential for robust design engineering for this type of test was exploited. Then, robust design was achieved by setting the design factors at some levels such that the impact of stress factor variation on the degradation rate can be minimized. Finally, to validate the proposed approaches and methods, different case studies were presented.

To my family,

Rebeca and Camila for being the light of my life;

my wife Erika as she is my engine.

My parents Luis Javier and Mirosalba for the unmeasurable love and support,

and my brother Isaac whom I keep learning from.

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INTRODUCTION

1.1 Problem Statement

In today's world, new products are being introduced at a high rate to satisfy an increasingly strict demand; consumers demand highly reliable products, hence turning reliability into a default requirement. To achieve this, engineers and designers are developing efficient methods to assess reliability.

Reliability statistical information can be originated from a variety of sources during a product's life cycle. Most commonly, failure observations data provide an ideal scheme to build the product's failure distribution model. However, capturing those data results in a time consuming and complicated task, especially in early development such as the product design phase.

The scarcity and poor quality of reliability data during the design phase has become a challenging problem. Therefore, several sources of information need to be considered to gain reliability insight. In contrast, generally new products are being designed based on changes or upgrades on similar existing products or technologies. Consequently, failure data and information of these current products that have been in the field (also called parents) become of vital importance. Initial testing results, such as accelerated life testing, also provide an excellent insight into the reliability of the new product. In addition, a key source of information is the reliability input provided by experts. Finally, customer expectations and requirements are the first sources for any reliability target. All of these sources contain valuable reliability information, and when appropriately managed, it is possible to make a reliability assessment for a new product in early development.

The ultimate goal for early reliability analysis is to ensure that the design of the new product will meet all requirements set forth (e.g., quality, performance, durability, customer satisfaction, etc.). However, even if early reliability has proven to be a valuable technique for assessing the performance and risk of new products, it also presents itself as a challenging engineering problem. Perhaps one of the most difficult aspects of new product reliability assessment is the integration of multiple sources of information. Thus, how the available information should be consolidated to estimate reliability when a design is proposed? In this dissertation this question is explored and answered under the framework proposed. In the end, the purpose of this research is to gain reliability insight in early stages of the design of a new product using different sources of information; with the objective of making prompt and assertive reliability decisions towards designing a more robust product.

1.2 Motivation

Traditionally reliability had been considered in a passive perspective, that is, just a measure of quality over time. Nowadays, a proactive approach has seen reliability as a measure of impact on performance improvement. This approach, defined as build-in-reliability (BIR) or design for reliability (DFR) philosophy, drives reliability since the design concept of new products. One of the advantages of performing reliability analysis in earlier phases of a project (new product) is that it allows design changes to be more flexible while costs are acceptable.

Furthermore, a less documented engineering procedure is capturing experts' opinion regarding a product's performance. Experts' opinion represents an excellent source of information for reliability estimation, but some approaches aiming to obtain opinions are rather subjective. To gain objectivity, an elicitation process needs to be developed.

In conclusion, multiple sources of information must be considered to build a reliability (or failure) structure for a new product. In this case the information available is collected from parent products, expert's opinion, initial testing results, customer expectations and design constraints. They would need to be consolidated at milestones of the new product's design to verify that the requirements are met. As mentioned previously, assessing reliability at the front-end in a new product's design will lead to performance improvements, better design decision-making process and as a consequence, it will reduce warranty costs.

1.3 Applications

Reliability for any product or service is crucial; its importance resides in the impact on areas such as reputation, customer satisfaction, warranty costs, cost analysis, customer requirements and competitive advantage. It becomes vital for those products and services that cannot fail. For instance, in the military world, weapon systems must perform at the highest requirements. The same happens in some manufacturing domains, e.g., the aerospace industry (including space shuttles) and automotive industry. Moreover, there have been great developments in the energy field, e.g., nuclear plants, hydrogen devices, etc. Subsequently, for new products in these applications, reliability must be considered in the design phase to meet all the requirements given the high risks in case of failure.

Chapter 2

BACKGROUND AND FRAMEWORK

2.1 Background

In this section an overview of basic concepts is provided.

2.1.1 Design, Reliability and Design for Reliability

Design engineering is a sequential process to address an identified problem by creating/developing a solution to cover a need. Pahl et al. (1995) classified this process in three major phases once the problem has been identified. These are:

1. Conceptual design phase. The conceptual design phase involves the establishment of function structures, the search for suitable solutions and their combination into feasible systems.

2. Embodiment design phase. In this phase, the designer, starting from the concept, determines the layout and forms (prototype), and develops a technical product or system in accordance with technical and economic requirements.

3. Detailed design phase. This is the phase of the design process in which the arrangement, form, dimensions and surface properties of all the individual parts are finally laid down, the materials specified, the technical and economic feasibility re-checked and all the drawings and other production documents produced.

Design engineering is widely used in all fields of engineering. It is mostly applied when creating new products or services; but can be extended to different applications such as medical fields or psychology research (Dym et al., 2004).

On the other hand, reliability definition has been seen in different literature as the probability of a system performing its intended functions under a set of operation conditions for a specific period of time (Ireson et al., 1996; O'Connor & Kleyner, 2011; Elsayed, 2012). Or in a simple way: "Quality over time". Moreover, reliability engineering is the discipline that tackles the design and production of a reliable product (El-Haik, 2005, Pahl et al., 1995).

Design for reliability (DFR)can be defined as a structural design methodology that guides decision making processes with reliability models to meet reliability objectives during all design phases (Huang & Jin, 2009). Therefore, DFR, also known as build-in-reliability (BIR), is adopted as a philosophy to a achieve a robust system through design engineering.

Under the philosophical influence of DFR, the efforts in industry to implement different approaches are quite significant. For example, the use of computer support analysis (i.e., computer simulation) by designers is widely spread (Fajdiga et al., 1996). The goal of reliability simulation is to help the designer achieve the reliability requirement while minimizing the use of resources (Minehane et al., 2000). Most of the techniques developed under the BIR philosophy are, however, resource intensive (Tan, 2003), as product design does not result from a sole quantitative analysis. In other words, it comes with subjective procedures for decision making, particularly in the conceptual design stage in which design details are not yet available (Chin et al., 2008). As a complement to these computer simulation tools, experts' opinion and quantitative information from similar existing designs are also important to BIR. Some recent research starts to address this problem. For example, Chin et al. (2008) developed a methodology to aid engineers in the design phase to select materials, components and define costs with reference to product requirements. They utilized a fuzzy-based knowledge-based Failure Modes and Effects Analysis (FMEA) to incorporate customer requirements, engineering characteristics and critical parts characteristics. Also, Braglia et al. (2007) provided an adaptation of the Quality Deployment Function (QFD) to the reliability environment called the House of Reliability. The methodology introduces the study of the correlation between failures through the 'roof' of the house, and develops the reliability function deployment. This is done to perform cost analysis incurred by improving the reliability. In the case of Guérin et al. (2003), they use Bayesian methods based on dependability studies (e.g., FMEA, Functional Analysis, Fault Tree, Block Diagram) to define a prior distribution for reliability estimation. They depicted three different methods to assess the failure probability: propagation of error, Monte-Carlo simulation and First Order Reliability Method (FORM).

In summary, following a DFR based methodology would have a deep impact on the design decisions to meet reliability requirements for new products. Therefore, this research is developed under the DFR philosophy.

2.1.2 Sources of Information

The most common source for reliability information is failure occurrence. However, during the early design stage there are no physical components that can fail. In such cases, different information sources must be considered. In Table 2.1 those sources for early reliability information are presented.

The closest information to actual failures in the early design phase (e.g., conceptual and embodiment phases) is the failure observations data from similar products currently in use. Defined as "parents", those products provide, in general, the reliability behavior of the new product. This means that parent reliability information becomes the basis for the failure structure of the new design; hence the importance of selecting parents. Experts' opinion is another source of importance, although is

Source	Description	Methods	Type	Uses
Parents	”Parents” are selected given similarities with new design; it is assumed they share a similar failure structure. Hence, all failure information existent for the parent (e.g. field failure observations, test data, warranty analysis, etc.) are a vital source for reliability of the new design.	The majority of parents’ reliability information is captured in databases. Methods for retrieval depend on the database’s architecture.	Objective	Determine parent failures causes, failure modes, failure rates, etc.; they will form the basis of the failure structure under the new design.
Experts	Experts have great insight on the risks that some changes originate, thus an important source of information is experts’ opinion.	Different methods exist to gather reliability opinions, the most common are: Elicitation methods and Failure Mode and Effect Analysis.	Subjective	Risk assessment for the new design.
Initial tests	Although most of the time there is no physical product to perform tests, techniques as computer simulation and material testing provide reliability information.	Most methods are computer developed; such as simulation, structural analysis, etc.	Objective	Provide an initial sense of the reliability for the new design.
Customers	Customers’ input leads eventually to the reliability requirements. In consequence, they are an important source of information.	The approach to reach the customers is market research. There are several techniques to transform their requirements (i.e. House of Reliability).	Subjective	Set reliability requirements
Studies	Different studies are performed before and during the design of new products. These studies aid to the understanding of the new design characteristics.	Studies variate according what is needed. Examples are: Functional Analysis, Cause-Effect model, Benchmarking, Cost Analysis, etc.	Both	The studies define the framework where reliability must be analyzed
Other	As every design is unique, there are additional sources of reliability information available for each case. External sources reside in this category, for example journals, organizations, reliability standards, etc.	The method to obtain any information depends in great part on the source and the information type.	Both	Additional information which aids to estimate the reliability for new products.

Table 2.1: Sources of Information for Reliability in Design Phase

commonly oversight given its subjective nature. However, using objective methods (e.g., elicitation process) experts' opinion emerges as a strong information source. Once in the detailed phase of the design process it is possible to have initial testing on prototypes or production intent components. Those initial testing provide the opportunities to perform the first reliability inferences, but with resources constraints they are scare. Finally, customer expectations and requirements set the bases for the reliability goals. In the end, reliability and design engineers must use any available information that supports their reliability decision-making process.

2.1.3 Integration of Information

In reliability analysis, one of the most difficult tasks is to integrate multiple sources of information in a proper manner. For instance, one basic example is the integration of failure information from each component to asses system reliability. This becomes more complicated when failure information of subsystems is available, experts provide their opinion and/or system testing data are captured. In the literature there are approaches focused on those issues, for example, Easterling & Praire (1971) present simple cases where component information can be extracted from system results and combined with component results. More recently, Wilson et al. (2006) provide a review of methods to combine reliability information over time for one component with multiple sources of information, for system reliability with multiple levels of data and for complex systems. Lately, Bayesian approach is being widely used to address this topic (e.g., Johnson et al., 2003 and Hamada et al., 2007), which provides a more comprehensive methodology when prior information is available.

In early reliability, the integration of information is a logical step to follow. An example is Johnson et al. (2005), whom compared similar systems among manufacturers using a Bayesian hierarchical model to asses the reliability. However, it does not take into consideration the failure structure (e.g., relationship between failure modes, components, failure causes, etc.) to improve the reliability assessment in product design process. Hence the need for a more detailed methodology.

2.1.4 Elicitation Process and Expert Opinion

Elicitation embraces a large variety of definitions and interpretations. A formal elicitation process refers to the act of obtaining information from specific sources. Expert elicitation is the synthesis of experts' knowledge on one or more uncertain quantities (O'Hagan et al., 2006). Here, expert is defined as someone who has useful and organized knowledge in a specific matter (Cooke, 1991). Although there are a variety of elicitation procedures, there is no single elicitation method that can be applied to all problems. Rather, a suitable elicitation method depends on the nature of the situation and the form of the distribution that will be used to model the expert's knowledge. Summarizing much of the literature that proposes several classifications, expert elicitation methods can be seen as indirect and direct, or parametric and non-parametric. Indirect elicitation codes the judgment of the expert in familiar terms that will lead, the analyst, to an indirect estimation of a probability; e.g., betting rates (Ramsey and De Finneti, 1964) or age replacement estimations (Ayyub, 2001). Direct methods elicit a degree of belief from experts by directly asking for it. It is the simplest form of elicitation and has a better performance when experts are familiar with probabilities (Cooke, 1991). On the other hand, parametric elicitation is used when a particular class of probability distribution is suspected for the expert's stated summaries. In contrast, non-parametric elicitation refers to a representation of a probability distribution when it cannot be obtained. Pioneers in this discipline are Blavatskyy (2006) and O'Hagan et al. (2006).

Additionally, to deal some with some of the drawbacks of the elicitation process, such as bias, more than one expert is suggested (Cooke, 1991). Therefore, a methodology for combining experts elicitation is needed. There are three major approaches that can be used (Clemen & Winkler, 1999): (1) Weighted combination or axiomatic approach, which includes the linear opinions pool and logarithmic opinions pool. This approach is widely used where the majority of literature is focused in determining weights (see French, 1985, Genest & Zideck, 1986 and Cooke, 1991). (2) Bayesian approaches are based on Bayes's theorem that require the decision maker to supply prior information (see Lindley, 1986, Cooke, 1991 and Jacobs, 1995). These methods depend in great proportion on the knowledge of the decision maker. (3) Behavioral approaches (see Cooke, 1991) where relative intensities of psychological stimuli are estimated to improve the integration of information. These behavioral models have not been fully studied and present several drawbacks in their validation. For more information on the validation for elicitation techniques please refer to Appendix A.

Similarly, techniques for combining experts' opinion in the elicitation procedure must be selected or developed accordingly to the unique characteristic of each situation.

2.1.5 Accelerated Life Testing

Accelerated life testing (ALT) is widely used to obtain timely information on a product's reliability or failure distribution. Such testing involves subjecting the products to harsher-than-normal stress conditions. Through ALT, stress levels are increased and reliability information for the product is captured. These failure data are then used to derive, usually by extrapolation, the failure distribution under use condition based on some life-stress relationship. The information obtained has a substancial effect on decisions regarding system configuration, warranties and preventive maintenance schedules. In past literature Nelson (1990), Elsayed (1996), Bagdonavičius & Nikulin (2002), and Escobar & Meeker (2006) provide comprehensive reviews of statistical models and inference methods for analyzing ALT data. Furthermore, for general guidelines for planning ALTs please refer to Meeker & Hahn (1985).

In the design stage of a new product ALT becomes impractical and expensive. The key element resides in the relationship between the failure mechanism during the test and the failure mechanism under normal use conditions. Some previous work on the field include Nelson (2001), Liao & Elsayed (2006) and Pan (2008). However, accelerated degradation tests (ADT) provides the information of an ALT with less resources (Meeker et al., 1998). Therefore, the possibility of using this alternative to ALT to gain reliability information and have a robust product is explored in this research.

2.1.6 Robust Design

Robust design is a well establish methodology to measure and minimize the impact of external forces or noises to the system performance. It is used in different fields such as automotive industries, electronics, software, telecommunication, etc. Consequently, it has been defined several times. However, Phadke (1995) defines it as an "engineering methodology for improving productivity during research and development so that high-quality products can be produced quickly and at low cost."

Park et al. (2006) provided an excellent overview on robust design. They defined its objective to reduce the variations in the performance of a system even though there is an input variation. Variations can be classified as external factors (or noises), product factors, and internal factors. Examples for external factors are temperature, humidity, weight, operation error, etc. Secondly, variations in the product come from dimension error, material differences, etc. Finally, internal factors are inherent to the use of the system such as wear, discharge, etc. Robust design focuses on external factors and product factors. Meanwhile reliability engineering deals with the internal factors.

Currently, there are three major approaches used towards robust design:

1. The Taguchi method. This method is the most widely known and used in engineering fields. The approach is to perform and analyze experiments with different factors in such a way that a configuration can be obtained so the system to be designed is insensitive to use conditions' noises.

2. Robust optimization. Robust optimization is a more comprehensive approach since it consider all design variables through an optimization process.

3. Robust design with the axiomatic approach. It uses a robustness index based on axiomatic design that helps to rank the highest probability of success with the smallest variation.

For more information please refer to Park et al. (2006).

2.2 Framework

For the purposes of this research, the design phase of a new product is classified as shown in Figure 2.1.

The framework contains three different 'windows' to reliability on the different stages of the design process. Each one of them has different sources of information and a tool or tools to integrate that information. The information sources are highlighted and they are: existing products or 'parents' that provide information through field data and warranty databases. Secondly, functional analysis is presented as the main source of information which is created in the conceptual design process based on reliability requirements. Finally, initial testing for the new product when

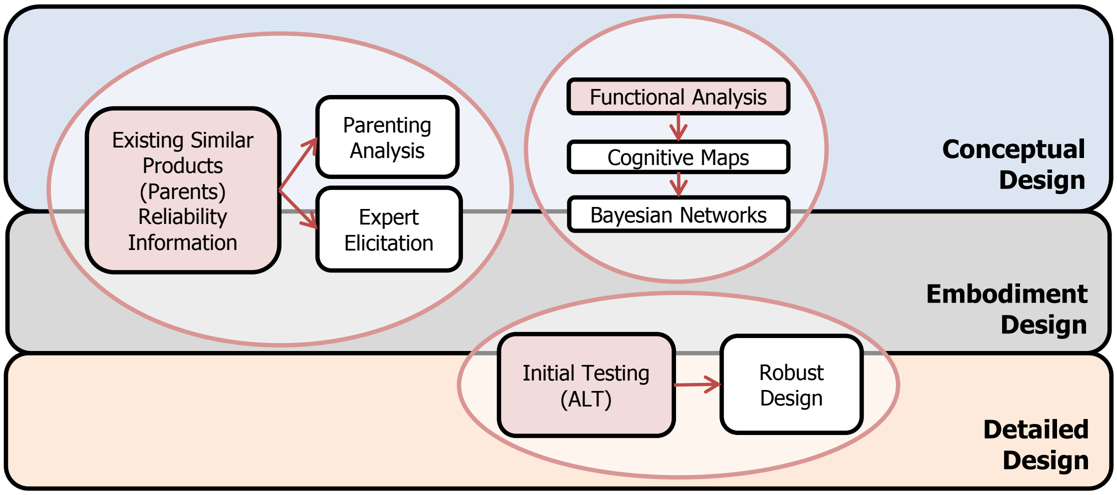


Figure 2.1: Framework for Reliability Information and Testing Integration for New Product Design

resources allow them. These information sources, along with the design constrains and product's requirements are consolidated with novel techniques to gain reliability knowledge. These techniques include: parenting process, expert elicitation, cognitive maps, Bayesian networks and robust design. In the following chapters these techniques are further developed and discussed.

2.3 Organization

The rest of the dissertation is organized as follows: Chapter 2 describes in detail the enhanced parenting process that incorporates an elicitation process under the DFR philosophy. Chapter 3 introduces a methodology to provide reliability insights in early conceptual design phase. The methodology is then used for decision-making process based on reliability requirements. Chapter 4 proposes a method to achieve product robust design by using certain type of ALT in order to meet all the requirements and improve performance. Finally, Chapter 5 presents a general discussion on the contributions of this research as well as the future work.

Chapter 3

AN ENHANCE PARENTING PROCESS: PREDICTING RELIABILITY IN THE PRODUCT DESIGN PHASE

3.1 Introduction

The design for reliability philosophy has been widely adopted by today's manufacturing industry, as customers demand higher product reliability for all products. Ideally, statistical inference on a product's reliability is obtained from failure observations during the product's life cycle. However, when introducing new products it is very difficult, if not impossible, to capture representative failure data. Testing prototypes is extremely expensive, and it may not provide useful information if the test was not properly planned. On the other hand, new products are often introduced based on changes or upgrades on existing products. For example, new features or functions are added, new materials are used, or new manufacturing processes are implemented. Note that these changes are often driven by customer demands and technology improvements, instead of reliability requirements directly; however, these changes may inadvertently affect the product's reliability. Therefore, a sensible approach to predict new product's reliability at its very early design stage is to use reliability information from these existing products (or parents) and map design changes to reliability quantification (e.g., Groen et al., 2004). This is called "parenting process" throughout the remainder of this document. Parenting processes have been implemented at a major companies in a practical, but more or less arbitrary way (e.g., automotive industries). In other words, the methods have not been built on a solid theoretical foundation, as little or no literature on parenting process exists.

