MASTER

The application of Bayesian belief networks for reliability prediction

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The Application of Bayesian Belief Networks for Reliability Prediction

by

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Abstract

This report presents the findings of the application of a Bayesian Belief Network for reliability prediction. Bayesian Belief Networks are able to reason under uncertainty and to combine heterogeneous data, such as expert opinion, historical failure data and other data that become available during the product development process. A Bayesian Belief Network is constructed at Philips Healthcare as a feasibility study. The study focuses on the building process and the problems identified during the modeling process, instead of on the resulting model itself, since this is a feasibility study.

Preface

The Master Thesis you are about to read is the result of a seven-month internship at Philips Healthcare in Best. The thesis is written in partial fulfillment for the title of Master of Science in Operations Management and Logistics.

I would like to particularly thank my TU/e supervisor Peter Sonnemans for his supervision of the research project and Maurits Houben for his assistance on the topic of Bayesian Belief Networks. Especially at times that I was not sure of the success of my project, Peter supported me greatly. At the same time, Maurits was always available for questions about the content of the research. Peter and Maurits, thank you for the significant amount of time and effort that you have both spent on my project.

Furthermore, I would like to thank Arend van Dam, my supervisor at Philips Healthcare, for giving me the opportunity to execute my Master Thesis project at Philips Healthcare and Jos Trienekens, my second TU/e supervisor, for taking the time to read and give feedback on my writings.

Last but not least, I like to thank my family for their support during my many study years and Karen for her emotional support especially during the last months of the graduation project.

Enjoy reading this Master Thesis!

Jaap Houben
Eindhoven, August 2008

Executive Summary

This report is the result of a graduation project executed by Jaap Houben. The research project was conducted at Philips Healthcare and is part of the research at the Quality and Reliability Engineering section of the department of Technology Management at the Eindhoven University of Technology.

The topic of the research project was the application of Bayesian Belief Networks for reliability prediction. Bayesian Belief Networks are able to reason under uncertainty and to combine heterogeneous data, by quantifying the expert opinion and combine it with the already available historical failure data and other data that become available during the product development. Additionally, "Bayesian Belief Networks combine the advantages of an intuitive visual representation with a sound mathematical basis in Bayesian probability" (Neil et al., 2005).

Modeling Process

Following the literature study on the theory of Bayesian Belief Networks, a case study was conducted at Philips Healthcare to apply the methodology in practice. The aim of the project was to walk through the whole modeling process of building and using a Bayesian Belief Network to identify the problems arising at the different stages of the modeling process. For the construction of the Bayesian Belief Network, the stages of the modeling process identified by Sigurdsson et al. (2001) were used. These modeling stages are depicted in Figure S1. Figure S1 also shows the steps that were executed within each of the stages and the techniques used to execute the steps.

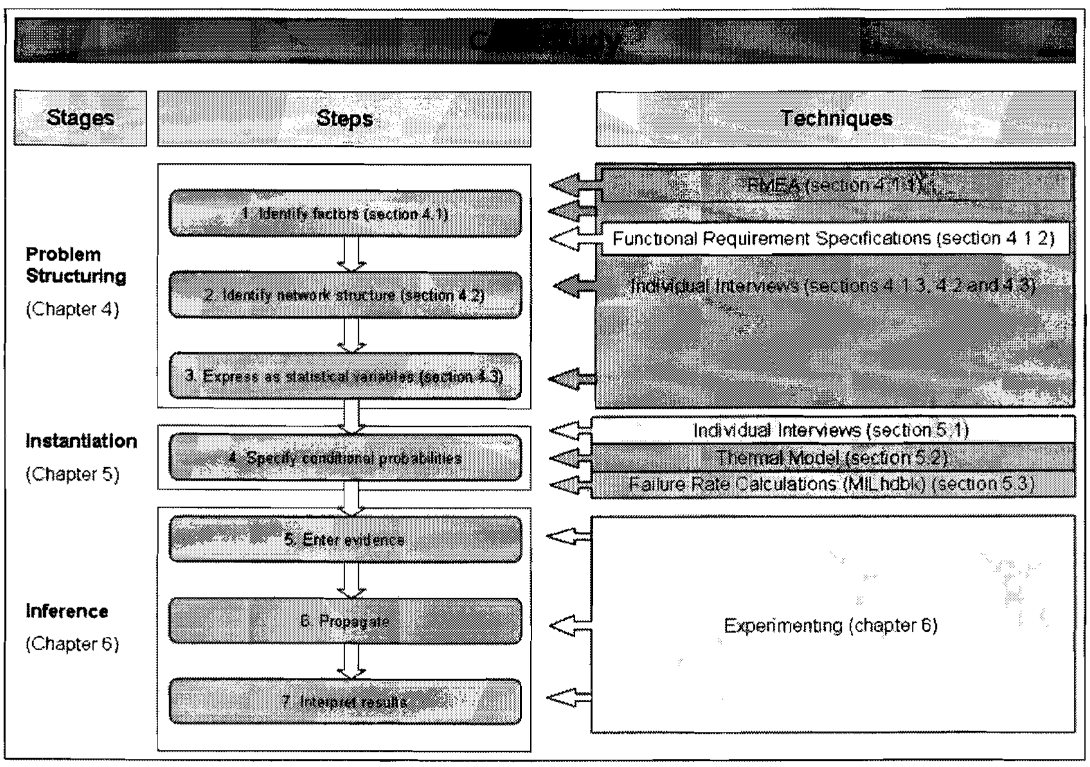

Figure S1. Overview of the techniques used in each of the modeling stages

Results

The Bayesian Belief Network that resulted from the research project is shown in Figure S2. The network structure is based on the functional structure of the module that is modeled. The white top node represents the reliability of the module. The blue nodes represent the failure rates of its functions and sub-functions. Finally, the yellow nodes represent the failure rates of the components which determine the reliability of the functions.