This chapter aims to develop an enhanced parenting process by formalizing its mathematical foundation and by integrating it with an expert opinion elicitation method. The scenario considered herein consists of a new product introduction with similar reliability/failure structure as its parent product(s), for which warranty data is available. Based on the reliability structure, a relationship between failure modes and causes is depicted. Experts are asked their opinions on the design changes and their impact on each failure cause by comparing the new product with its parents. Finally, an estimation of the failure mode probability for the new product is computed.

3.2 Background

Under the philosophical influence of build-in-reliability (BIR) and design for reliability (DFR), the manufacturing industry has made significant efforts to consider reliability prediction in the early phases of a project. For example, computer-supported analysis (i.e., computer simulation) is widely used by designers and engineers (Fajdiga et al., 1996). The goal of reliability simulation is to help the designer to achieve the reliability requirement while minimizing the use of resources (Minehane et al., 2000). However, most of these techniques are resource intensive, as product design does not result from a sole quantitative analysis (Tan, 2003). As a complement to these computer simulation tools, experts' opinion and quantitative information from similar existing designs are also important to DFR. They are the focus of this study.

A parenting process is used to evaluate the reliability of a new product while attention is given to areas with unreliability (i.e., areas exhibiting a lack of reliability). Typically performed at the early design stage for a new product, it helps to align the technical expectation of the new product's reliability with the realistic estimation based on its parent's warranty history. Thus, the parenting effort is centered around the existing products/systems and subsystems that have similar attributes and applications to the product/system under design. The warranty data from these existing products/systems is analyzed to identify the failure modes and estimate corresponding failure causes probabilities. Next, a "parent factor" is elicited to take into account the risk releasor/aggravators as a result of design changes in the new product.

One of the drawbacks of the current parenting process is that it has not been conducted in a formal, mathematically rigorous manner. The process is conducted by reliability engineers along with design, manufacturing and testing experts for the new product. Opinions are gathered about which feasible changes or improvements the new product requires and the impact on the reliability for those modifications. Subsequently, a consensus for risk factors is eventually achieved by debating differences among opinions. However, this strategy (i.e., gaining consensus) results difficult and often produces inaccurate reliability predictions. Recent research starts to address this problem. Chin et al. (2008) developed a methodology to aid engineers in the design phase to select materials, components and cost with reference to product requirements. They utilized a fuzzy-based knowledge-based FMEA to incorporate customer requirements, engineering characteristics and critical parts characteristics. Braglia et al. (2007) provided an adaptation of a the Quality Deployment Function (QFD) to the reliability environment called the House of Reliability. The methodology introduces the study of correlation between failures through the "roof" of the house, and develops the reliability function deployment in order to perform cost analysis incurred by reliability improvements. Guérin et al. (2003) described three different methods to assess the failure probability: propagation of error, Monte Carlo and first order reliability method, and proposed to use dependability studies to define a prior distribution for reliability estimation. Different from these proposals, this study tries to address the problem of reliability prediction at a product's early design stage by emphasizing the use of quantitative data from parent products combined with expert opinion.

3.3 Methodology

Figure 3.1 presents the procedure for the parenting process with integrated quantitative analysis of product failure structure and expert opinion. In the following sections each one of the steps in Figure 3.1 is discussed. The desired outcome of the methodology is a glimpse or initial estimation of the failure probabilities for a new design at an early stage where information from the new product is no other than the design itself.

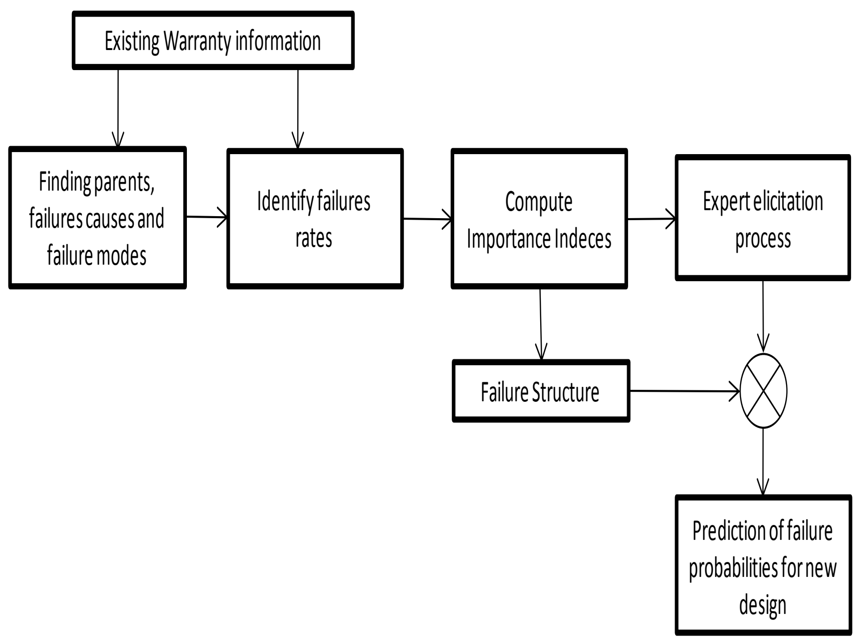


Figure 3.1: Enhanced Parenting Process for Reliability Assessment in Product Design Phase

3.3.1 Finding the Parent(s)

In industry, a product design concept may emerge from an existing need, but often it is also based on improvements for already designed products. Selecting the parent (or parents) during the design phase will determine the failure structure of the new product if no new failure modes are introduced due to the design change. This assumption provides the basic information for the reliability assessment of the new product.

Identifying parents might result in a straightforward exercise when new products are conceptualized based on the ones already designed. However, product proliferation, high complexity, new technologies, etc., make the parent selection process more challenging. For this cases, clustering approaches such as group technology (GT) can be used to select parents. Please refer to Appendix B for more information.

The warranty database of parent products is utilized as the source of information for finding failure modes and failure causes. In warranty analysis, failure causes (c_i) are represented as the explanation on why a failure happens, such as vibration, excessive loading, miss-assemble, etc. Failure modes (m_j) are described as the ways that a failure can occur, such as material crack, distortion, leakage, etc. Both failure modes and causes are typically recorded in a warranty database. Their frequencies are then used to form the failure structure of the parents.

Equations 3.1 and 3.2 present the failure rates for causes and modes respectively (Yang, 2007). These equations represent the ratio of the increase in frequency for c_i or m_i, respectively, at a given time t with respect to T (usually end of warranty) to the quantity of survivors (N_s) at time t.

$$\lambda_{c_i}(t) = \frac{\partial N_{c_i}(t)/\partial T}{N_s(t)} \tag{3.1}$$

$$\lambda_{m_j}(t) = \frac{\partial N_{m_i}(t)/\partial T}{N_s(t)} \tag{3.2}$$

These failure rates estimate the probability of occurrence for c_i and m_i, which dictates the behavior of the failure distribution for c_i and m_i respectively.

3.3.2 *Parent Matrix and Importance Indices*

A failure structure represents the logical interrelationship from failure causes to a specific failure mode. It is of vital importance to determine what and how failure causes contribute to failure modes. Various techniques, such as Failure Tree Analysis (FTA) or Reliability Block Diagrams (RBD), have been used for describing failure structures. However, failure structures in the current manufacturing environment are fairly complex and most of the time they cannot be explicitly derived by these tools. Nevertheless, failure structures can be obtained empirically through warranty analysis from similar products. The result of this process is an element called "parent matrix".

First, one needs to define the importance index as the relative importance of a failure cause to a failure mode. Birnbaum (1969) described component importance and introduced one of the most widely used importance indices, Birnbaum index ($I_i^B(t)$). It is the rate of increase (at time t) of the system reliability with respect to the components' reliability increase, i.e.,

$$I_i^B(t) = \frac{\partial R_S(t)}{\partial R_i(t)} = \frac{\partial F_S(t)}{\partial F_i(t)}. \tag{3.3}$$

In this analysis, the importance index represents the relative importance of a failure cause (c_i) to a failure mode (m_j). For example, in the case of a known failure structure depicted by a FTA, failure causes c_i correspond to the "leaves" and failure modes m_j refer to the "top event".

Therefore, it generates a corresponding index, $I_{i,j}^P$, representing the probability that given that the system has failed, m_j is caused by c_i. That is,

$$I_{i,j}^P = \frac{\partial F_{m_j}(t)}{\partial F_{c_i}(t)} \ . \tag{3.4}$$

Note that the importance index is time dependent. Therefore, it is necessary to evaluate it at different times of interest. In practice, it is common to use t as the end of a warranty period.

When the failure structure is unknown, $I_{i,j}^P$ can be obtained based on the relationships of c_i and m_j outlined in the warranty database and engineering knowledge. Consequently, the importance index formula is slightly modified in Equation 3.5. Now the importance index is represented by the ratio of functions of the failure modes and failure causes multiplied by a frequency q_{ij}, where q_{ij} is the standardized frequency of failure cause i when failure mode j occurs, $\sum_i q_{ij} = 1$.

$$I_{i,j}^P = \frac{F_{m_j}(t)}{F_{c_i}(t)} q_{ij}. \tag{3.5}$$

As a result, Equation 3.5 is an index obtained from warranty analysis when the failure structure is unknown.

A parent matrix represents the failure structure shared by the parents as well as the new product. Organizing the important indices in a matrix form characterizes the relationships between failure causes and failure modes. It also provides a better understanding of the overall importance of c_i,

$$\mathbf{I^P} = \begin{array}{c} \\ c_1 \\ c_2 \\ \vdots \\ c_n \end{array} \begin{array}{c} \begin{array}{cccc} m_1 & m_2 & & m_l \end{array} \\ \left| \begin{array}{cccc} I_{1,1}^P & I_{1,2}^P & \cdots & I_{1,l}^P \\ I_{2,1}^P & I_{2,2}^P & \cdots & I_{2,l}^P \\ \vdots & \vdots & \ddots & \vdots \\ I_{n,1}^P & I_{n,2}^P & \cdots & I_{n,l}^P \end{array} \right| \end{array} \tag{3.6}$$

where the columns represent the failure modes m_j and the rows are the failure causes c_i.

3.3.3 Elicitation Process

Once the failure structure is represented in the the parent matrix, the concept design of the new product needs to be considered. A risk assessment would provide the necessary measures to acknowledge uncertainties created by the introduction of changes in the new product. However, risk assessment in the design phase is complicated as there is no physical product to associate such risk. For this reason, a suitable expert elicitation process is implemented.

In this study, parametric estimation is used and more specifically, the weighted combination approach is used for its simplicity and popularity in industrial applications (Cooke, 1991).

Following suggested guidelines (Cooke, 1991) and practices (Ayyub, 2001), a questionnaire tool is created (see Appendix C) to facilitate the elicitation process of experts' opinions on the risks of new product designs. The form is filled out by the expert or designer with the guidance of the engineer (or decision maker) who performs the analysis. The first step elicits the modifications or changes to the existing products (parents). This section reflects the design concept planning. Secondly, it is needed to identify existing failure causes c_i that are directly affected by the specific changes. After that, the decision maker elicits the parameter estimates from the experts on the change in failure rate (or MTTF) for failure causes under the new design. In this step, the decision maker executes the elicitation procedure described in the following section. It is important to note the implications from this procedure such as obtaining accurate and realistic estimates from subjective answers (see discussion).

Finally, statements on why these changes affect the failure causes are written. As a result a parenting factor, γ, is elicited.

Elicitation Procedure

Assuming experts are able to provide an estimation of the parameter of interest given their expertise (from simulation, part testing, modeling, etc.) a two-step model is applied. According to Cooke (1991), experts became comfortable with a two-step procedure as the assessment is divided in a "best estimate" and a "degree of uncertainty" task. The original procedure was developed for the European Space Agency (Preyssl & Cooke, 1989), and its implementation presupposes that experts' distributions are approximately lognormal (see also Dalkey, 1969 and Martino, 1970); however, it may be applied to any distributions determined by two parameters. Therefore, breaking the elicitation down into two steps and adapting this model to the parenting process, the procedure to follow is:

1. The expert provides an estimate of the median for the parameter in question. In this case for the median of γ_i which represents the magnitude in change (i.e., for failure rate or MTTF) from the parent to the new design for the failure cause c_i. Denoted as M_{γ_i}, it can be interpreted as the risk associated for c_i based on the new design.

2. The expert is asked how certain he/she is about the estimates elicited providing an upper and lower limit, with confidence level of 95 percent that the true value lies within the interval.

From both steps it is possible to obtain the distribution's parameter of γ_i. The mean is obtained by step one: $\mu_{\gamma_i} = \ln M_{\gamma_i}$. And the standard deviation can be calculated from step two, using the two limits set to the 2.5th and 97.5th percentiles.

At the end, one would have a parent factor: $\gamma_i \sim \text{lognormal}(\mu_{\gamma_i}, \sigma_{\gamma_i})$, with a density function as shown in Equation 3.7.

$$f(\gamma_i) = \frac{1}{\gamma_i \sqrt{2\pi}\sigma_{\gamma_i}} e^{\frac{-(\ln \gamma_i - \mu_{\gamma_i})^2}{2\sigma^2_{\gamma_i}}}. \tag{3.7}$$

Multiple Experts

To deal with some drawbacks of the elicitation process, such as bias (see discussion), more than one expert is suggested. Synthesizing information from multiple experts is not a simple task. One of the most commonly used methods for combining experts' opinions is the linear opinion pool, or the classical model. This model is a weighted linear combination of the experts' probabilities, i.e.,

$$\gamma_i = \sum_{h=1}^{k} w_h \gamma_{ih}, \tag{3.8}$$

where k is the number of experts, γ_{ih} represent expert h's probability distribution for γ_i and w_h is the weight assigned to expert h. Additionally, in order to have consistency, the weights w_h must sum to one.

Moreover, the weighted combination of experts satisfies a number of properties of importance to the elicitation process (for example, the marginalization property [1]). In addition, scoring factors for the elicitation process such as calibration and entropy can be determined and selected by assigning w_h (see Appendix A). A considerate effort has been put in assigning weights, but Winkler (1968) generalizes four ways to determine w_h:

1. Assign all experts equal weights. In this case, the decision maker has no reason to think that there is much difference among experts, therefore the willingness to assign equal weights.

[1] If the combination rule is such that the probabilities are unaffected by refinements of the partition of alternatives (i.e., parameters to be estimated), then the rule is said to possess the marginalization property (Cooke, 1991).

2. Assign weights proportional to a ranking system. Rank the experts according to "goodness" where a higher rank indicates a "more experienced" assessor. Then assign weight to each expert according to their rank, for example an expert ranked as 3 from 5 experts has a weight of 0.2 (i.e., 3/15). This rules presumes that the decision maker feels that experts can be meaningfully ranked.

3. Let experts weight themselves. Have experts rate themselves on a scale predefined by the decision maker. Then assign each expert a weight proportional to his/her self-rating, where proportionality is determined such that the weights sum to one. The reason for this rule is that an expert specializes in a given field, but the expertise may vary from topic to topic within the field. Therefore, the expert might be the best judge of how competent he/she is with regard to the specific topic or parameters in question.

4. Use proper scoring rules. This proposal of assigning weights is not well defined. Winkler (1968) suggest assigning weights based on some comparison of previously assessed distributions with actual outcomes (i.e., using scoring rules). Another suggestion is looking at likelihood ratios to compare the predictive ability of two experts; this involves the application of Bayes' theorem to formally revise the weights after each assessment and the related observation. Cooke (1991) points out the drawbacks of this procedure such as bias and loss of accountability.

It should be emphasized that the final assessments of weights should be based on the decision maker's judgments, and the use of these rules are only if the resulting weights do no harm to those judgments.

3.3.4 Failure Mode Probabilities for New Design

Once the parenting factor γ_i is elicited, it is possible to translate this shift to the failure rate of the new design. Equation 3.9 shows the shift of the occurrence rate of failure cause c_i.

$$\lambda^*_{c_i} = \gamma_i \lambda_{c_i}, \tag{3.9}$$

λ_{c_i} is estimated from the warranty database of parent products ,or Equation 3.9 and it is assumed that it follows a lognormal distribution, i.e., $\lambda_{c_i} \sim \text{lognormal}(\mu_{\lambda_{c_i}}, \sigma_{\lambda_{c_i}})$. As the multiplication of two lognormal distributions produces another lognormal distribution, then $\lambda^*_{c_i} \sim \text{lognormal}(\mu_{\lambda^*_{c_i}}, \sigma_{\lambda^*_{c_i}})$, where $\mu_{\lambda^*_{c_i}} = \mu_{\gamma_i} + \mu_{\lambda_{c_i}}$ and $\sigma_{\lambda^*_{c_i}} = \sqrt{\sigma^2_{\gamma_i} + \sigma^2_{\lambda_{c_i}}}$. Furthermore, the failure probability of c_i under the new design can be estimated following the assumption of exponential failure time (i.e., constant failure rate). Hence,

$$F^*_{c_i} = 1 - e^{-\lambda^*_{c_i} t}, \tag{3.10}$$

where $F^*_{c_i}$ is the cumulative probability of failure of c_i by the time t. The density function of $F^*_{c_i}$ is given by

$$f_{F^*_{c_i}}(p) = \frac{\exp\{-[\ln(t) - \ln(-ln(1-p)) + \mu_{\lambda^*_{c_i}}]^2/(2\sigma^2_{\lambda^*_{c_i}})\}}{(p-1)\ln(1-p)\sqrt{2\pi}\sigma_{\lambda^*_{c_i}}}, \quad 0 \le p \le 1. \tag{3.11}$$

From the above equation, different percentiles or confidence intervals can be found for the $F^*_{c_i}$ estimate.

As failure time is assumed to be exponentially distributed, gamma distribution seems to be a natural choice for λ_{c_i} (as gamma distribution is the conjugated prior distribution of failure rate for exponential failure times). However, lognormal distribution can approximate other nonnegative distributions, such as gamma distribution. Vaz & Fortes (1988) have shown the similarities of gamma and lognormal distributions. Graphical methods and the method of moments can produce similar results for either the gamma model with constant coefficient of variance or the lognormal model with constant variance. Additionally, lognormal distribution is well known in reliability modeling for its flexible probability density function and failure rate function.

Finally, to estimate the occurrence rate of failure mode m_j under the new design the parent matrix $\mathbf{I}$ is used, which is to transform $F^*_{c_i}$ to $F^*_{m_j}$ under the assumption that the failure mode and failure cause relationship will not be altered in the new design. Then, $\mathbf{I}$ is described as a pivotal element between previous designs and the new one. Additionally, it depicts the failure structure between failure causes and modes, therefore $F^*_{m_j}$ is shown as a linear transformation from the probabilities of failure causes to the probabilities of failure modes. That is,

$$F^*_{m_j} = \sum_{i=1}^{n} I^P_{ij} F^*_{c_i}, \tag{3.12}$$

or,

$$\mathbf{F}^*_{\mathbf{m}} = (\mathbf{I}^{\mathbf{P}})^{\mathbf{T}} \times \mathbf{F}^*_{\mathbf{c}}.$$

3.4 A Case Study

A new cylinder head gasket (CHG) is being introduced to be used in a diesel engine. A cylinder head gasket (CHG) is the most critical sealing application between the cylinder block and cylinder head. The new CHG maintains the same failure structure as the previous design; hence the previous CHG is selected as the parent. The warranty database is analyzed and the information from the parent [2] is gathered in Table 3.1, where three failure causes and two failure modes are identified: non-standard design (c_1), fatigue (c_2), unreasonable dimension (c_3), gas leakage (m_1) and water leakage (m_2).

[2] All values are presented in repairs per hundred.

Failure Causes	$\widehat{\lambda}_{c_1} = 0.063$ $\widehat{\lambda}_{c_2} = 0.026$ $\widehat{\lambda}_{c_3} = 0.028$
Failure Modes	$\widehat{\lambda}_{m_1} = 0.089$ $\widehat{\lambda}_{m_2} = 0.00071$

Table 3.1: Failure Rates for c_i and m_j From Parent Warranty

Furthermore, through the warranty analysis and historical information, it is established that $\lambda_{c_i} \sim \text{lognormal}(\mu_{\lambda_{c_i}}, \sigma_{\lambda_{c_i}})$. Test data analysis from the parent CHG also revealed that failure rate of c_i follows a lognormal distribution. The results are presented in Table 3.2.

Failure Rate	Distribution	$\mu_{\lambda_{c_i}}$	$\sigma_{\lambda_{c_i}}$
λ_{c_1}	Lognormal	-2.765	0.053
λ_{c_2}	Lognormal	-3.65	0.071
λ_{c_3}	Lognormal	-3.575	0.051

Table 3.2: Failure Rates for c_i From Warranty Analysis

Additionally, q_{ij} is obtained by the relative frequency of each failure cause for a given failure mode. These values are shown in Table 3.3.

Then, assuming exponential failure times and setting the time to one warranty period, Equation 3.5 is used to compute the importance indices (Table 3.4) and build the parent matrix. The parent matrix, presented in Equation 3.13, shows the relative importance of each of the failure causes to the specific failure mode. For example, in

m_1	m_2
$q_{11} = 0.714$	$q_{12} = 0$
$q_{21} = 0.286$	$q_{22} = 0.5$
$q_{31} = 0$	$q_{32} = 0.5$

Table 3.3: Values of q_{ij} From Warranty Database

this case c_1 (nonstandard design) has an importance index of 0.996 for m_1 (leak gas) and no effect on m_2 (leak water). Finally, the parent matrix is seen as the failure structure for the CHG.

Failure Mode	I^P
m_1	$I^P_{1,1} = (F_{\lambda_{m1}}/F_{\lambda_{c1}})q_{11} = 0.996$ $I^P_{2,1} = (F_{\lambda_{m1}}/F_{\lambda_{c2}})q_{21} = 0.948$ $I^P_{3,1} = (F_{\lambda_{m1}}/F_{\lambda_{c2}})q_{31} = 0$
m_2	$I^P_{1,2} = (F_{\lambda_{m2}}/F_{\lambda_{c1}})q_{12} = 0$ $I^P_{2,2} = (F_{\lambda_{m2}}/F_{\lambda_{c2}})q_{22} = 0.014$ $I^P_{3,2} = (F_{\lambda_{m2}}/F_{\lambda_{c3}})q_{32} = 0.013$

Table 3.4: Importance Indices for Parent Matrix (I^P)

$$\mathbf{I^P} = \begin{vmatrix} 0.996 & 0 \\ 0.948 & 0.014 \\ 0 & 0.013 \end{vmatrix} \tag{3.13}$$

Meanwhile, experts' opinion are elicited on γ_i. In this case, four experts are consulted. Using the questionnaire tool described in Appendix C, the decision maker conducts the elicitation process independently with each one of them. The decision maker then obtains the expert's opinion for each design change and for each failure cause affected. Their estimations for γ_i are given in Table 3.5.

		Expert 1	Expert 2	Expert 3	Expert 4
γ_1	Median	0.8	0.75	1	0.86
	Lower limit	0.72	0.65	0.95	0.75
	Upper limit	0.91	0.9	1.3	1
γ_2	Median	0.5	0.6	0.75	0.6
	Lower limit	0.45	0.5	0.66	0.55
	Upper limit	0.65	0.7	0.84	0.69
γ_3	Median	1.2	1	1.2	1.1
	Lower limit	1	0.9	1.1	0.95
	Upper limit	1.3	1.2	1.32	1.19

Table 3.5: Values Elicited From Four Experts

In order to make use of the elicited values, they need to be combined. The decision maker decided that the four experts are equally knowledgable on CHG design. Therefore, it is possible to combine these expert's opinions using linear combination with equal weight. With the assumption of $\gamma \sim lognormal(\mu, \sigma)$ let $\theta = \ln \gamma$, then $\theta \sim normal(\mu, \sigma)$; so it is that,

$$\theta_i = \sum_{h=1}^{4} w_h \theta_{ih}, \tag{3.14}$$

where $w_h = 0.25$ for all h. In this case, Table 3.6 presents the combination of the results obtaining the combined parenting factor.

The next step in the process is to obtain the occurrence rates for the failure causes under the new CHG design. Combining the recently obtained parent factor (γ_i), the failure cause occurrence rate of parent product (λ_i) and Equation 3.9 we are able to compute λ_i^*. Table 3.7 shows these results.

Finally, to predict the occurrence of each failure mode under the new design, Equations 3.10 – 3.12 are applied. We can obtain the point estimation, as well as the

Parameter	Distribution	μ	σ
θ_1		-0.165	0.047
θ_2	Normal	-0.501	0.044
θ_3		0.115	0.029

Table 3.6: Parenting Factor From Combined Expert Opinions

Failure Rate	Distribution	Median	$\mu_{\lambda^*_{c_i}}$	$\sigma_{\lambda^*_{c_i}}$
$\lambda^*_{c_1}$	Lognormal	0.0534	-2.93	0.071
$\lambda^*_{c_2}$	Lognormal	0.0158	-4.15	0.084
$\lambda^*_{c_3}$	Lognormal	0.0314	-3.46	0.059

Table 3.7: Failure Rates for c_i Under New CHG Design

confidence interval (CI), for both $F^*_{c_i}$ and $F^*_{m_j}$. For the probability of failure cause, its CI is a transformation of the CI of corresponding failure cause occurrence rate, i.e., $\left[1 - e^{te^{\mu_{\lambda^*} - \sigma_{\lambda^*}\Phi^{-1}_{(1-\alpha/2)}}}, 1 - e^{te^{\mu_{\lambda^*} + \sigma_{\lambda^*}\Phi^{-1}_{(1-\alpha/2)}}}\right]$. For the probability of failure mode, its CI is computed by combining corresponding failure cause estimations. Tables 3.8 and 3.9 present the resultant estimations for the new CHG design.

Failure Cause	Confidence	Lower	Median	Upper
$F^*_{c_1}$	95%	0.0454	0.0520	0.0595
$F^*_{c_2}$	95%	0.0133	0.0156	0.0184
$F^*_{c_3}$	95%	0.0276	0.0309	0.0346

Table 3.8: Confidence Intervals for $F^*_{c_i}$ Under New CHG Design

In conclusion, the reliability engineer has a preliminary estimation of failure mode probabilities under the new CHG design. These probabilities bring out the visibility of the impact of design changes on product reliability at the product's early design

Failure Mode	Confidence	Lower	Median	Upper
$F^*_{m_1}$	90.25%	0.0578	0.0666	0.0767
$F^*_{m_2}$	90.25%	0.0005	0.0006	0.0007

Table 3.9: Confidence Intervals for $F^*_{m_j}$ Under New CHG Design

stage, so managers and engineers can plan for future reliability improvements when the cost does not poses as a major constraint.

3.5 Discussion

This chapter discusses and proposes an enhanced parenting process for predicting reliability at a product's early design stage. The key idea is to utilize the reliability information of parent products that had already existed in warranty database. The relationships between failure modes and failure causes can be found from these historical data. Expert's opinions on the effects of design changes on individual failure cause are elicited. Integrating both objective and subjective reliability information, insights are provided into the nature of the early reliability prediction problem. The main purpose here is to present the basic elements and a logical structure that leads to the reliability prediction in a product's design phase.

It should be emphasized that this methodology does not produce a robust reliability predictor, but a baseline to start the reliability thinking at the early stage of product design. One of the major disadvantages when eliciting probabilities lies in the subjective nature of the opinions that could lead to predictable "errors". These errors are known as biases that might be rendered as "misperceptions" of probabilities or "distortion of judgement" (Cooke, 1991). Consequently, it is important to be aware of these biases when designing techniques for eliciting subjective probabilities. In the end, the elicitation process must be performed as objectively as possible. In the future, various methods could be studied to minimize the impact of biases. For example, different techniques for combining expert's opinions, further warranty analysis for indices computation, and the Bayesian approach to the parenting process, etc. Nevertheless, general guidelines for early reliability assessment are now proposed.

Chapter 4

OBTAINING RELIABILITY INSIGHTS OF A NEW PRODUCT IN ITS CONCEPTUAL DESIGN STAGE

4.1 Introduction

Accurate early reliability prediction becomes a common requirement for new product's development as systems have grown to be more complex (Gen & Kim, 1999). However, in the design phase of new products there are not physical samples to assess or prove reliability. On the other hand, under the philosophical influence of design for reliability (DFR) or build-in-reliability (BIR), significant efforts had been put on reliability improvement by product design.

In recent years with the aid of new computational technologies, several design approaches have been proposed with the use of Bayesian reliability. Bayesian methods for system reliability analysis have been studied extensively in the works of Hamada et al. (2007), Wang et al. (2009) and Pan & Rigdon (2009). Those works have depicted the possibility of assessing a new product's reliability before a physical sample is feasible by taking into consideration all available information. Such information can include component and subsystem data, information from similar existing systems and expert's opinions. Nowadays, there is also broad literature considering the reliability information integration aspect. Johnson et al. (2003), Hamada et al. (2004) and Wilson et al. (2006) proposed a fully hierarchical Bayesian method for reliability assessment of multi-component system. They studied the multilevel data scenario with pass/fail, lifetime or degradation data (also see Pan, 2008). Further extensions to these works include Anderson-Cook et al. (2008), Graves & Hamada (2010) and

Reese et al. (2011) whose focus were on binomial data or lifetime data under a known failure structure situation. These previous studies might well be applied under DFR framework. Such is the case of Johnson et al. (2005), where the authors described a hierarchical Bayesian model for assessing the early reliability of complex system.

However, even prior work that moves towards the reliability integration had overlooked the design process. A product design process consists of three major steps: conceptual design, embodiment design and detailed design (Pahl et al., 1995). Conceptual design refers to the analysis and identification of design concepts and the construction of functional structures for new products that meet the accorded requirements. The developing or embodiment design phase occurs when a detailed structure is defined and corresponding physicals structures (prototypes) are created for further validation. Finally, in the detailed design phase improvements are implemented, manufacturability is reviewed and production is scheduled. Hence, most of the DFR approaches in literature are implemented at the embodiment design or detailed design, but there are few that explicitly addressed it during the conceptual design stage. Such are the cases of Huang & Jin (2009), that under the framework of DFR they reduced a "gap" between reliability requirements and conceptual design by using stress and strength interference theory. Also, Derelöv (2008) provided a qualitative model for potential failure modes in the conceptual design phase. He developed a descriptive approach to model the failure behavior while also outlining a failure identification process. Finally, Stone et al. (2005) introduced product functionality in early design phases with their function to failure design method. This research was extended by Kurtoglu & Tumer (2008) where they presented a function-failure identification and propagation process through a hierarchical model of the system functions in the conceptual design phase.

Conceptual design phase usually does not produce detailed physical information as there is no physical part to test. Then, all the common reliability methods cannot be used. Furthermore, traditional methodologies operate under the assumption that there is a failure structure that can be derived by reliability tools. However, deriving new products' reliability structure (e.g., reliability model) for complex products is also a challenging task in conceptual design.

Nevertheless, it is required to have a reliability insight during this phase as it guides the decision making process for the new product development. For example, early reliability knowledge for a new product drives the reliability improvement plan, improves the test planning process and ultimately takes into consideration the minimization of warranty cost when changes are feasible. Hence, in order to assess reliability in the conceptual design stage a non-classical approach was needed.

This research addresses the challenges in reliability assessment at a products conceptual design. The investigation started from the idea of integrating information from similar proven concepts (parents) into a new product's conceptual design. In order to achieve this, a methodology was proposed. The approach included a coherent and novel system reliability structure revelation process that would provide insights into product reliability at its conceptual design phase. The proposed methodology called for the study of the new product's parented functional structures via a cognitive map. Then, the cognitive map was converted to a Bayesian network using parenting analysis and expert opinion elicitation. Finally, once the Bayesian network was completed, the designer can assess and validate the new product's reliability requirements.

The remainder of this chapter is organized as follows. In Section 2, the basics of functional analysis, cognitive maps and Bayesian network were introduced. Section 3 discusses the proposed methodology, where the integration of the parent information and eliciting information modeled a reliability structure for a new product in the conceptual phase. For better understanding of this proposed methodology a case study was exhibited in Section 4. Lastly, in Section 5 a discussion was held and further work was presented.

4.2 Background and Framework

4.2.1 Conceptual Design

As the first phase of engineering design process, conceptual design can be summarized as the creation of function structures and their combinations that meet specific requirements that would be translated into the physical plane to satisfy an established need. In other words, what are the new product's functionalities that would cover an existing need.

There are different approaches to conceptual design, as they can be developed for specific products. For example, they differ when designing complex versus non-complex products. However, the most common approach is the one defined by Pahl et al. (1995). Additionally, Huang & Jin (2009) described the typical tasks based on different approaches. In a general sense, the steps included in the conceptual design phase are stated in Table 4.1. Also, Table 4.1 shows the reliability considerations that should be made in all the steps. This is, from having reliability requirements in step 1 to meet technical reliability targets in step 5.

Conceptual Design Process Steps	Reliability Considerations
1. Abstractly identify essential requirements against design criteria	New products main function is formulated. Reliability requirements must be set in this step as they will aid in identifying which ones are essential functions of the new design.
2. Establish functional structures	When creating functional structures there are three considerations that are recommended: (1) Logical consideration (2) Physical considerations and (3) Reliability considerations. For reliability the functional structures must take into account those reliability requirements defined in the previous step.
3. Search and combine solution principles to satisfy the requirements.	Reliability requirements must be present when looking into different solution alternatives/combinations that will fulfill the functional structures previously defined. This can be done using conventional methods or bias/unbiased related approaches for the searching and systematic (logical) or/and using mathematical models for combining (Pahl et al., 1995).
4. Select suitable candidates for concept variants	In order to start evaluating the possible solution they must meet different criteria. The criteria might include: manufacturability, safety, maintainability and reliability
5. Evaluate technical and economic feasibility for concept variants.	Reliability constraints must carry a high weight into the selection and optimization process.

Table 4.1: Conceptual Design Approach with Reliability Considerations

However, the consideration of reliability in these steps does not provide an assessment of product reliability at this point, but merely specify the reliability requirement of the new design. Hence, a more systematic approach was needed in order to ensure reliability in conceptual design phase.

4.2.2 Functional Analysis

Various definitions of product function can be found in literature (Blanchard et al., 1990; Pahl et al., 1995; Hirtz et al., 2002; Van Wie et al., 2005 and Erden et al., 2008). In summary, a product function is defined as the relationship between inputs and outputs that satisfies a need or requirement.

Function analysis is a systematic process that identifies all functions of a system as well as the relationships and interactions between them and their elements (subfunctions). It has the main objective of reducing product complexity by dividing the principal characteristic of the system into manageable functions. A primary (overall) function can be decomposed to several subfunctions, and the decomposition can be performed in several levels as necessary. For more information on the methodologies and techniques of functional analysis please refer to Pahl et al. (1995), Otto & Wood (2003) and Stone & Wood (2000). In general, these methodologies may be synthesized into two steps: (1) Identify all elements involved, and (2) depict their relationship. These relationships are usually graphically demonstrated (i.e., matrices or graphs). Therefore, a common end result of functional analysis is known as the functional structure. In consequence, functional structures provide not just the relationship among its element but also depict and identify interactions between functions that would be able to describe the system in question. This becomes critical to reliability assessment when there is no an actual physical system.

Summarizing, functional analysis will provide a structure illustrating subfunctions that often present interactions usually missed in other "traditional processes", for example, Failure Mode and Effect Analysis (FMEA), Fault Tree Analysis (FTA) and Criticality Analysis (FMECA) (Arunajadai et al., 2004).

Figure 4.1 shows the transition between functionalities of the conceptual design selected to the breakdown of those functions. The graphic representation of those subfunctions is known as the functional structure.

Functional structures are then depicting the relationship between subfunctions. Therefore, a system might have several functional structures for each one of its func-

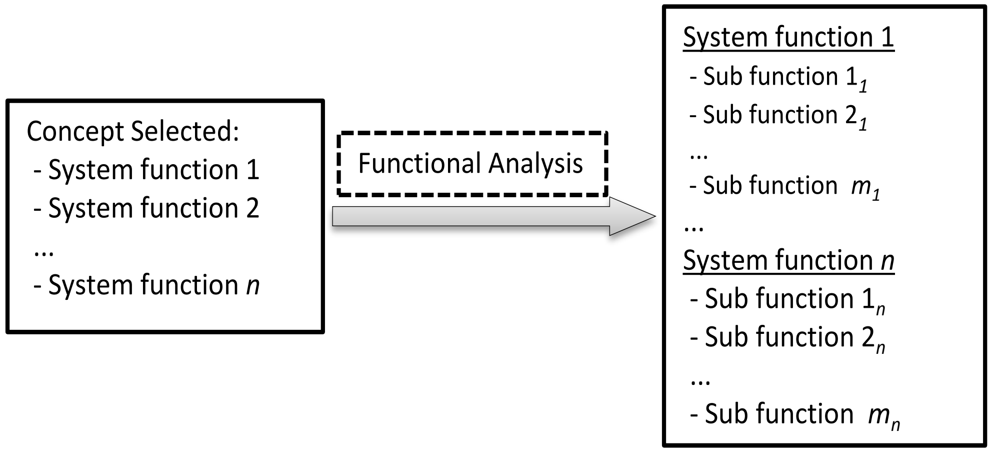


Figure 4.1: Functional Analysis for a New Product in Conceptual Design Phase

tionalities. Figure 4.2 graphically shows the assumed functional structures for each system function. Then, let S_i be the functional structure set for system function i containing $s_{1i},\ s_{2i}, \ldots,\ s_{mi}$ subfunctions. Then the total system functionality for the new product can be seen by:

$$\bigcup S_i \qquad \text{for} \quad i = 1, 1, \ldots, n\ . \tag{4.1}$$

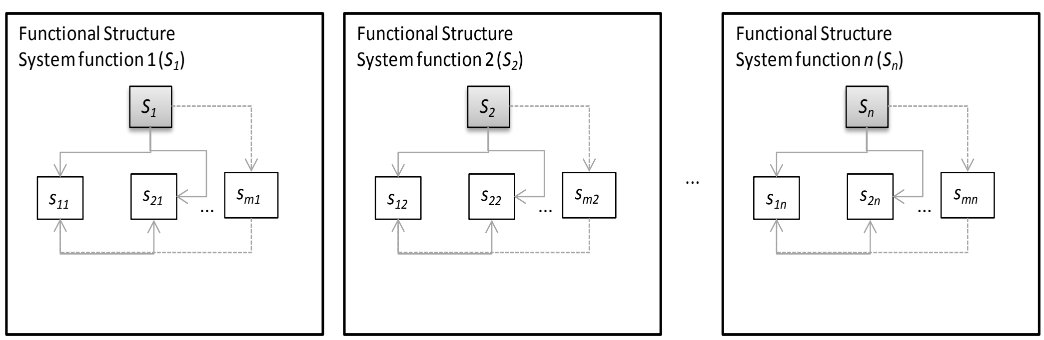


Figure 4.2: Functional Structures for System Functions of a New Product

In the past decade an increment of use of functional analysis in reliability has been seen. Moreover, there are some studies related to having functional analysis for reliability in the conceptual design phase. Such are the cases of Tumer & Stone (2003), Bryant et al. (2005) and Kurtoglu & Tumer (2008). Their research was focused on the function to failure design method. Their method promoted early identification of potential failures by linking them to product functions. The approach consisted on defining the relationship between system functions and its failure modes in a matrix form. They used historical data, existing data and expert input to define those relationships as well as standardized design taxonomies for functions and failure modes. The methodology provided a starting point for determining system failure structure based on a set of functions that the system requires. Therefore, it only provides a qualitative approach to recognizing potential functional failures before a concept is selected.

Stone et al. (2000) developed an approach to transform customer needs and function structures into quantitative models. Then, Tumer & Stone (2003) extended this concept to mapped systems functions to failure modes. In other words, it is possible to define a failure when a function is not executed as expected as there is a fail to satisfy its intent during its designed lifetime. Therefore, failure modes can be stated in terms of deviation of functions.

In this research the function to failure approach was used. Furthermore, the use of functional analysis was to set the baseline for revealing reliability insights in the conceptual design stage. To depict the risk for failures in functions, a parenting process was chosen to assess failure rates; to identify relationships between functions a graphical structure was created through a cognitive map (Augustine et al., 2012). Moreover, inside the parenting process there is a branch called elicitation process (Mejia Sanchez & Pan, 2011). Expert elicitation is the synthesis of experts' knowledge on one or more uncertain quantities (Cooke, 1991). Hence, the elicitation process was used to gain the desired insight into the reliability of the new product via the parenting process. This process is explained in further sections.

4.2.3 Cognitive Maps

Cognitive map (CM) is essentially a graphical representation of the knowledge or the perception of a given system. It can be defined as a signed digraph where nodes represent concept variables and directed arcs are the causal relationships (Augustine et al., 2012). Tolman (1948) first introduced the CM concept and it was defined as a visual representation of an influence network between concepts. Since then CMs have been applied in several different fields including medical, psychology, software and engineering among others. Therefore, nowadays there exist a vast collection of definitions and methodologies in literature (El-Haik, 2005; Lee & Chung, 2006 and Lee & Kwon, 2014)

To illustrate the process, Figure 4.3 presents one of their general uses of a cognitive map for a given system.

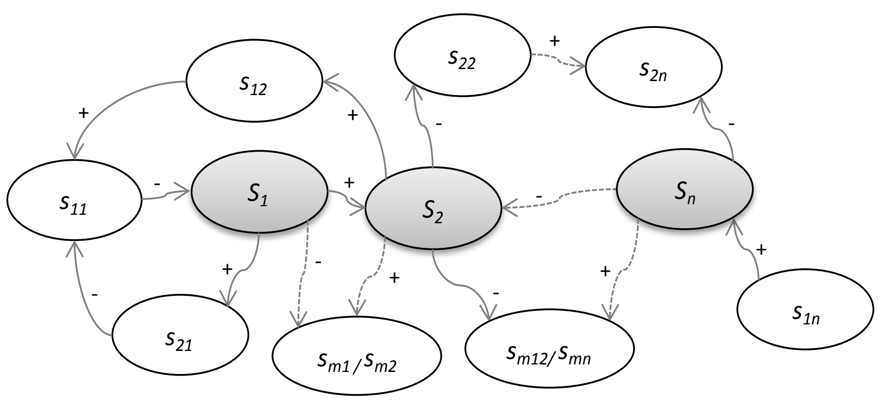


Figure 4.3: High Level Cognitive Map for New Product's Functions/Requirements

The "+" or "-" sign indicates either positive or negative correlation between the conceptual functions, respectively. As observed, this type of maps just graphically represents qualitative information for causality but does not allow for any kind of quantitative computation. In order to enhance the uses of CM, fuzzy cognitive maps (FCM) were introduced in literature (Kosko, 1986 and Glykas, 2010).

FCMs are one of the first approaches to offer quantification in CM. In a FCM a weight is used to depict the strength of causalities as well as a numerical value is assigned to each node, which would express its state or level. Then, FCMs are simulated in discrete or continuous time while the weights remain constant, but the state/level values change. During the simulation, a premeditated threshold function is used to evaluate the updating value i by transferring the weighted sum of all values that are input to node i. Hence, final inference for a CM would end in one of the following three outcomes: a) unique (trivial) solution, b) a limit cycle, or c) chaos (Augustine et al., 2012). Therefore, there are instances where there is no answer. Other disadvantages of FCM include the use of thresholds that need to be previously defined, the evaluation through simulations that produce variability in results, and as other fuzzy systems: the incapability of self-learning when new evidence is collected (Stach et al., 2005).

CM provides an excellent graphical representation of conceptual relationships. In this research, cognitive maps were used to move one step towards graphing the reliability-wise relationships of functions. This allowed a better understanding of the functional behavior that lead to system failure.

4.2.4 Bayesian Networks

Bayesian networks (BNs), also called belief networks, are used to represent knowledge about an uncertain domain (Ben-Gal, 2007). To be more specific, BNs represent a set of Bayesian random variables and their conditional dependencies via a directed acyclic graph (DAG). In the graph, each node represents a random variable, while the arcs/edges between the nodes represent the probabilistic dependencies among the corresponding random variables. These conditional dependencies in the graph are often estimated by using known statistical and computational methods.

The use of BNs in reliability has proved to have significant advantages over traditional approaches (Langseth & Portinale, 2007). One of these advantages over Reliability Block Diagrams (RBD) and Fault Tree Analysis (FTA), resides in the use of the probabilistic relationships. For example, given the deterministic nature of the gates for a FTA it is difficult to incorporate the uncertainty seen in the conceptual phase of the design. Conditional probabilities in a BN allowed capturing this uncertainty between the functional relationships. Furthermore, BN also provided the opportunity of combining different sources of information (i.e., expert's input) to present an overall assessment of a system.

In a mathematical sense BN is defined as a compact representation of a multivariate statistical distribution function. Then, its graphical model encodes the set of conditional independence statements. This grants the possibility of calculating the joint probability function as:

$$f(x_1, \ldots, x_n) = \prod_{i=1}^{n} f(x_i|\text{pre}(x_i)) \ , \tag{4.2}$$

where pre(x_i) represents the predecessor nodes of variable x_i, hence f(xi|pre(x_i)) is defined as the conditional probability function for variable node x_i given its predecessors.

Furthermore, BNs have two different sets of information. The qualitative part of the model is represented by the DAG structure, which for this study it was defined from the CM and functional analysis. Secondly, the quantitative aspect is provided on the parameters of the model. These parameters were specified on a conditional probability functions, where the dependencies of each node are depicted according to its predecessor nodes. The values of these parameters can be determined by using statistical data as well as using parenting information and expert elicitation.

Figure 4.4a presents a basic BN structure which includes the probabilities that would form the joint probability distribution. Additionally, the use of binary variables (e.g., fail or functional) is really common; thus Figure 4.4b shows how the probability tables can be represented in a matrix form.

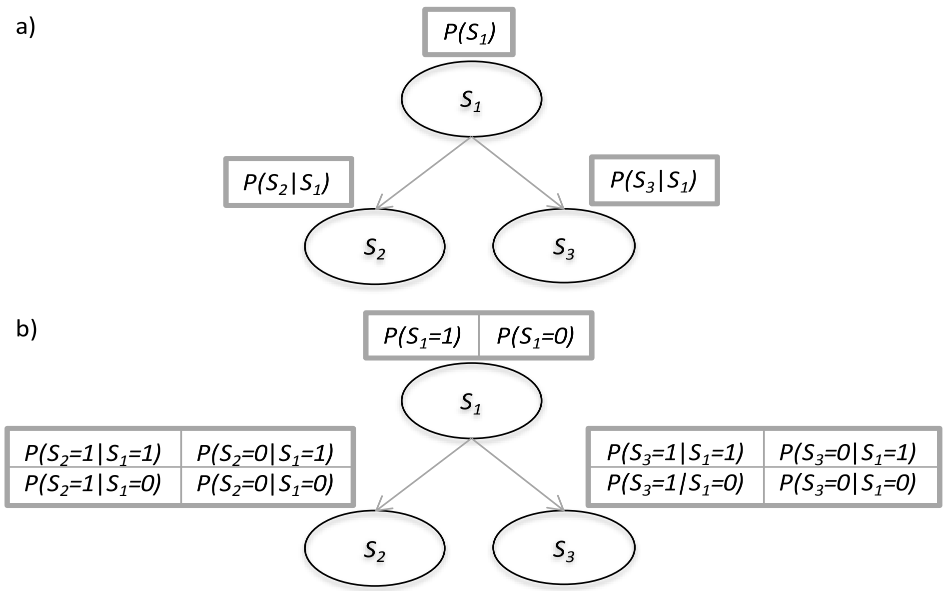


Figure 4.4: Bayesian Network Representations a) BN With Conditional Probability Function b) BN With Conditional Probability Table (Binary Variables)

It has been proven that inference in BN could be a NP-hard problem (Cooper, 1990). Nonetheless, several approaches and algorithms exist in order to exploit the network structure for a probabilistic inference. Generally these inferences can be classified in two: (1) Causal inference which can be seen graphically as top down approach (from failure cause to failure mode). (2) Evidential inference or bottom up, where from an observation of a variable it is possible to infer a different one given the conditional dependencies.

Furthermore, inferences are made by queries. In the product design framework, queries are made based on what designers need to evaluate. There are simply queries such as the posterior marginal distribution that might be used to assess the reliability of a concept. Moreover, there also exist conditional queries that help designer to make decisions or provide information in features of the design. Additionally, sensitivity analysis can be implemented to investigate if the design specifications meet the proposed requirements.

The algorithms to solve these queries are divided in two: those that provide exact inference such as enumeration, belief propagation (polytrees), variable elimination or Clustering/Joint tree algorithms. On the other hand, the ones that provide an approximate inference like stochastic simulation / sampling methods, Markov chain Monte Carlo methods, genetic algorithms, neural networks, simulated annealing or mean field theory. For more information please refer to Bishop et al. (2006).

The goal for this research is to gain a reliability insight in the conceptual design. BN can provide this insight into the system (concept). BN represented the reliability/failure structure where now inference can be performed to further decipher the conceptual system. The methodology proposed to achieve this is described in the next section.

4.3 Methodology

In order to assess new product's reliability it was needed to take into consideration different factors such as new product definition, level of change, design purposes, etc. In other words, analysis and tools are applied case by case. However, the proposed methodology presented a general approach to have a reliability insight regardless of those factors. The framework of this methodology is depicted on Figure 4.5. It shows the progression between each one of the phases and their tools to link them.

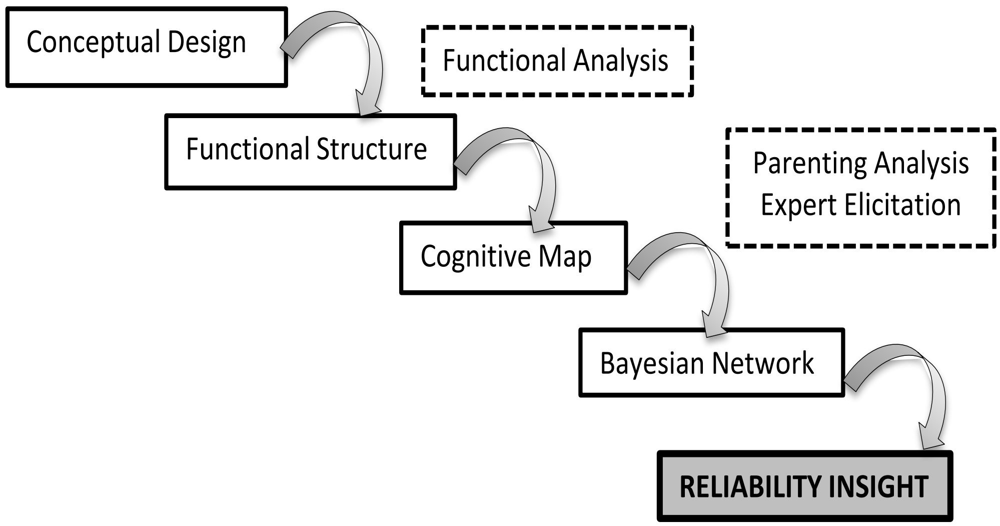


Figure 4.5: Methodology Framework to Gain Reliability Insight on Design Phase for a New Product

4.3.1 Concept and Functions

The methodology starts in the conceptual design phase, when a concept has been selected. Since there are not physical design representations at this time, the requirements are translated to functionalities of the new product. Therefore, either new functions or already established ones are identified and/or defined as the outcome of this phase.

4.3.2 Function to Failure Structures

Once the system functions are defined a functional analysis needs to be conducted. The first step consists in the identification of the primary or main function(s) and all the subfunctions involved. Secondly, the relationships between them need to be depicted. It was recommended to use a graphical representation when performing both steps to define the functional structures.

In order to have a reliability structure (or failure structure) in the early design process it was important to identify failure modes even when physical components were just conceptualized. In this instance, using function to failure approach (Stone et al., 2005) created the possibility to define a failure when a function is not executed as expected.

However, given the uncertainty in conceptual design, assessing the failure probability for all the functions can be challenging. On the other hand, those functions can be identified and related to different existing products or parents. Moreover, additional functional information can be obtained by other sources. For example, simulation, expert opinions, early experimentation, literature, etc. Then, parent information might be defined as the existing available information coming from current design/products that have similar functions or subfunctions of the new design/product.

4.3.3 Functional Structures to Cognitive Map

Following the methodology depicted by Augustine et al. (2012) it was possible to obtain a cognitive map model from functional structures. The procedure incorporates in a stepwise manner, all structural, functional, and causal aspects of the system. Cognitive Maps Fragments (CMF) are formed for the each one of the system functions identified. After the CMFs are finalized, they can be automatically aggregated into the final cognitive map (CM) structure by using the simple union operation expressed in Equation 4.3:

$$\mathrm{CM} = (\bigcup_{m=1}^{i} N_m) \bigcup (\bigcup_{m=1}^{j} A_m) \ , \tag{4.3}$$

where, N_m represent the set of i nodes and A_m the j arcs from the CMFs.

The construction of the cognitive map should be taken with expert inputs. In the creation of the cognitive map redundant subfunctions (i.e., subfunctions that are shared by more than one system function) are depicted as such and it also reduces the complexity of the graph. Then, the relationships between each one of the functions were explicitly stated given the arcs in the map. Moreover, when creating the CMFs there is the possibility to capture additional functions to depict interactions between failure modes that were not capture by the functional analysis.

4.3.4 Cognitive Map to Bayesian Network

A general structure has been already defined by the functional cognitive map. FCM might use some existing information such as expert elicitation (Augustine et al., 2012), however choosing the arc's weights will not provide an objective form to gain the desired reliability insight.

A more objective approach to integrating information and moreover to integrating furthers updates was the use of a Bayesian network (BN). BN is a tool that aggregates the impacts of changes on components/subfunctions to the system/main function level and allocates the total risk to different subfunctions (i.e., identify subfunctions with high failure risk).

A few publications have discussed the similarities and differences between CM and BN. Nadkarni & Shenoy (2001) and Nadkarni & Shenoy (2004) are part of the few that provide a more direct approach on how to derive BNs from CMs. They pointed out the main differences (or biases) between CM and BM as follow:

- Conditional Independence. In CM, arcs between variables depict dependence; however the absence of an arc does not imply independence. On the other hand, the lack of an arc among variables in a BN it does implies conditional independence among them.

- Cause Effect relations. This bias refers to the perception of the effect coming from causes or if the relationship is depicted from effects to causes. It is important to establish a deductive relationship (causes to effects) which is the proper way to have CM to be converted into a BN. Furthermore, it is recommended to be cautious with adductive relationships (causes from effects).

- Direct vs. Indirect relationship. Differentiation between direct and indirect cause effect arcs permits the incorporation of conditional independencies in CM. Thus, this facilitates the translation to a BN.
- Circular relations. They exits in CM as subjective judgments are made and also they might represent time changing relations between variables. However, they violate the acyclic graphical structure for BN. Hence, it is required to eliminate circular relations to make CM compatible with BN.

Moreover, in their research they present a 4-step procedure to construct Bayesian cognitive maps (BCM). These steps are (1) Expert elicitation, (2) Derivation of CM, (3) Modification to CM to create BCM and, (4) Derivation of the parameters of BCM. Step (1) and (2) are defined by a structured interview to the experts and coding the answers into a cause-effect map. Step (3) is focused on making the CM compatible with the BCM considering the four biases presented above along with expert elicitation. Finally in step (4) a probability assessment is implemented in two steps: identifying the state space of nodes via expert elicitation; and the derivation of conditional probability, using probability encoding techniques. Once the parameters are identified, probability propagation (i.e., Bayesian belief propagation) algorithms might be used to make inferences. An example of this process is presented in Aktaş et al. (2007) where they use this approach to improve the efficiency of resource allocation in a health care facility.

In this research, the proposed methodology already covers steps (1) and (2) by going from the functional analysis in conceptual design to the CM. Step (3) was the generalization of graphically converting a CM to a BN, tackling the four biases described above. For step (4) parenting processes would be used.

Parenting process provides an objective data analysis process for transferring CM to a BN. The general guidelines are provided in Mejia Sanchez & Pan (2011). This approach would be especially helpful when dealing with Conditional Probabilities Tables (CPTs). If this is the case, there are two main approaches to obtain the parameters values: expert elicitation or summarizing failure information from parent functions. Following the guidelines for eliciting probabilities (Cooke, 1991) and parenting process, the expert would be asked to provide an assessment of the marginal conditional probability inside the CPT. On the other hand, if there are existing products performing similar functions under the same conditions, their failure information can be translated or used directly into the CPT (e.g., root nodes).

Aside from parenting and expert elicitation there is another possible approach to estimate probabilities when information is scarce. This approach is known as Meta-analysis. Meta-analysis refers to methods that focus on contrasting and combining results from different studies, in the hope of identifying patterns among study results, sources of disagreement among those results or other interesting relationships that may come to light in the context of multiple studies. Often used on medical fields to gather information from previous studies, e.g., several clinical trials of a medical treatment, in an effort to obtain a better understanding of how well the treatment works (Chow & Liu, 2013). Here are the main steps to conduct a meta-analysis:

1. Formulation of the problem
2. Literature review
3. Selection of studies ('incorporation criteria')

4. Decide which dependent variables or summary measures are allowed. For instance: discrete data vs. continuous data

5. Model selection

   (a) Fixed effect models

   (b) Random effect model

   (c) Quality effect model

This approach is usually more time consuming then the others previously mentioned. However, when parent information is limited and experts are unavailable, it can be a powerful approach.

4.3.5 Bayesian Network Inference and Evaluation

It is noteworthy to point that the probabilities or parameter values obtained are concept dependent. In other words, a concept needs to be selected in order to have an insight on its reliability. For example, when a set of components is chosen to perform a function it would have a specific probability of failure; however, if it is decided to use a different set of components then the failure probability would change. Nevertheless, if resources are available, it is possible to use the gained reliability insight to differentiate different concepts and perform an evaluation in accordance to the DFR framework.

The quantitative part of the BN was constructed after obtaining the parameter values or probabilities. Therefore, it can be used now to make inferences about the functions in the model. The scope of this research was to have a graphical insight to the reliability on a new product in the conceptual phase by obtaining a BN. Next steps depend on each specific case, e.g., concept evaluation, assessment of unobservable parameters or conduct a sensitivity analysis. If concept evaluation is needed, researchers could use the joint probability distribution from the different concepts and proceed with a decision making process. Marginal conditional distribution and conditional dependencies can be used to estimate variables or parameters that were not observed. This was achieved through the joint distribution of BN, i.e., probabilistic inference (Shachter & Peot, 2013). Lastly, evidential inference (or evidence propagation) refers to the ability to obtain marginal probabilities of parameters of interest, conditional on arbitrary configurations of other parameters based on the observed evidence (Spiegelhalter et al., 1993).

There are several commercial software tools for inference and analysis of BN such as Hugin (www.hugin.com) or Netica (www.norsys.com). There are also some development tools as MSBNx (research.microsoft.com/msbnx) or SamIam (reasoning.cs.ucla.edu/samiam) that automate the process of inference based on existing algorithms (Neapolitan, 2012). These tools allow the user to enter the BN structure graphically, input the observable details, and then do inference of either type (i.e., probabilistic or evidential).

4.4 A Case Study

In order to better demonstrate and validate the proposed methodology a case study is introduced. The graphical approach taken would explore and clarify the concepts presented in the methodology section. A reduced example is chosen to better facilitate the implementation and understanding, but methods can be easily extrapolated into more complex scenarios.

It is important to disclaim that given the possibility of disclosing sensitive information the values presented were masked and certain variables were removed. Nevertheless, this does not affect the methodology deployment or the exemplification.

4.4.1 A Contaminant Reduction Device

An automotive industry was developing a contaminant reduction device (CRD) to launch in the upcoming years. Since the Environmental Protection Agency (EPA) had restricted the emission levels on the years ahead, a new CRD was needed to comply with the new regulations. To achieve this, the design team proposed several improvements on their CRDs currently in production. Hence, the requirements for the new CRD were laid out and the team was in desperate need to design a reliable product while meeting deliverables and regulations.

A CRD is a device used to convert exhaust emissions, usually toxic, into less-toxic substances. The main objective of CRDs is to stimulate a chemical reaction through the exhaust flow and additives in which contaminants are reduced.

The development of the CRD was in the conceptual design phase; hence, to maximize resources and minimize further costs, the reliability team was tasked to assess the product's reliability at this early stage. Since data for the new model was scarce, the reliability team proposed the methodology described in this chapter to create a graphical model to depict all information available.

A concept was already selected based on the predetermined requirements and customer expectations. Therefore, it was relatively easy to list the different functions that the new CRD was going to perform.

Once system functions were identified, then a graphical structure was needed. The team performed a functional analysis where the basic functional structure was defined; Figure 4.6 shows the results of this exercise:

Following the rules established on Augustine et al. (2012) for function taxonomy, a follow up exercise was conducted to name the functions that were going to be used in the next step of the methodology. In this exercise, flow OF exhaust gas was considered

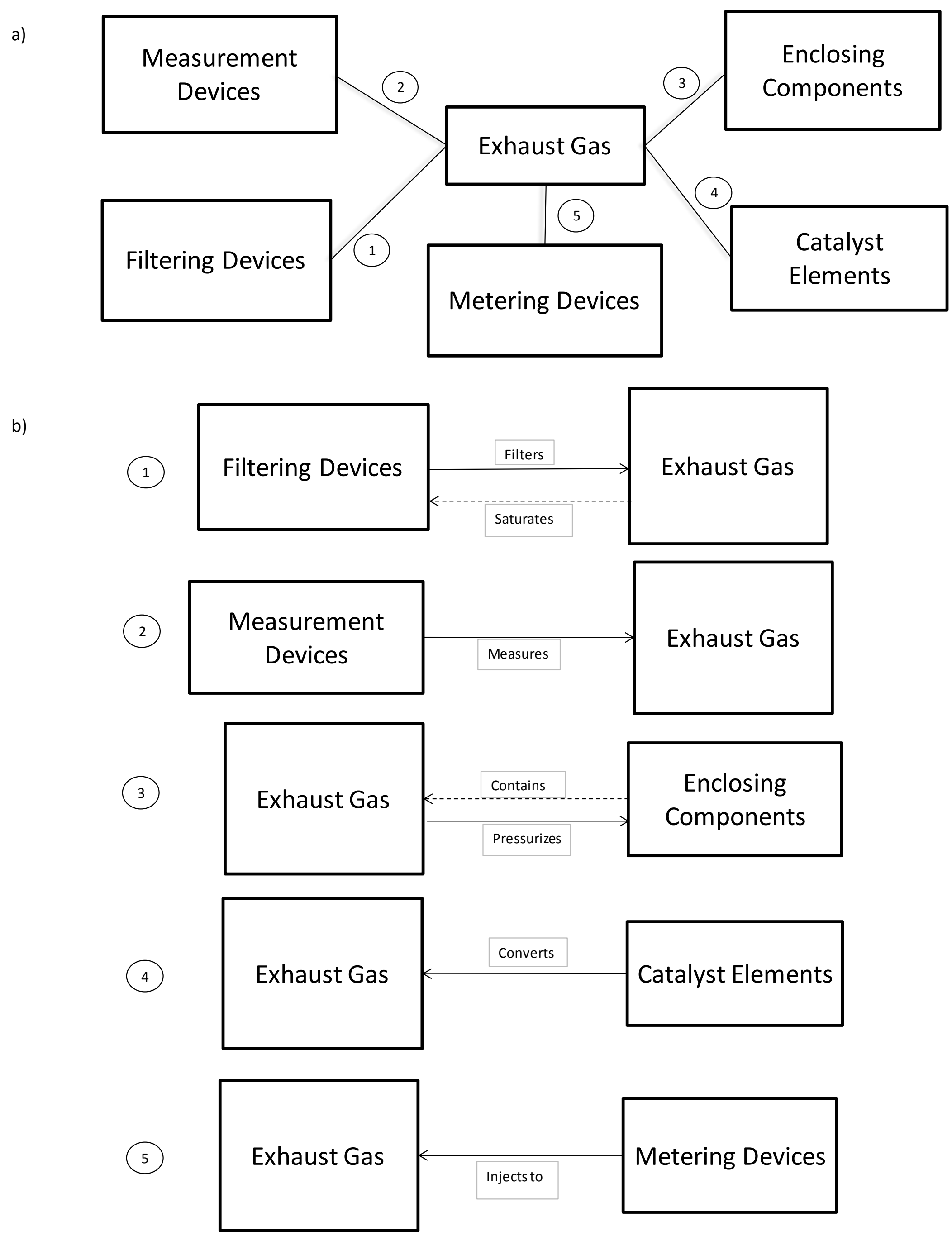


Figure 4.6: Functional Analysis for the New CRD Where a) Presents the System Functions and Subfunctions, and b) the System's Functional Structures

the main function of the system and it is expressed by its main subfunctions that form the failure functional structure in Figure 4.6a. The final list of the subfunctions was stated as follow including the functional structure where they came from in Figure 4.6b. For example injection OF fluids shows a 5 and a 2, therefore this subfunction comes from the functional structure number 5 and 2.

- Saturation OF filters (1)
- Amount OF contaminants (2) (1)
- Backpressure AT outlet (3)
- High temperature OF elements (2) (4) (3)
- Injection OF fluids (5) (2)
- Residence time OF catalysis (4) (2)
- Heat and mass transfer OF elements (2) (4)

Next, the list of functions from the functional structures needed to be represented in a graphical display. Then, a CM was used to organize the different functional structures and to establish the causal relationships between all the concept's functionalities including subfunctions that might be repeated on different functional structures. Figure 4.7 presents the final CM map after combining the different CMFs as Augustine et al. (2012) methodology dictates.

Continuing with the methodology, the obtained CM needed to be converted into a BN. An extensive session was held to receive feedback from experts within the design team. Then, the conversion of the CM on Figure 4.7 into a BN was executed following the recommendations made by Nadkarni & Shenoy (2001) and Nadkarni & Shenoy (2004). The resultant BN can be observed in Figure 4.8

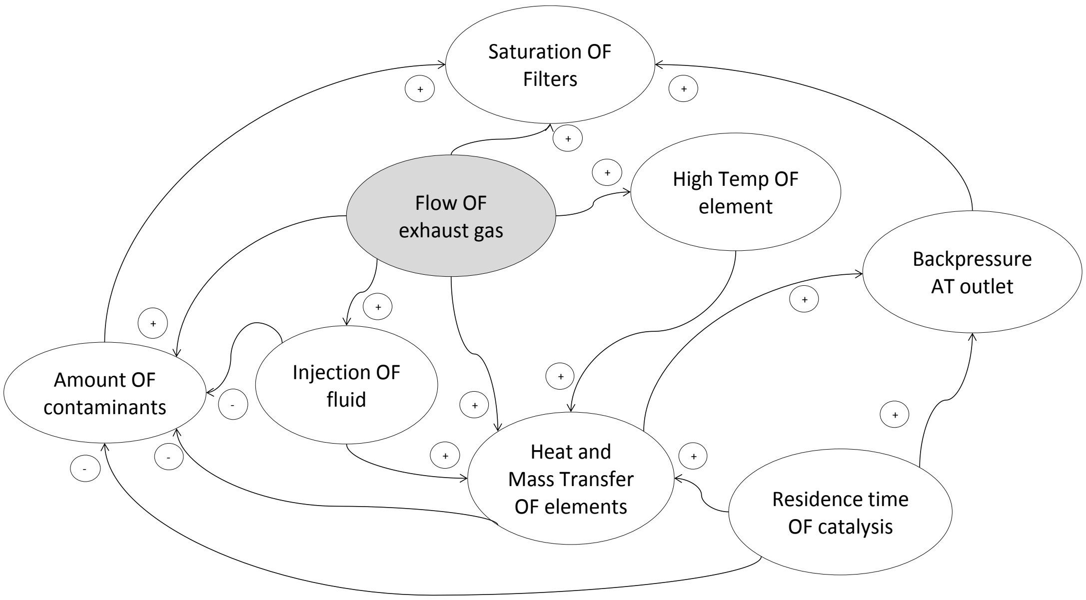


Figure 4.7: Cognitive Map Given Functional Structures for the System Functions of New Product

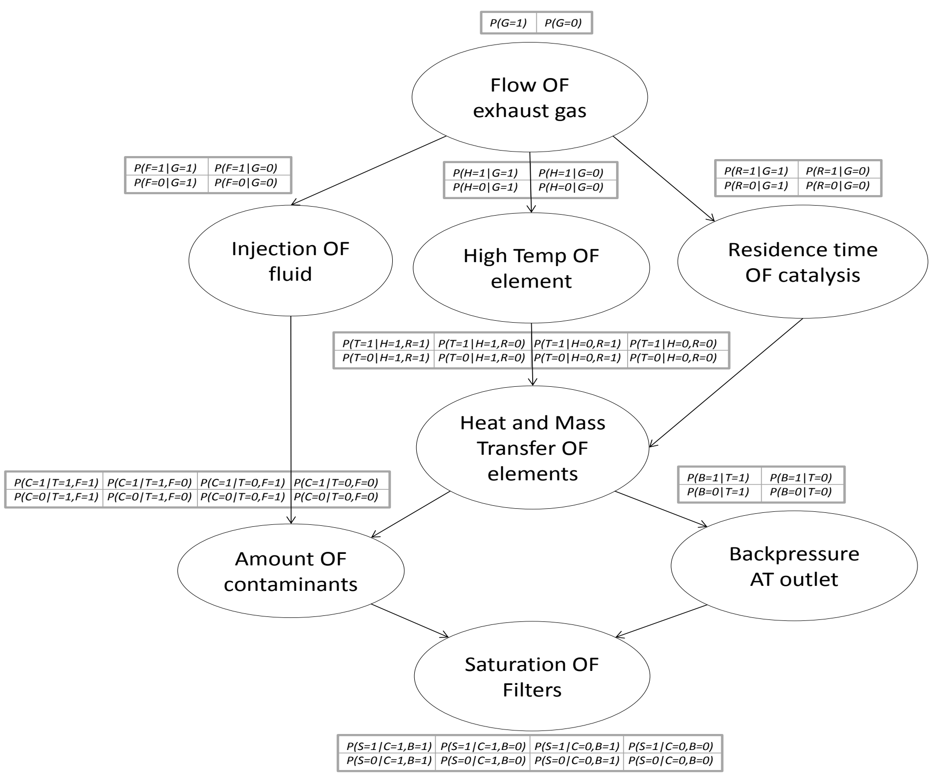


Figure 4.8: Bayesian Network Given Functional Structures From Cognitive Map

Figure 4.8 represents the qualitative part of the BN. It depicts the relationship between the different functional structure more objectively than the CM. Then, the next step is to obtain the conditional probability for each node. The main approach to produce these probabilities is using conditional probabilities tables. CPTs denote the conditional probability of the state of the function (e.g., failure mechanisms of the function). These states are more commonly expressed in binary variables: function failure or Nonfunctional (1) or function performing properly or Functional (0).

For the new CRD, once that the BN variables were defined, the parameter values needed to be determined. Given the resources available, it was decided to use CPTs in a way to facilitate the elicitation process. A parenting processes session was held to properly assess the CPTs. The detailed process is described below:

- Node [Flow OF exhaust gas (G)]. As main function it did not required to change on is general functionality. Hence, CPT was obtained directly from current function's failure information.

- Node [High Temperature OF element (H)]. Previous catalytic element had the latest technology available and there is no plan to change if it meets the proposed requirements. In consequence, its CPT for the function H would be also obtained by using the current function failure information.

- Node [Injection OF fluid (F)]. After an elicitation process for this particular function, it was determined that the metering devices would need to change in order to meet new standards. In this elicitation session with the experts the CPT for the function was found and it is stated on Figure 4.9.

- Node [Residence time OF catalysis (R)]. The time for the chemical process to take place has great variability. Hence, an elicitation process was required to have a better understanding of the function. A CPT was provided based on parent information and expert input as shown Figure 4.9.

- Node [Heat/Mass Transfer OF elements (T)]. The CPT for this function was obtained by a similar process of the enhanced parenting process from Mejia Sanchez & Pan (2011). The translation is simple when H, F and R are seen as the failure causes for each state (0 or 1) and in consequence state of T represents the failure mode.

- Node [Amount OF contaminants (C)]. As new standards are imposed regarding the amount of allowable quantity of contaminants out of the system; new measure devices are needed to verify that this function is performing adequately. In order to obtain more objective estimates, different sensor groups were elicited and a consensus was reach on its CPT depicted in Figure 4.9.

- Node [Backpressure AT outlet (B)]. One of the biggest requirements was to overhaul the enclosing components. It was required to change in size and form. Therefore, this function was one the main concerns. After several sessions of elicitation, experts were able to evaluate the CPT given that the characteristic of this functionality were seen in a different application.

- Node [Saturation OF Filters (S)]. Functionality of the filtering devices did not suffer major changes as they would be required to operate under the same conditions. Hence, direct parenting provided the CPT for this function.

For the better understanding of the teams, all information was compiled in Figure 4.9.

The CPTs completed the quantitative part of the BNs. Consequently, the structure obtained from the final BN fulfills the scope of this research. In other words,

Flow OF exhaust Gas (G)	Nonfunctional	P(G=1) = 0.074			
	Functional	P(G=0) = 0.926			
Flow OF exhaust gas		Nonfunctional	Functional		
High Temperature OF elements (H)	Nonfunctional	P(H=1|G=1) = 0.714	P(H=1|G=0) = 0.044		
	Functional	P(H=0|G=1) = 0.286	P(H=0|G=0) = 0.956		
Flow OF exhaust gas		Nonfunctional	Functional		
Injection OF Fluids (F)	Nonfunctional	P(F=1|G=1) = 0.979	P(F=1|G=0) = 0.012		
	Functional	P(F=0|G=1) = 0.021	P(F=0|G=0) = 0.988		
Flow OF exhaust gas		Nonfunctional	Functional		
Residence time OF catalysis (R)	Nonfunctional	P(R=1|G=1) = 0.963	P(R=1|G=0) = 0.027		
	Functional	P(R=0|G=1) = 0.037	P(R=0|G=0) = 0.973		
High Temperature OF elements		Nonfunctional		Functional	
Residence time OF catalysis		Nonfunctional	Functional	Nonfunctional	Functional
Heat and mass Transfer OF elements	Nonfunctional	P(T=1|H=1,R=1) = 0.993	P(T=1|H=1,R=0) = 0.834	P(T=1|H=0,R=1) = 0.982	P(T=1|H=0,R=0) = 0.005
	Functional	P(T=0|H=1,R=1) = 0.007	P(T=0|H=1,R=0) = 0.166	P(T=0|H=0,R=1) = 0.018	P(T=0|H=0,R=0) = 0.995
Heat and mass transfer OF elements		Nonfunctional		Functional	
Injection OF fluids		Nonfunctional	Functional	Nonfunctional	Functional
Amount OF Contaminants (C)	Nonfunctional	P(C=1|T=1,F=1) = 0.998	P(C=1|T=1,F=0) = 0.862	P(C=1|T=0,F=1) = 0.334	P(C=1|T=0,F=0) = 0.059
	Functional	P(C=0|T=1,F=1) = 0.002	P(C=0|T=1,F=0) = 0.138	P(C=0|T=0,F=1) = 0.666	P(C=0|T=0,F=0) = 0.941
Heat and mass transfer OF elements		Nonfunctional	Functional		
Backpressure AT outlet (B)	Nonfunctional	P(B=1|T=1) = 0.918	P(B=1|T=0) = 0.069		
	Functional	P(B=0|T=1) = 0.082	P(B=0|T=0) = 0.931		
Backpressure AT Outlet		Nonfunctional		Functional	
Amount OF Contaminants		Nonfunctional	Functional	Nonfunctional	Functional
Saturation OF filters (S)	Nonfunctional	P(S=1|B=1,C=1) = 0.984	P(S=1|B=1,C=0) = 0.743	P(S=1|B=0,C=1) = 0.946	P(S=1|B=0,C=0) = 0.022
	Functional	P(S=0|B=1,C=1) = 0.016	P(S=0|B=1,C=0) = 0.257	P(S=0|B=0,C=1) = 0.054	P(S=0|B=0,C=0) = 0.978

Figure 4.9: Chart With Probabilities Values (CPTs) Obtained for Each One of the Functions on the BN

the BN provided the insight to reliability for the new CRD in the conceptual design phase. However, the different uses or insight angles towards reliability depend on the queries made to the BN. For example, for the new CRD team there were three different scenarios that were looked at. Those are presented in the next sections.

4.4.2 Sensitivity Analysis

The main need to have a reliability insight is to verify that the functions for the chosen CRD concept would meet the requirements established from the different environmental regulations and customer expectations.

On the CRD's BN, all functions' CPTs in Figure 4.8 were able to be elicited or parented. Hence, at this point both teams (design and reliability) were interested to see if the current concept was capable to meet specific requirements to measure emission compliance standards by 90%, and more importantly, which function parameters needed to be improved in order to meet the specification.

The teams decided to use the software SamIam as it provides an engine for sensitivity analysis. Figure 4.10 shows the CRD's BN with the monitors displayed by SamIam. The monitors are estimated based on the CPTs from Figure 4.9, and was observed that the amount OF contaminants (C) function was only functional about 82% of the time; or $P(C = 0) = 0.82$. Therefore, it was not meeting the stated requirement. A sensitivity analysis was proposed for the event shown in in Equation 4.4. The reliability team then used SamIam's sensitivity analysis engine to evaluate such constraint.

$$P(C = 1) \leq 0.1 \tag{4.4}$$

The sensitivity analysis was conducted by using the Shenoy-Shafer algorithm as it is one of the main methods for probability propagation in a joint tree (Park & Darwiche, 2003). The sensitivity analysis section of the software is depicted in Figure 4.11 and it presents the event constraint establish in Equation 4.4. After running the analysis, it resulted in two different recommendations. First, Figure 4.11a is the multiple parameter suggestion for C's CPT where the recommended changes are highlighted in red. The second alternative is shown in Figure 4.11b where, in a similar manner, presents the highlighted recommendations for T's CPT.

The reliability team presented the results with the design team and suggested to study both options and their the Log-odds or Δlo (see Chan & Darwiche, 2001) provided by the software. Log-odds represents the difference of the natural logarithm of the odds after applying a change in the parameters. The definition of Δlo is stated

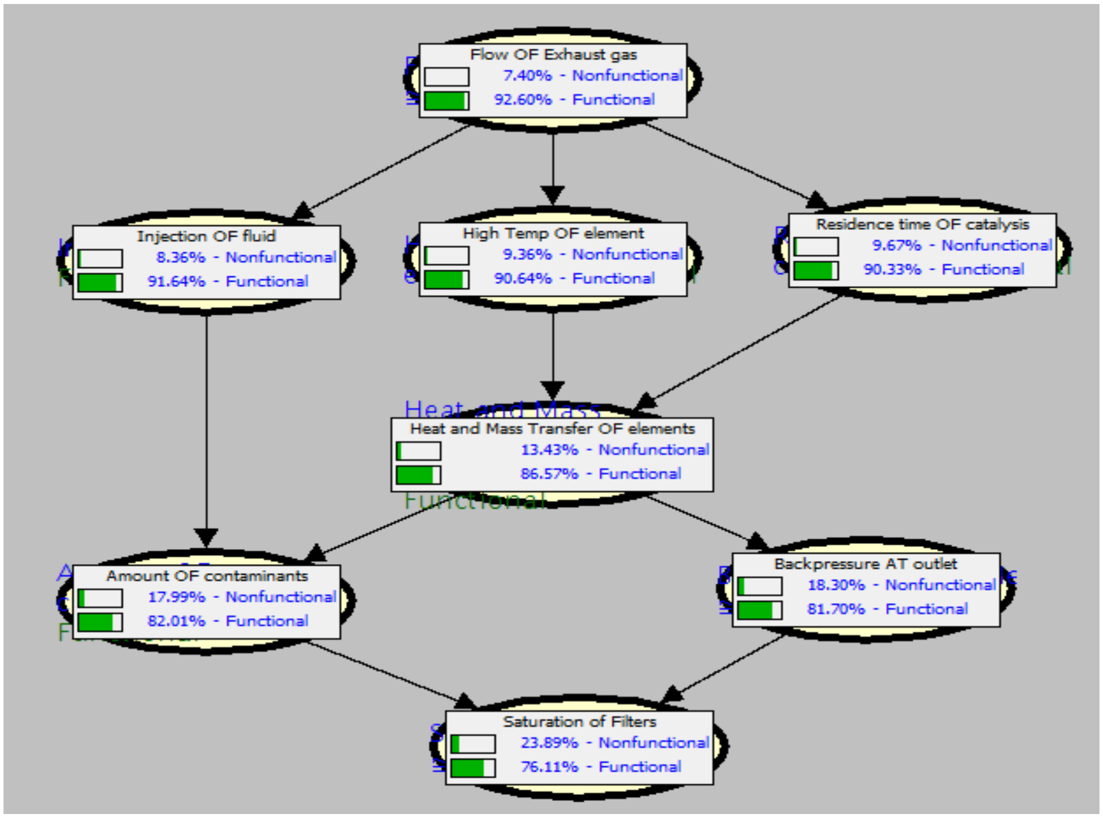


Figure 4.10: Bayesian Network From Example on SamIam With Monitors Displayed

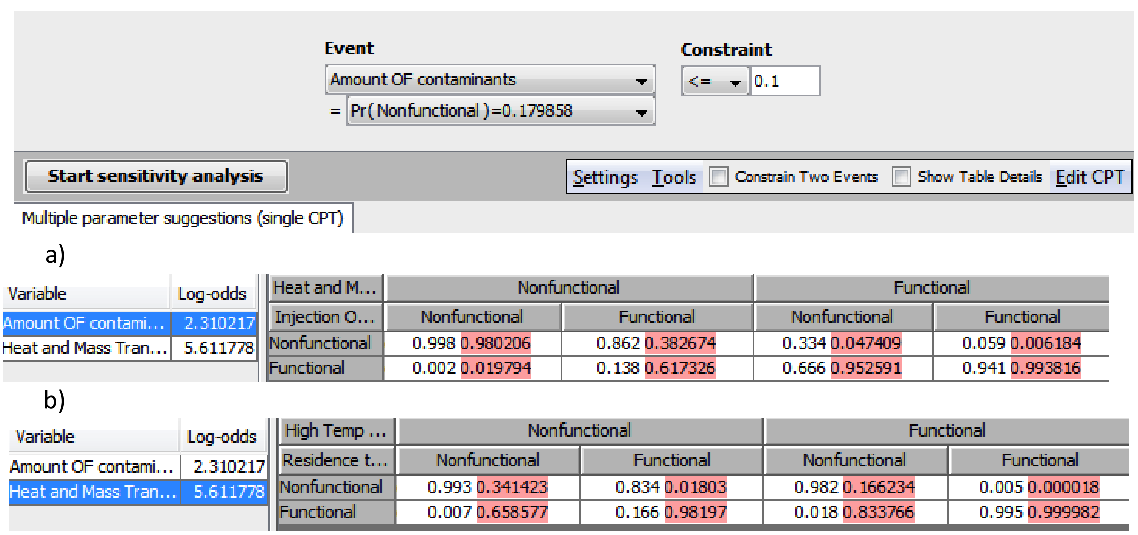


Figure 4.11: Sensitivity Analysis in SamIam Resulting in a) Recommendations for C's CPT and b) Recommendations for T's CPT

on Equation 4.5:

$$\Delta lo(P(\text{Function}_i = X|\text{Pre}_i)) = |\ln(O'(\text{Function}_i = X|\text{Pre}_i)) - \ln(O(\text{Function}_i = X|\text{Pre}_i)| \tag{4.5}$$

where, X is a binary variable (0 or 1) and $O(\text{Function}_i = X|\text{Pre}_i)$ represents the odds for function i equal to X given its predecessors. $O'(\text{Function}_i = X|\text{Pre}_i)$ denotes the odds of that event after having applied the suggested change. Hence, the greater the value of Δlo, the greater the required change. In consequence, after comparing $\Delta lo(C) \approx 2.31$ versus $\Delta lo(T) \approx 5.31$, it was decided to evaluate the feasibility of the recommendations for C's CPT or option in Figure 4.11a. The final decision can be validated when studying the highlighted recommendations on the CPTs. For example, Figure 4.11b is recommending that $P(T = 0|H = 1, R = 1) = 0.007$ needed to change to $P(T = 0|H = 1, R = 1) \approx 0.658$ even further for $P(T = 0|H = 1, R = 0) = 0.166$ to $P(T = 0|H = 1, R = 0) \approx 0.981$ The difference between the original and the suggested values for both probabilities is so large that makes the suggestion almost infeasible.

The teams were able to obtain an insight into the reliability of the system and, in particular, its relationship with the function (C). Furthermore, the sensitivity analysis provided a more objective decision making process. The experts involved in this study were able to determine that a more robust approach is needed in the way C is affected by its predecessor nodes (F and T).

After further analysis on the marginal conditional probabilities it was found that the major marginal difference was on $P(C = 0|T = 1, F = 0) = 0.138$ since the highlighted suggestion was marked to be $P(C = 0|T = 1, F = 0) \approx 0.617$ In other words, C needed to be functional even when T was nonfunctional and F functional around 62% of the time. However, given the suggestion of multiple parameters change and not just single marginal conditional probabilities, the approach that needed to take place was more about how to improve the functionality of the three functions. In a simple way, it was interpreted as the necessity to increase the conditional independence of T and F given C. This analysis helped designers better choose robust components for those functions with the aim to meet the established requirements.

4.4.3 Extended Sensitivity Analysis

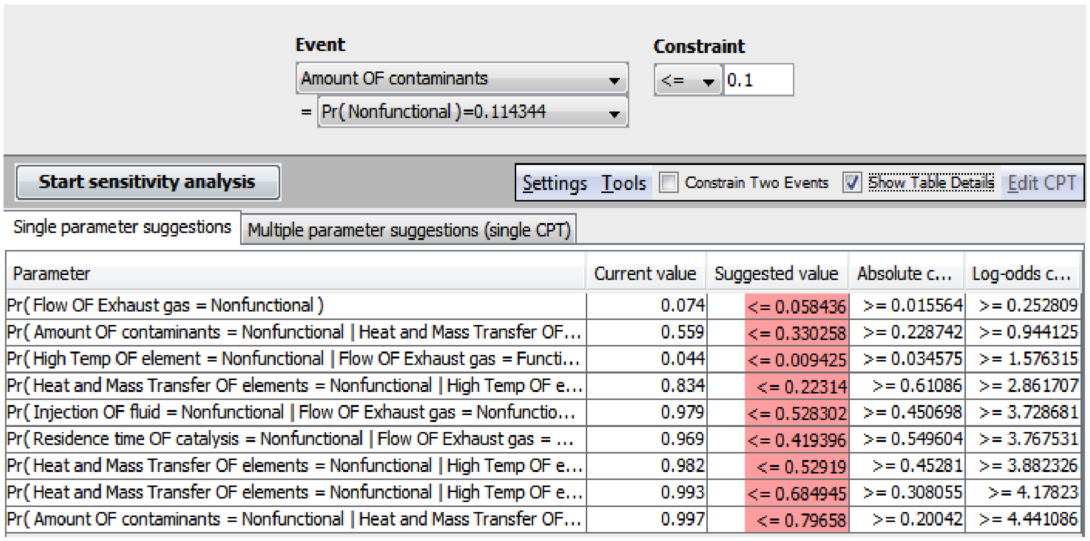
The design team acknowledged what needed to be improved based on the sensitivity analysis. They studied different design features to improve C given F and the only feasible solution without impacting functionality of C given T was a new sensor coating. The new coating improved C given the reaction it has when in contact with fluids injected while exhaust gas density and heat were not affected. Unfortunately, after an initial assessment of this new design feature, it was discovered that the suggested probabilities for C's CPT were not obtainable. The teams reunited and were provided an initial evaluation of the new coated sensor by the experts that leaded to the CPT in Figure 4.12.

Heat and mass transfer OF elements		Nonfunctional		Functional	
	Injection OF fluids	Nonfunctional	Functional	Nonfunctional	Functional
Amount OF Contaminants (C)	Nonfunctional	P(C=1|T=1,F=1) = 0.997	P(C=1|T=1,F=0) = 0.559	P(C=1|T=0,F=1) = 0.092	P(C=1|T=0,F=0) = 0.008
	Functional	P(C=0|T=1,F=1) = 0.003	P(C=0|T=1,F=0) = 0.411	P(C=0|T=0,F=1) = 0.908	P(C=0|T=0,F=0) = 0.992

Figure 4.12: Chart for C's Conditional Probability Table After New Design Feature

The reliability team proposed to do a new sensitivity analysis with the new C's CPT from 4.12. The intent of this extended sensitivity analysis was to evaluate the feasibility of the requirement in Equation 4.4 for other functions different of C.

The network was updated and confirmed that $P(C = 1) \approx 0.114$ as shown in Figure 4.13 which violates Equation 4.4. Then, also in Figure 4.13, the extended sensitivity analysis was run.



Parameter	Current value	Suggested value	Absolute c...	Log-odds c...
Pr(Flow OF Exhaust gas = Nonfunctional)	0.074	<= 0.058436	>= 0.015564	>= 0.252809
Pr(Amount OF contaminants = Nonfunctional | Heat and Mass Transfer OF...	0.559	<= 0.330258	>= 0.228742	>= 0.944125
Pr(High Temp OF element = Nonfunctional | Flow OF Exhaust gas = Functi...	0.044	<= 0.009425	>= 0.034575	>= 1.576315
Pr(Heat and Mass Transfer OF elements = Nonfunctional | High Temp OF e...	0.834	<= 0.22314	>= 0.61086	>= 2.861707
Pr(Injection OF fluid = Nonfunctional | Flow OF Exhaust gas = Nonfunctio...	0.979	<= 0.528302	>= 0.450698	>= 3.728681
Pr(Residence time OF catalysis = Nonfunctional | Flow OF Exhaust gas = ...	0.969	<= 0.419396	>= 0.549604	>= 3.767531
Pr(Heat and Mass Transfer OF elements = Nonfunctional | High Temp OF e...	0.982	<= 0.52919	>= 0.45281	>= 3.882326
Pr(Heat and Mass Transfer OF elements = Nonfunctional | High Temp OF e...	0.993	<= 0.684945	>= 0.308055	>= 4.17823
Pr(Amount OF contaminants = Nonfunctional | Heat and Mass Transfer OF...	0.997	<= 0.79658	>= 0.20042	>= 4.441086

Figure 4.13: Second Sensitivity Analysis in SamIam Resulting From New Design Feature

This analysis was able to provide single parameter suggestion as well as multiple parameter suggestions. The teams focused on the single parameter tab to evaluate the feasibility of changing a specific marginal conditional probability. This tab provided different opportunities for improvement. After reviewing all possible changes, it was decided to proceed with the one that involved less change or $\min\{\delta lo\}$. Consequently, $P(G = 1) = 0.074$ was suggested to be change to $P(G = 1) \approx 0.058$ However, function G was not under control of the design team, this function is controlled by the customer since they ensure the functionality of the flow OF exhaust gas. Therefore, the CRD's program management team reached a warranty agreement with the customer and updated the technical profile to establish that failure rate for G needed to be $P(G = 1) <= 0.0585$ in order for the system to meet the requirement of $P(C = 0) >= 0.9$.

4.4.4 Evidence Impact Analysis

Finally, one of the major changes that were planned for the new CRD was regarding function B. Designers needed to justify that improvements proposed to the functionality of B were towards having a more robust product. After consulting the reliability team it was proposed an evidence impact analysis where the system's effect on the different sates of a function has can be evaluated.

The analysis was easily performed on SamIam. Figure 4.14 presents the impact on the network for the two states of B.

The mathematical evaluation for the impact analysis was performed by the software. However, it can be appreciated graphically the different effects the states of B have on the other nodes of the network. The objective of the evidential impact analysis is to determine the positive or negative effect when evidence of a variable is available. In this case, the CRD's experts had general knowledge on the behaviour of the system when $B = 1$ (nonfunctional) given parenting data (Figure 4.14b). Therefore, without the graphical representation of the system, it was difficult to justify an improvement on B since the positive (or negative) impact for $B = 0$ was uncertain. On the other hand, with the BN seen in Figure 4.14a, the improvements on the functionality of all the other nodes were quite significant. Hence the changes for B were justified as they would deliver a more robust CRD.

4.5 Discussion

The proposed methodology can be summarized in three major steps in the conceptual design phase. The first one is the functional analysis and the function to failure process which will depict the functional structure for a conceptual system. Once determined the functionalities, it is necessary to identify and establish the re-

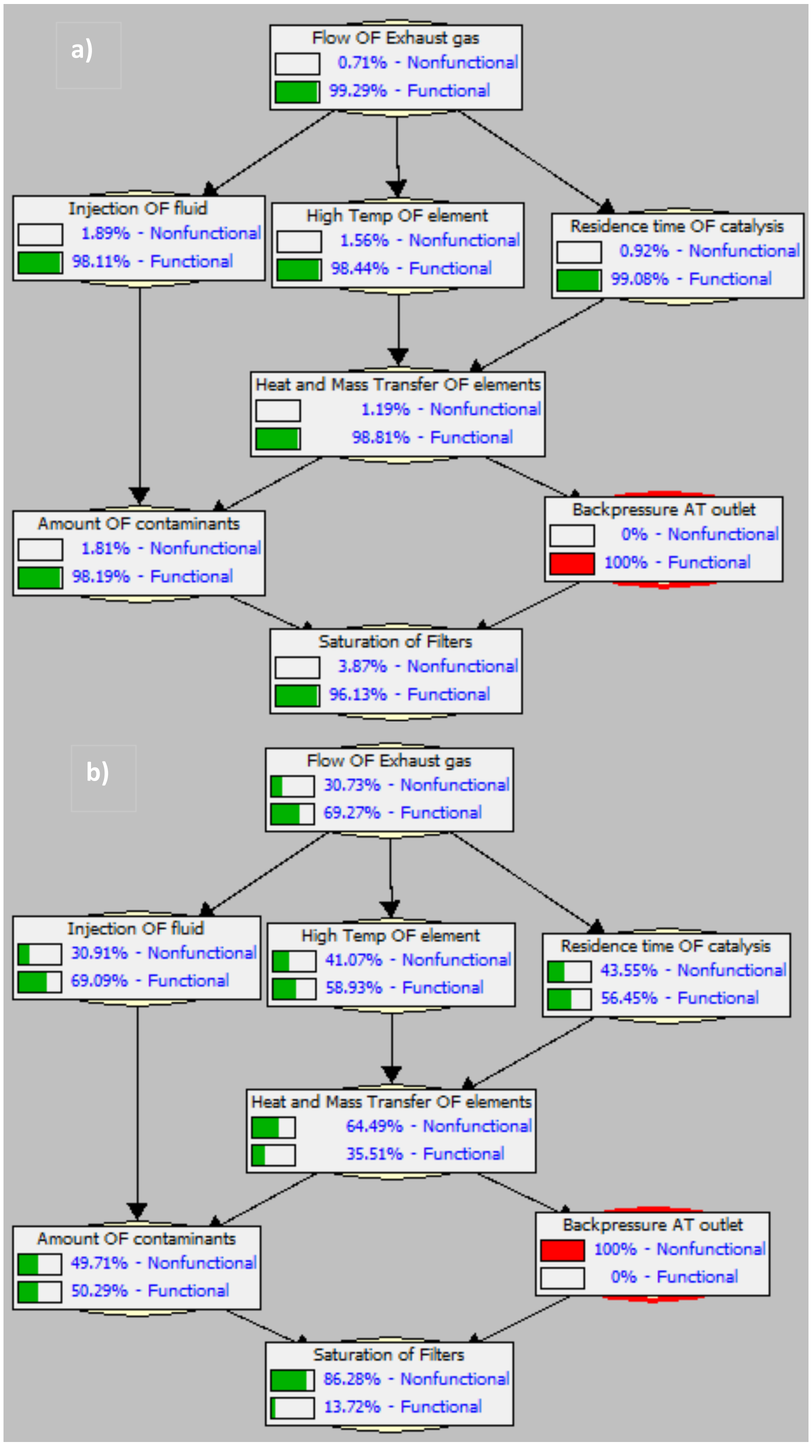


Figure 4.14: Bayesian Network Functional Impact Analysis of a) $P(B = 0) = 1$ and b) $P(B = 1) = 1$

lationship between them. This task is performed by constructing a cognitive map, which formalizes those relationships in the form of a functional structure. Finally, by adding a quantitative (objective) aspect, cognitive map is transformed into a Bayesian network, where designers have the possibility to evaluate different reliability scenarios, measure functional impact of changes or verify that requirements are met. Thus, with this approach an insight into the reliability of the new product in its early design phases is possible.

One of the main advantages of the proposed methodology is the graphical representation of the functional and failure structures through the CM and BN. This approach facilitates the decision making process when dealing with new designs in conceptual phase. Furthermore, having an insight to the reliability of the system in the conceptual design phase has its own advantages. For example, verify that the requirements are met, early performance improvements, better design decision-making process and as a consequence reducing warranty costs.

The case study presented illustrates that the proposed methodology serves as a general guideline on how to obtain reliability knowledge at the conceptual design phase. Moreover, it exemplified the utilization of the obtained BN to generate the reliability insights through three different scenarios. In the first one, an investigation was performed to analyze how to meet the requirements and where the efforts needed to be focused. Secondly, after the first scenario improvements and the infeasibility to meet the requirement, an extended analysis was executed. The end result for this scenario conveyed the involvement of a different aspect of the reliability other than the design. It required signed warranty agreement between customer and suppliers which sometimes is overlooked. Finally, in scenario three, the impact of changes was evaluated and the resource spending towards a more robust product was justified.

Although the case study through its scenarios only utilized the sensitivity analysis capacities of BN, the scope can be extended more broadly with different characterizations of BN. Subsequently, there are different paths to extend this process. For example, different approaches need to be considered as new algorithms for BN are being developed for more complex structures (e.g., quantum inference and genetic algorithms). Consequently, it would be worthwhile to analyze different tools to create the functional structure and facilitate the use of the BN. Also a functional repository could be created to expedite the methodology. Finally, guidelines to navigate through different scenarios such as robustness and simultaneous requirements might be created.

Chapter 5

PRODUCT ROBUST DESIGN VIA ACCELERATED DEGRADATION TESTS

5.1 Introduction

Product reliability is about meeting product quality requirement over time, which is critical to building a reputation and maintaining a competitive edge for a company. Engineers are developing various methods in order to design highly reliable products. Robust design is a methodology of identifying and setting design variables such that the detrimental effect of external factors (noises) on product performance can be reduced. In this chapter a method of achieving reliability robustness via accelerated degradation tests is discussed. Nowadays, using new technologies, industries are manufacturing more durable products. Traditional hardware reliability measures, such as time to failure, cannot be observed within a reasonable product testing period, even by accelerated life testing (ALT). Accelerated degradation testing (ADT) is an alternative to ALT. In ADT experiments, which are conducted under some pre-specified levels of design factors and elevated stress factors, a product quality characteristic is repeatedly measured over time so that the product failure time can be inferred before observing actual failures. This type of experiments is often used for product reliability verification, but it also provides opportunities for investigating the effect of product design variables on reliability, thus for improving product design. Reliability robustness refers to the concept of consistent product reliability performance in spite of the "noisy" use condition, where external stresses, such as ambient temperature or humidity, may vary and cannot be controlled. Thus, data from ADT experiments may provide the information of product's performance under the stress factor that could be a random variable at use condition. Degradation data analysis has been researched extensively. Meeker et al. (1998) provided an excellent overview of modeling and data analysis techniques for ADTs. Optimal experimental designs of ADTs were discussed, for example, in Li & Kececioglu (2004). However, the use of ADTs for achieving product robust design has not been thoroughly investigated until recently. By applying Taguchi's robust parameter design method, Joseph & Yu (2006) demonstrated a way of improving the reliability robustness using degradation experiments. In this chapter, an approach of response surface methodology (RSM) is presented and the model estimation and optimization process for degradation experiments is developed. A general procedure of robust parameter design via ADTs is described as well as the methodology of degradation path modeling, parameter estimation and design factor optimization. The chapter also provides a case study to illustrate the effectiveness of the proposed method on a window wiper switch experiment.

5.2 Robust Parameter Design Via ADT

In robust parameter design, factors are classified as controllable factors and noise factors. Controllable factors are those that can be designed into a product, e.g., material, dimension, etc. Noise factors are those either very difficult or impossible to control at the product's normal use condition, e.g., temperature, humidity, voltage, etc. The variation of noise factors at use condition may cause undesired fluctuation of product performance; thus, the degradation characteristic measurement may exhibit larger variation over time. Let $D_i(t)$ be the true degradation path of a test unit i , the degradation characteristic measurement is

$$Y_i(t) = D_i(t) + \epsilon_i, \tag{5.1}$$

where ϵ_i is a measurement error and $\epsilon_i \sim N(0, \sigma_\epsilon^2)$. The true degradation path depends on the initial quality of the test unit, which is determined by product design variables (controllable factors) only, and the degradation rate, which can be affected by both design variables and stress variables (noise factors). Therefore, we use two types of parameter vectors, and , as the stress-independent and stress-dependent process parameter vectors, respectively. Figure 1 shows the model structure of a quality characteristic with degradation path and measurement error. A degradation test of electrical connection in window wiper switches will be discussed in Section 4. In this example, there are ten performance measurements over the total testing time for each test unit. We plot these measurements from eight test units in Figure 2, where four of them are tested under one experimental condition (Data 4) and others are tested under another condition (Data 5). One can see that the first-time measurements of these units are clustered around two distinct values and the slopes of degradation paths (increasing trends in this example) vary among individual units, while Data 5 exhibits larger variation in slope. This dataset will be further analyzed in Section 4.

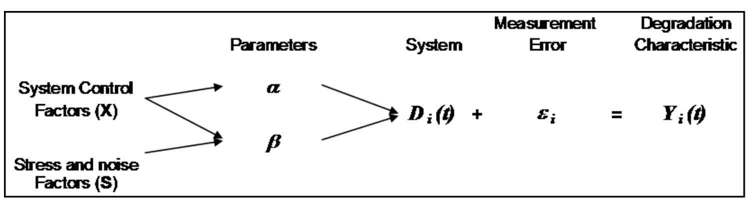


Figure 5.1: Structure of the Degradation Characteristic Measurement

In this chapter, repeated measurements of a product quality characteristic that are to be performed at evenly spaced points of time during ADT experiments are considered. The experiment is set up by selecting a combination of design variable values and stress variable values. Several test units may be tested under the same testing condition. Different testing conditions are used so that the effects of design

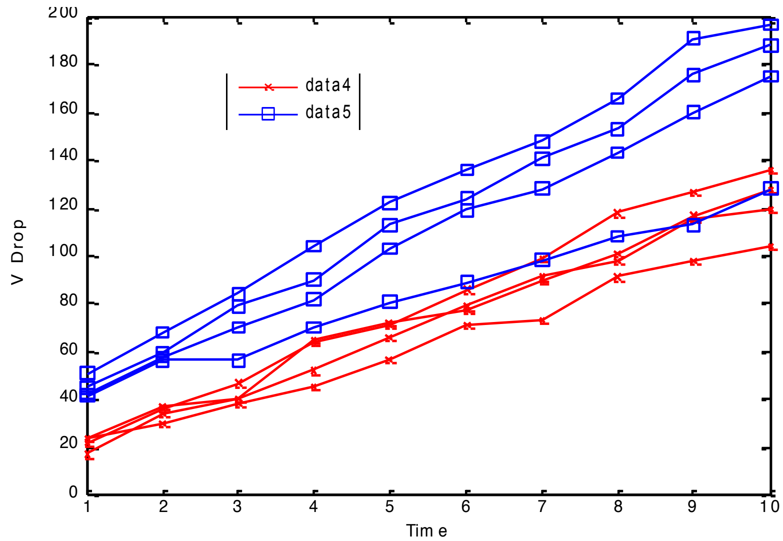


Figure 5.2: Degradation Paths of Multiple Test Units

variables and stress variables can be studied. The difference between ADT and the traditional experiment for studying product quality resides on the repeated measurements performed through the ADT process.

Before starting to construct the model a few more steps have to be considered. First of all, before planning an ADT, the most significant failure mechanism needs to be identified. It is important to determine the quality characteristic that is related to this failure mechanism in order to plan an accelerated testing on it. It is assumed that this step has already been conducted and the failure mechanism under study is the most significant one. In addition, assessing ADT experimental design requires the experimenter has had some knowledge on the process, such as the important factor to be analyzed. The source of variation in response may come from the controllable design factors, as well as the uncontrollable stress factors that emerge from the product use environment. Thus, the knowledge of the source of variation will help in planning ADT experiments and generating a more accurate ADT model.

The process of achieving reliability robustness via ADTs is summarized in the following general steps:

1. Identify product failure mechanisms.

2. Identify the source of variation in quality characteristic. Some sources of variation may come from the controllable factors that can be designed into the product and some are noise factors that emerge from the product use environment, like stresses.

3. Plan ADT experiments. Typically factorial and fractional factorial experimental designs will be used. Some other types of RSM experimental designs, such as central composite design, can also be applied if a nonlinear response surface is expected.

4. Model the degradation path. A degradation model (either deterministic or stochastic) must be determined before conducting ADT experiments. A threshold (either fix or random) on the degradation characteristic represents the approximated level of quality where the product fails. The acceleration model will be built upon the degradation path as a function of stresses.

5. Perform data analysis and model parameter estimation. Many techniques and tools have been proposed for the parametric model estimation and data analysis. Some nonparametric regression techniques have also been applied on accelerated degradation data.

6. Design variable optimization. Optimization is performed based on the estimated regression model. The ultimate goal is to minimize the product degradation rate, as well as the variability of the degradation process influenced by both design and stress factors.

Steps 4-6 will be discussed in detail in the next section.

5.3 Methodology

5.3.1 *Model of Degradation Path*

There are a variety of models that have been developed for analyzing degradation data given different testing options of ADT. This study considers consider the case where repeated measurements on a group of degrading units are available. Degradation path is modeled as a function of time. Some commonly used models are:

$$\text{Model 1:} \qquad D_i(t) = \alpha + \beta_i t \ , \tag{5.2}$$

where α is a constant, representing the initial quality of the product, and $\beta_i(t)$ is the rate of degradation of test unit i . This is a linear model with constant intercept and varying slope. It is reasonable to assume that $\beta_i(t)$ follows a lognormal distribution, so $D_i(t)$ is a monotone function of time with the same trend for all units.

$$\text{Model 2:} \qquad D_i(t) = \alpha_i + \beta_i(t) \ , \tag{5.3}$$

where the random intercept, α_i, is the initial quality of test unit i. This model is appropriate when one considers the initial quality variability among products due to manufacturing variation.

$$\text{Model 3:} \qquad D_i(t) = \alpha + \beta_{1i}(t) + \beta_{2i}t^2 \ . \tag{5.4}$$

It is a nonlinear model. Since it is a quadratic function of time, time t needs to be specified to be less than a certain value so that the degradation function is a monotone function of time.

$$\text{Model 4:} \qquad D_i(t) = \alpha(1 - e^{-\beta_i(t)}) \ . \tag{5.5}$$

It is another nonlinear model. The initial value of this function is 0 and the curve of this function will approach to an asymptote as time becomes large.

The focus of this chapter is on the first model. In ADT experiments there are two types of experimental factors. One is the product design variable (X), such as material, geometry dimension, etc.; and the other one is the environmental stress variable (S), such as temperature, voltage, etc. During experiments, both design variables and stress variables are controlled at some specific levels for study. However, under the product use condition, stress variables are most likely uncontrollable. For example, if the product is used in an outdoor environment, the temperature may vary from time to time. Therefore, the stress factor at use condition should be treated as a random variable. Based on the methodology of product robust design, the design engineer's aim is to find the setting of design variables such that the effect of the randomness of stress factors on the product performance can be minimized.

At a combination of design and stress factors, (x_i, s_i), the degradation rate, β_i, in Equation 5.2 can be modeled by

$$\log \beta_i = h(\mathbf{x}_i) + \mathbf{b}\mathbf{s}_i + \mathbf{c}\mathbf{x}_i\mathbf{s}_i + e_i \ , \tag{5.6}$$

where $h(\mathbf{x}_i)$ is the impact of design factors on log degradation rate, $\mathbf{b}$ is the effect of stress factors and $\mathbf{c}$ the effect of the interaction between design and stress variables. Note that $\mathbf{x}_i$ and $\mathbf{s}_i$ are vectors. Let $e_i \sim N(0, \sigma_\beta^2)$, which gives the variation of degradation rate among different test units. Thus, the conditional distribution of β_i at an experimental condition $(\mathbf{x}_i, \mathbf{s}_i)$ is a lognormal distribution as

$$\beta_i|(\mathbf{x}_i, \mathbf{s}_i) \sim \log N(\mu_{\beta i}, \sigma_\beta^2) \ , \tag{5.7}$$

and

$$\mu_{\beta i} = h(\mathbf{x}_i) + \mathbf{b}\mathbf{s}_i + \mathbf{c}\mathbf{x}_i\mathbf{s}_i \ . \tag{5.8}$$

The overall model of response is given by

$$y_i(t) = \alpha(\mathbf{x}_i) + \exp(h(\mathbf{x}_i) + \mathbf{b}\mathbf{s}_i + \mathbf{c}\mathbf{x}_i\mathbf{s}_i + e_i)t + \epsilon_i \ . \tag{5.9}$$

5.3.2 Model Parameter Estimation

There are two variance components in Equation 5.9, while one is associated with the measurement error the other one is associated with the randomness of degradation path of individual test units. This model has a hierarchical structure, which is depicted in Figure 5.3 . Given repeated measurements, $y_i(t)$, we can perform maximum likelihood estimation to estimate the model parameters involved. When the degradation rate is small, the probability density function of $y_i(t)$ can be approximated by a normal distribution such as

$$y_i(t) \sim N(\alpha_i + (1 + h(\mathbf{x}_i) + \mathbf{b}\mathbf{s}_i + \mathbf{c}\mathbf{x}_i\mathbf{s}_i)t, \sigma_y^2(t)) \ , \tag{5.10}$$

where $\sigma_y^2(t) = \sigma_\beta^2 t^2 + \sigma_\epsilon^2$.

In practice, we use SAS PROC NLMIXED to obtain the parameter estimation. NLMIXED is a SAS procedure for parameter estimation of nonlinear multi-level models. It allows the random coefficient, which is β_i in this problem, to enter the model nonlinearly and fits models by numerically maximizing an approximation to the marginal likelihood, i.e., the likelihood integrated over the random effect. Different integral approximations are available the primary one being adaptive Gaussian quadrature. This approximation uses the empirical Bayes estimates of the random effects as the central point for the quadrature, and updates them for ever iteration. The resulting marginal likelihood can be maximized using a variety of alternative optimization techniques, such as a dual quasi-Newton algorithm.

5.3.3 Optimization

The purpose of the parameter robust design is to design the product such that its performance will be insensitive to noise factors which are uncontrollable in the product use environment. As discussed previously, stress factors that are tested in ADT experiments are actually random variables at use condition, which can be assumed to be normally distributed as $S \sim N(0, Var(S))$. Product engineers would like to find the setting of design factors that can minimize the effect of stress variation on product reliability. According to Equation 5.9 and the hierarchical model in Figure 5.3, the initial quality is determined by design factors only. Stress factors affect production degradation rate, or product quality over time. Therefore, minimizing the variation on the degradation rate, β (Level 2), would lead to minimizing the variance of the performance measures, $y_i(t_k)$ (Level 1), and producing a consistent quality over time. For simplicity, this study will work with the logarithm of β, which has a conditional normal distribution as shown in Equation 5.7. Therefore,

$$\begin{aligned} Var(\log\beta) &= Var(E[\log\beta|S]) + E[Var(\log\beta|S)] \\ &= (\mathbf{b}+\mathbf{c}\mathbf{x})^T Var(S)(\mathbf{b}+\mathbf{c}\mathbf{x}) + \sigma_\beta^2. \end{aligned} \tag{5.11}$$

There are several practical constraints that need to be considered in ADT robust design process. Firstly, the initial product quality must be higher than a certain specification. The smaller the quality characteristic, the better, so the first constraint becomes $\alpha(\mathbf{x}) < q_0$. Secondly, the mean degradation rate should be lower enough that the quality characteristic at time t is smaller than q_t. We assume that stress factors at use condition are normally distributed. From Equation 5.9, the mean of the quality characteristic at time t is derived as the following:

$$\begin{aligned} E[y(t)] &= E[E[y(t)|S]] \\ &= E[\alpha(\mathbf{x}) + \exp[h(\mathbf{x}) + (\mathbf{b}+\mathbf{c}\mathbf{x})^T S + \sigma_\beta^2/2]t] \\ &= \alpha(\mathbf{x}) + \exp[h(\mathbf{x}) + (\mathbf{b}+\mathbf{c}\mathbf{x})^T Var(S)(\mathbf{b}+\mathbf{c}\mathbf{x})/2 + \sigma_\beta^2/2]t\ . \end{aligned} \tag{5.12}$$

Therefore, the optimization for robust design is formulated as

$$
\begin{aligned}
Min_x \quad & (\mathbf{b}+\mathbf{cx})^T Var(S)(\mathbf{b}+\mathbf{cx}) \\
S.T. \quad & \\
& \alpha(\mathbf{x}) < q_0 \\
& \alpha(\mathbf{x}) + \exp[h(\mathbf{x}) + (\mathbf{b}+\mathbf{cx})^T Var(S)(\mathbf{b}+\mathbf{cx})/2 + \sigma_\beta^2/2]t < q_T \ . \qquad (5.13)
\end{aligned}
$$

The second constraint may be evaluated at several points of time or at a presumed terminal time only.

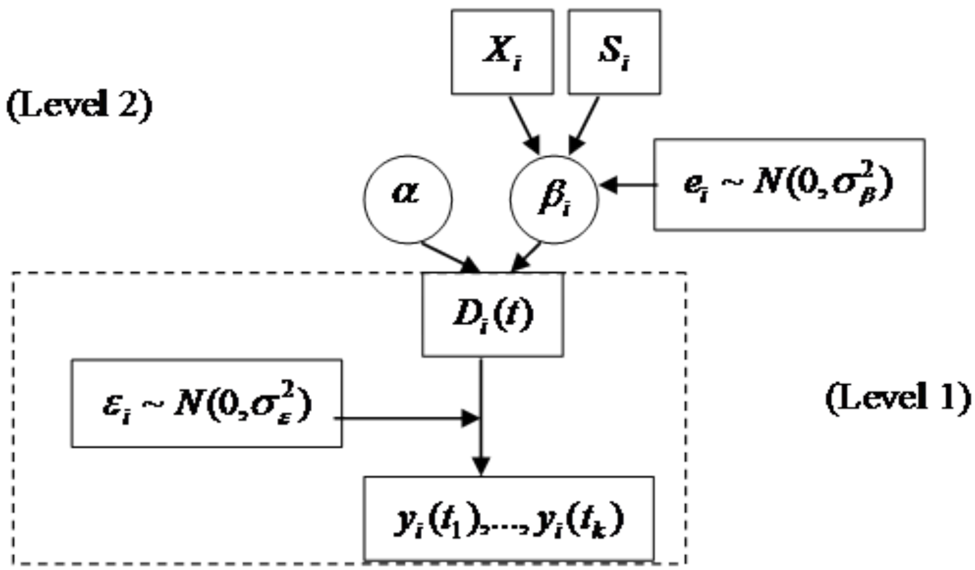


Figure 5.3: Structure of the Hierarchical Model

5.4 An Illustrative Example

The case of window wiper switch experiment that was described in Wu & Hamada (2000) is used to illustrate the model parameter estimation and robust design optimization methods developed in this paper. The data was previously analyzed by Joseph & Yu (2006) using a DOE approach for fractional factorial design; however, the analysis presented here focuses directly on modeling degradation path variation and the results are more interpretable.

The experiment consists on five experimental factors (A-E), where four of them (B-E) are tested on two levels and one factor (A) is tested on four levels. For each window wiper switch, the initial voltage drop across multiple contacts is recorded (i.e., first inspection), and then recorded every 20,000 cycles thereafter up to 180,000 cycles, resulting in 10 inspections. The degradation data is shown in the Table 5.1. Figure 5.2 shows the time series plots of several test units. it can be seen that the response exhibits a general upward trend along the time and this trend varies among those test units. There is no explanation of which factor is a design factor and which one is an environmental stress factor in the original text. Therefore, the statistical significance of these factors is first tested on the initial value of the response variable and the deviation value of the response variable after 10 observations.

Run	Factor					Inspection									
	A	B	C	D	E	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	24	37	40	65	72	77	90	101	117	128
						22	36	47	64	71	86	99	118	127	136
						17	34	40	52	66	79	91	98	115	119
						24	30	38	46	57	71	73	91	98	104
2	0	1	1	1	1	45	60	79	90	113	124	141	153	176	188
						51	68	84	104	122	136	148	166	191	197
						42	58	70	82	103	119	128	143	160	175
						41	56	56	70	81	89	98	108	113	128
3	1	0	0	1	1	28	40	56	69	87	86	110	121	132	146
						46	50	81	95	114	130	145	161	185	202
						45	54	79	90	111	132	143	168	185	202
						37	58	81	99	123	143	166	191	202	231
4	1	1	1	0	0	54	51	64	66	78	84	90	93	106	109
						47	45	50	53	58	57	61	55	61	66
						47	54	63	68	70	77	88	86	91	102
						53	55	66	68	91	90	98	104	118	120
5	2	0	1	0	1	18	35	48	56	65	81	89	98	117	124
						20	37	52	53	67	75	85	95	112	122
						32	54	76	98	119	143	158	181	205	231
						28	39	54	73	89	98	117	127	138	157
6	2	1	0	1	0	44	50	48	46	55	63	65	71	68	76
						43	44	55	56	58	62	66	66	72	72
						40	46	45	49	55	62	61	61	64	66
						55	67	73	75	91	88	102	111	115	119
7	3	0	1	1	0		47	58	72	84	104	109	129	143	154
						29	42	55	67	82	91	104	117	130	136
						36	45	56	80	93	101	121	138	154	170
						31	40	60	72	82	98	103	117	130	146
8	3	1	0	0	1	61	67	69	86	86	88	95	103	107	118
						68	75	82	90	95	109	107	118	120	133
						60	72	85	84	87	98	99	111	113	125
						65	68	69	75	79	84	95	96	101	100

Table 5.1: Voltage Drop Data for the Wiper Switch Experiment

5.4.1 Preliminary Analysis

The effects of the five main factors on the production initial quality are first analyzed. Assuming these factors are continuous variables, they are assigned 0 and 1 to the lower and higher factor levels, respectively, for Factors B-E that have only two levels. Values 0,1,2,3 are assigned to Factor A that has four levels. A simple linear regression model is built for the first inspection variable of voltage drop. It is found that Factor D has no significant effect on the product initial quality. However, when the difference of the first voltage drop and the last voltage drop after ten inspection periods is modeled by a linear regression function on these factors, it is found that Factor D is a significant factor that will affect the change of response over time. Therefore, in the remaining analysis we treat Factor D as an environmental stress factor, and along with other factors, it will determine the degradation rate of the individual test unit.

5.4.2 Model Selection

A full model considered in this study includes the main effects of all design and stress factors, as well as their interactions. Since the product initial quality depends on its design factors only, in Equation 5.9 the intercept is modeled by the following function:

$$\alpha_i = d_0 + d_1 A + d_2 B + d_3 C + d_4 E + d_5 AB + d_6 AC + d_7 AE + d_8 BC + d_9 BE + d_{10} CE \; . \tag{5.14}$$

The mean slope μ_β is modeled as

$$\begin{aligned}\mu_\beta = a_0 + a_1 A + a_2 B + a_3 C + a_4 E + a_5 AB + a_6 AC \\ + a_7 AE + a_8 BC + a_9 BE + a_{10} CE \\ + b_1 D + c_1 AD + c_2 BD + c_3 CD + c_4 ED \ .\end{aligned} \tag{5.15}$$

The result of model fitting shows that some coefficients,

$$d_9, a_3, a_4, a_6, a_8, a_{10}, b_1, c_1, c_2, c_4$$

are small enough that the effects of their associated factors are insignificant to the response. Based on the effect hierarchy, those interaction terms that are insignificant in the intercept model are removed one by one and refit the data to the reduced model. Then, both the remaining main factors and interaction terms are reanalyzed and reduced until all of the remaining terms are significant. Next, the terms of insignificant effects in the slope model are moved in the same fashion. Eventually, a parsimonious model is found to be

$$\alpha_i = d_0 + d_1 A + d_2 B + d_3 C + d_4 E \ , \tag{5.16}$$

and

$$\begin{aligned}\mu_\beta = a_0 + a_1 A + a_2 B + a_3 C + a_4 E + a_5 AB \\ + a_7 AE + a_9 BE + b_1 D + c_2 BD + c_3 CD + c_4 ED \ .\end{aligned} \tag{5.17}$$

The estimated values of regression coefficients are given in Table 5.2. The result also shows that the main effects of A, C, E and D are not significant to the mean slope but they are retained in Equation 5.17 because some interaction terms involving these factors are not significant.

Parameter	Estimation	Error	t Value	Pr $>\|t\|$
σ_τ^2	18.203	1.519	11.98	<0.0001
σ_β^2	0.1155	0.03048	3.79	0.0007
d_0	23.0905	1.0214	22.61	<0.0001
d_1	3.3683	0.341	9.88	<0.0001
d_2	21.0078	0.8863	23.7	<0.0001
d_3	-3.3626	0.8832	-3.81	0.0006
d_4	5.3901	0.8853	6.09	<0.0001
a_0	2.3969	0.171	14.02	<0.0001
a_1	-0.04557	0.05763	-0.79	0.4351
a_2	-0.2669	0.09866	-2.7	0.011
a_3	-0.07815	0.119	-0.66	0.5164
a_4	0.04291	0.07184	0.6	0.5546
a_5	-0.2608	0.06284	-4.15	0.0002
a_7	0.1419	0.05841	2.43	0.0211
a_9	0.2825	0.1183	2.39	0.0232
b_1	0.0457	0.0795	0.57	0.5696
c_2	-0.4985	-0.209	-2.38	0.0234
c_3	0.3783	0.1299	2.91	0.0066
c_4	0.3031	0.1453	2.09	0.0453

Table 5.2: Estimated Values of Regression Coefficients for the Wiper Switch Experiment

5.4.3 Robust Design

In robust design optimization, the effect of the variation of noise factors is intended to be minimized, which can be achieved through exploring the interaction between noise factors and the factors that can be controlled in design. According to Equation 5.13 and the estimated parameter values in Table 5.2, the objective function for robust design is given as,

$$\begin{aligned}
Min_{B,C,E} \quad & (0.002088 - 0.04556B + 0.034577C + 0.027703E \\
& 0.248502B^2 + 0.143111C^2 + 0.09187E^2 \\
& - 037717BC - 0.30219BE + 0.229325CE)Var(D) \ . \qquad (5.18)
\end{aligned}$$

Suppose that the product's initial quality and terminal quality at $t = 10$ are of interest. Thus, the constraints are,

$$23.0905 + 3.3683A + 21.0078B - 3.3626C + 5.3901 \leq q_0 \qquad (5.19)$$

and

$$\begin{aligned}
& 23.0905 + 3.3683A + 21.0078B - 3.3626C + 5.3901E + \\
& 10 \exp\{2.45465 - 0.04557A - 0.2669B - 0.07815C \\
& + 0.04291E - 0.2608AB + 0.1419AE + 0.2825BE + \\
& (0.002088 - 0.04556B + 0.034577C + 0.027703E \\
& 0.248502B^2 + 0.143111C^2 + 0.09187E^2 - 0.37717BC - \\
& 0.30219BE + 0.229325CE)Var(D)/2\} \leq q_{10}. \qquad (5.20)
\end{aligned}$$

Finally, for demonstration purposes, let $q_0 = 30$, $q_{10} = 140$, and $Var(D) = 1$. Table 5.3 lists the optimal solution of design factors, as well as one original design that also satisfy the initial and terminal quality requirements. Simulations for 100 degradation paths are run for each design and they are shown in Figure 5.4. One can see that the variation in the degradation path of the original design is much larger than that of the optimal design. This indicates that even though the average performance of the original design is acceptable, but due to the randomness of stress factors at product use condition, many units may fail long before their intended life.

By the robust design optimization, one can find a design that is insensitive to the environmental stress uncertainty, thus leading to a consistent quality over time.

	Original Design	Optimal Design
A	3	0
B	0	0.4225
C	1	0.5848
E	0	0
Initial Quality	29.8328	30
Constraint q_0	30	30
Performance (time 10)	132.5791	127.3366
Constraint q_t	140	140
Objective Function	0.1798	0.0

Table 5.3: Original and Optimal Design Values for the Wiper Switch Experiment

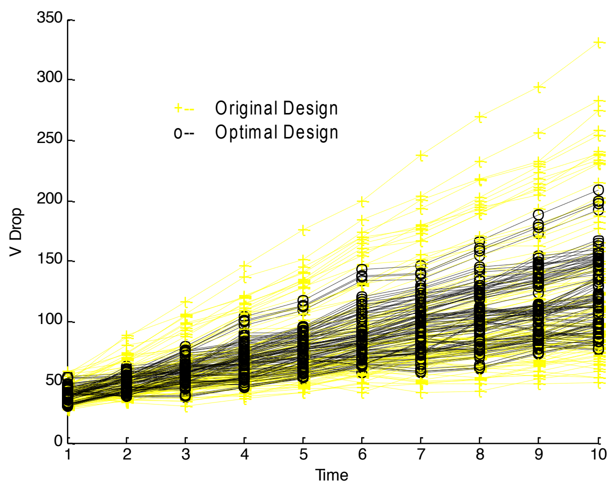


Figure 5.4: Degradation Paths of Multiple Test Units

5.5 Discussion

In this chapter, a response surface approach to the parameter robust design through accelerated degradation tests was presented. ADT is often used for product reliability verification, but its potential for robust design should not be overlooked. Unlike other methods of design for reliability discussed in literature, the observed product degradation process was modeled with two sources of randomness, which correspond to the measurement error and the random degradation rate at individual unit level. Therefore, using this model it is possible to directly study the effects of design and stress factors, as well as their interactions, on degradation path. Robust design is achieved by setting the design factors at some levels such that the impact of stress factor variation on the degradation rate can be minimized. The effectiveness of this method is also demonstrated by a case study.

Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This research is placed on the design process of a new product. A general engineering design process includes three phases: conceptual, embodiment and detailed. In all three phases it is challenging to obtain traditional reliability information such as failure times for the new design. However, this dissertation presented different sources of information (Table 2.1) that can be utilized to provide reliability inputs. The major contributors are: reliability information from similar existing products denominated as parents; elicited experts' opinions, initial testing in the embodiment and detailed design; customer voice for creating requirements in the conceptual phase; and different reliability studies performed during the design process that shed light on the reliability of the new product (e.g., functional analysis and cause-effect models). Hence, this dissertation used these sources of information and presented three different 'windows' in the design process to gain a reliability insight on new products.

Firstly an enhanced parenting process to assess reliability was presented. The key idea was to utilize the reliability information from existing products whose failure structure are shared with the new product, also known as parents. Under the assumption that this structure is unknown; a relationships between failure modes and failure causes came from the parents historical failure data. From the obtained data an importance index matrix between failure causes and failure modes was created (parent matrix). Then, expert opinions were elicited to provide the effects of design changes on individual failure cause (parent factor). Therefore, the multiplication of both matrices was used to integrate objective and subjective reliability information to provide a reliability assessment in early design process.

As an extension of the previous research, the focus moved into the conceptual design phase while the assumption of similar failure structure between parents and new product was relaxed. Therefore, a methodology was created to provide the reliability insight in the conceptual phase. The approach can be summarized in three sequential steps:

1. The first step is to conduct a functional analysis as well as the implementation of the function to failure process. This step provided the functional structure for a conceptual system.

2. In order to identify and establish the relationship between the functions from previous step a cognitive map (CM) was constructed. Then, the CM formalized those relationships in the form of a graphical functional structure.

3. Finally, by adding a quantitative (objective) aspect, the CM was transformed into a Bayesian network (BN). This transformation was performed by a set of guidelines, the parenting process and expert elicitation.

Once that the BN was obtained, designers have the opportunity to evaluate different reliability scenarios, measure functional impact of changes or verify that requirements are met. Thus, contributing to a better reliability decision making process.

The third area of research arises when there was the option to have initial testing on the new product (usually on detailed design phase). To minimize resources a special case of accelerated life testing was used: the accelerated degradation tests or ADT. ADT is often used for product reliability verification, but its potential for robust design was exploited. Hence, a response surface approach to the parameter robust design through accelerated degradation tests was presented. It was observed that there are two source of randomness: the measurement error and the random degradation rate at individual unit level. Then, a model was built to directly study the effects of design and stress factors, as well as their interactions, on degradation path. Robust design was achieved by setting the design factors at some levels such that the impact of stress factor variation on the degradation rate can be minimized.

Additionally, in order to validate the proposed approaches and methods, different case studies were presented in those chapters.

6.2 Future Work

Though this research made significant advances in gaining reliability insight in the conceptual design phase, there are more sources information that can be considered for future work. Moreover, there are many different research opportunities extended from the methods and approaches presented in this dissertation.

For example, the enhanced parenting process (Chapter 3) does not produce a robust reliability predictor given the uncertainty and some subjectiveness on the elicitation process. In the future, various methods could be studied to minimize the impact of expert's opinion biases to obtain a more objective estimator. This includes: different techniques for combining expert's opinions, hierarchical models to integrate different sources of information, improved warranty analysis for indices computation or different techniques to better select parents (i.e., group technologies).

The methodology presented in Chapter 4 was thought to be an extension of Chapter 3. One of the main challenges with this approach was the resources availability and time allocation to execute the proposed steps. To overcome the challenges a design repository could be created; it would be used to store function to failure arguments, function interaction and function to component translation, all for general use. Furthermore, after obtaining the BN structure, guidelines could be established for different applications such as: design concept feasibility study, concept comparison for concept selection, trade-off analysis, reliability problem identification and self-learning updates.

Lastly, ADT experiments provided opportunities for studying the effect of product design variables on reliability. However, impracticality was presented as there are no experimental units to be tested. Consequently, different sources of information need to be considered, such as degradation paths from parent products. Also, to model the new product degradation path a hierarchical model or a Bayesian framework could be used.

In the end, the ultimate goal was to use all reliability information available in the design process of a new product to produce a robust product.

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APPENDIX A

VALIDATION OF ELICITATION METHODS

Experts' Evaluation

The process of expert elicitation is about extracting beliefs from someone knowledgeable. In order to validate those opinions, the experts must be evaluated. As every elicitation procedure is different, a specific method to determine its validity cannot be appointed. Nevertheless, Kadane & Wolfson (1998) remarked three components that might be used to validate an elicitation process: (1) Reliability, (2) Coherence and (3) Calibration.

In the case of coherence, multiple answers from the same expert should follow the same trend or pattern. For the reliability component, an expert's opinion becomes reliable after previous satisfactory responses. Calibration, though, is a more complex component from the statistical point of view, as it represents a form of empirical control (i.e. deling with bias) on the expert's assessments. Therefore, scoring rules are set to comply with all three components.

Scoring

Scoring as defined by Cooke (1991) is a numerical evaluation of probability assessments based on observations. He also discussed two basic properties for scoring which will end in a valid elicitation process. Those properties are: entropy and calibration. Next, a general description is provided from a statistical point of view.

Entropy

Cooke (1991) sees entropy as a good measure of degree to which the density (or mass) function is 'spread out'. A mathematical representation is Equation A.1, where $H(P)$ is the entropy associated with a probability density function and $P(x)$ is the cumulative probability that the elicited parameter is x. When $P(x) = 1$, H(P)=0; hence an expert whose probability function has low entropy is desired.

$$H(P) = -\int P(x) \ln P(x) dx \tag{A.1}$$

Calibration

To get a sense on how a calibration score is defined, a statistical hypothesis is formulated (Cooke, 1991): $C(P) :=$ the uncertain quantities are independent and identically distributed with the probability density function provided by the expert (P). Moreover, assume that by observing the true values for all parameters a sample distribution is generated (S). Then, the discrepancy between S and P is given in Equation A.2, where $I(S, P)$ can be seen as a measure of surprise.

$$I(S, P) = \int S(x) \ln \frac{S(x)}{P(x)} dx \tag{A.2}$$

Cooke (1991) interpreted the calibration score as the probability under $C(P)$ of observing discrepancy in a sample distribution S' at least as large as $I(S, P)$, on n observations. Equation A.3 represents this probability which can be used to define statistical tests in the classical sense.

$$Prob\,[I(S', P) \geq I(S, P)|C(P), n] \tag{A.3}$$

Lastly, for more specific techniques (e.g. anchoring) dealing with calibration issues, such as bias, see Ayyub (2001).

Parametric Elicitation

Parametric elicitation and weighted combination of expert opinions are selected. The weighted combination of experts' opinion satisfies a number of validation properties to the elicitation process (i.e. the marginalization property). In addition, scoring factors for the elicitation process such as calibration and entropy can be studied by assigning the weights.

Therefore, a considerate amount of effort has been put in determining weight values. But, Winkler (1968) generalizes four ways to assign them as stated in the proposal. In the end, the analyst sets the scoring rules and in consequence the values of the weights accordingly to each elicitation case.

Conclusion

Beyond the scoring rules, an elicitation method becomes valid when the experts feel comfortable answering questions formulated under the basic mathematical criteria of coherence and experience (Kadane & Wolfson, 1998). Moreover, in an elicitation process, the true values eventually become known. Thus, time will set the proper conditions to validate the process.

APPENDIX B

GROUP TECHNOLOGY

B.1 GROUP TECHNOLOGY AND PARENT SELECTION

Group technology (GT) is a manufacturing philosophy that identifies and groups similar parts or components based on geometry, material, manufacturing attributes, etc. GT uses a code representation of the commonality in design, assembly, fabrication and material characteristics of a part (Jordan Jr et al., 2005). Therefore, a comparison of two different GT codes can allow for estimates of product similarity. There are three different coding schemes: hierarchical, chain-type or hybrid (Chang & Wisk, 1985). A hierarchical structure, also called a mono-code, is represented as a tree; where each code number is qualified by the preceding characters (or branch). A chain-type structure (poly-code) is presented in a list form, where every digit in the code position represents a distinct bit of information, regardless of the previous digit. The third type of structure, the hybrid scheme, is a mixture of both previous structures.

Currently, there are several GT coding systems used in the industry, and their use depend primarily on the application. Some of the widely implemented systems are described by Chang & Wisk (1985) as:

- The Opitz system. The Opitz coding system is probably the best known scheme, as it has been most generally used as the basic framework for understanding coding systems. It has a hybrid scheme with eight digits that makes it concise and easy to use.
- The CODE system. CODE is a system that codes and classifies in a hexadecimal value. It also has a hybrid scheme with eight digits.
- The KK-3 system. KK-3 was developed by the Japan Society for the Promotion of Machine Industry. It is one of the largest with its twenty-one digits decimal system.
- The MICLASS system. It has a chain scheme of twelve digits. The code is designed to be universal as it includes both design and manufacturing information, currently it is regulated by the Organization of Industrial Research.
- The DCLASS system. DCLASS is a tree-structured coding system intended to be a classification and decision making system. For components, an eight-digit code is used where each branch represents a condition.

As mentioned previously, there is no broad consensus for a particular coding system to be generally used. Most coding schemes have been specifically engineered for each situation. Furthermore, complexity increases in the case for reliability inference in new designs given the lack of this type of information in any code scheme.

Despite complications generated by the reliability estimation for a new design, it is possible to obtain them if similar components are found. In such case, following the methodology for the enhanced parenting process (Chapter 3), identifying parents could be performed through the use of GT by looking at the code scheme and outlining similar products. Once the parents are identified by GT, reliability information from parent's warranty data will be available for the new design based on those similarities. Additionally, to aid the process of parent search for reliability inference, a supplemental code may be incorporated into the actual coding scheme which will carry reliability information. However, in both scenarios a GT database must exists or be developed.

The GT database must be designed to efficiently assists the design retrieval process. In order to achieve this, Dowlatshahi & Nagaraj (1998) provide a methodology to classify data by designing logic trees and GT codes to create an efficient database. Therefore, a methodology will be outlined using a similar procedure.

There are five steps in the development of a GT databases (Dowlatshahi & Nagaraj, 1998): Data collection, data classification, data analysis, data coding and data querying. Next, each step is detailed.

Data Collection

Every design data created must be collected. The data range from company's design parts to standard purchased design items. Additional information regarding layouts, circuit diagrams, failure information and custom-built items must be collected as well.

Data Classification

Classification and coding refers to identifying similarities among components and relating them to a coding system. The similarities can be classified in several ways. For this case, they are from two types: (1) Design attributes, such as geometric shape and size, and (2) Reliability attributes, such as risk associated.

Data Analysis

The analysis of data represents one the most arduous stages of the procedure. The data collected are grouped into different families according to previous classification, where each element is analyzed at different levels of the hierarchy. Therefore, in order to identify each individual component, variation among groups, between groups and with other families must be defined. These variations will lead to the design of a coding system. For reliability purposes, data analysis will be related to classifying variations in the risk assessments.

Data Coding

A coding scheme consists of a sequence of symbols that identify product design and reliability attributes. Represented most commonly by a numeric code, it captures the variability and the uniqueness of the product. Consequently, coding systems are presented as the heart of the GT methodology.

In this case, an existing coding system may be chosen. For example, using an extension of the Opitz's GT code from Girdhar & Mital (2001) and Jordan Jr et al. (2005) it is possible to create a code system adapted to our needs. The final code will consists of five elements: Component, Material, Function, Reliability and Flow. Then, the reliability element will contain information of the risk associated to the product, which will be related to each function that the product will perform. Thus, the number of digits depends on the number of attributes identified previously and cannot be generalized for all cases. For the last part of data coding, a code layout must be established. The code layout serves as a starting point for the querying process, therefore it has to be adapted to each specific case.

Data Querying

Data querying refers to the process of retrieving product design and information from the code scheme. Once data are classified and coded, they are stored in the database as a function of these codes. Consequently, different algorithms (e.g. Genetic Algorithm) may be employed to improve the efficiency of the retrieval process.

Recommendation

In Chapter 3, GT methodology improves the process of selecting parent(s). It also expedites warranty searches and even provides with an additional source of reliability information (risk). However, in case that large companies do not possess an implemented GT system, the cost and amount of resources needed to develop it will compromise its implementation.

B.2 GROUP TECHNOLOGY AND ELICITATION PROCESS

Expert elicitation process refers to the act of obtaining information from someone knowledgeable on the matter in question. Group Technology (GT) methods may help in this task. The two-step elicitation method proposed in Chapter 3 consists in: (1) Asking the expert to provide an estimate of the parameter's median; and (2) Ask about how certain he/she is about the estimate.

The main difficulty using GT systems resides in the fact that GT codes do not carry any estimation that may aid the expert or the decision maker (analyst). However, a GT system might drive to a better estimate with less uncertainty. To the decision maker, a GT system will provide prior information about the product whose parameters need to be estimated; thus, a better planned elicitation procedure can be implemented. In case of the experts, having a risk value associated to the product motivates a higher level of confidence in the estimation, so confidence intervals will be smaller.

There is not a single elicitation process for every situation; hence, it is not possible to outline a general method where GT supports the elicitation procedure. Despite this fact, guidelines can be provided in order to have a successful elicitation process using the previous GT system. Next, an adaptation from Cooke (1991) practical guidelines for elicitation procedure is presented.

Practical Guidelines

- The questions must be clear. The analyst must formulate clear unambiguous questions. GT codes carrying prior information provide a sense of direction where the analyst needs to follow.

- Design an attractive format. Catching the attention of the experts with simple and graphic elicitation formats will expedite the process. For example, a description or even a small figure for the GT code selected should be present in the format.

- Perform a dry run. The analyst must test if the procedure is appropriate and will provide the desired results.
- All supporting material must be presented during the elicitation. If an expert is not familiar with all the elements of the GT code, all the additional information must be available during the procedure to clarify any concerns.
- Prepare a brief explanation for the procedure and how the information gathered will be used.
- Avoid coaching.
- Use time management. A session with the experts should not be longer than one hour.

Recommendation

Although Group Technology (GT) was created for manufacturing purposes, its application easily can be extended to other areas such design and reliability. When it is decided to adopt the GT philosophy, the scope must embrace more than a single application; otherwise the efforts and amount of resources needed to develop a GT structure are not justifiable.

APPENDIX C

RISK ASSESSMENT TOOL

Risk Analysis for New Technologies

System:

Component:

Date:

Name:

Comments:

	What is Changing? Major changes affecting principal functions	Which **Failure Causes** are affected?	**Median**	**Shift** **Lower Limit**	**Upper Limit**	Why?
1						
2						
3						
4						
5						