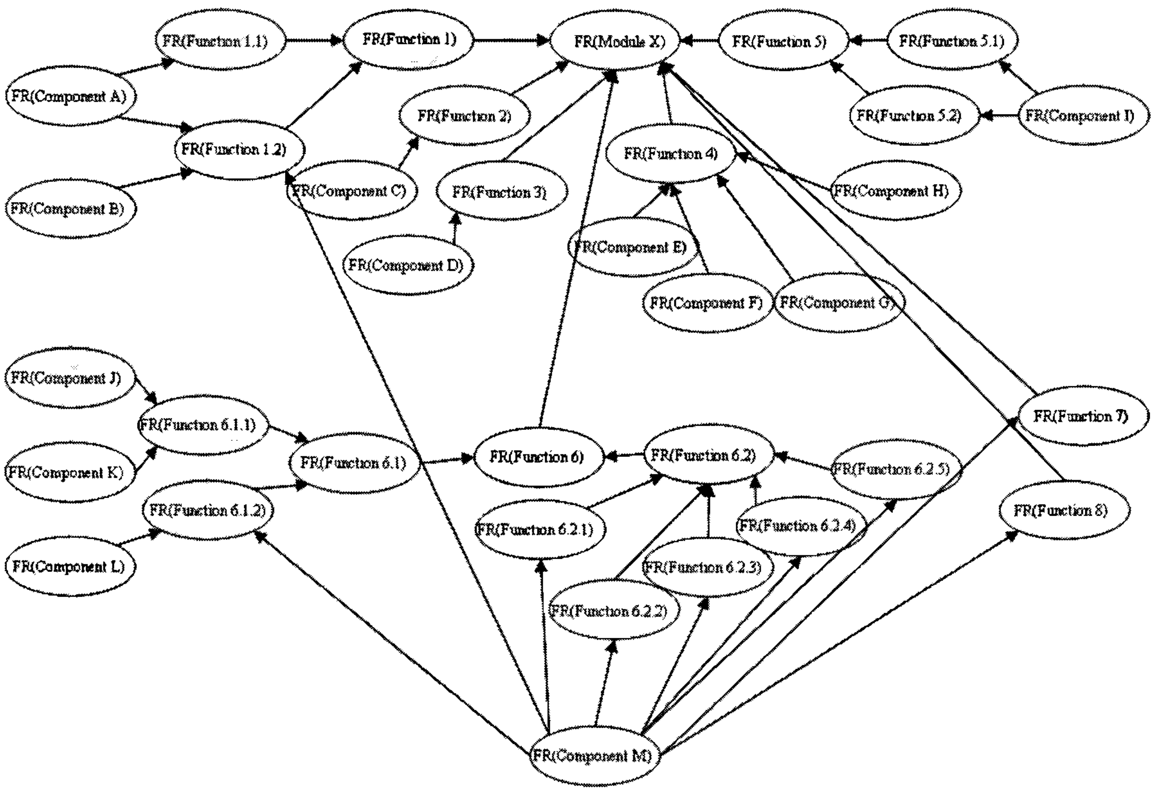

Figure S2. Resulting Bayesian Belief Network

The relationships between the variables are determined by treating the network as a series connection of components that lead to the reliability of the module. Although the relationships were determined by using a series connection, the network in Figure S2 is structured as a Bayesian Belief Network. In contrast to the representation of a series connection, the Bayesian Belief Network also gives insight in the influences of the components on the functions of the product by visualizing the functional structure. Bayesian statistics were used, as a result of the uncertainties incorporated in the model. Additionally, also expert opinion is included in the model. What is missing in the Bayesian Belief Network resulting from this research project is are the interaction effects between variables. By using the software as a "summation machine", the full functionality of the methodology is not used.

The problems which were identified during the modeling process were the following:

- Flexibility of the model
- Choice of generic or specific factors
- Size of the network
- Exploding Node Probability Tables
- Bias in the calculated probability distributions

For Philips Healthcare, the main benefit of the project is the functional structure. The structure is a visualization of the relationships between the module, its functions and its components. Another benefit are the insights gained from this project. By closely monitoring the project, Philips Healthcare has seen the application of the Bayesian Belief Network and could decide to apply it again, either for the same, or for a different purpose.

The goal of the case study for the research project was to gain experience with the application of Bayesian Belief Networks in practice and to identify problems during the different modeling stages. This resulted in a quantified Bayesian Belief Network, but the step of specifying the conditional probabilities by eliciting expert opinion became unnecessary, because the relationships became trivial in the series connection. Since the elicitation of expert opinion to quantify the conditional probabilities is an important step in the construction Bayesian Belief Networks described in literature, the absence of this step is a drawback of this project.

Although the possibility of Bayesian Belief Networks to model interactions between variables is not included in the model, the benefits of being able to reason under uncertainty, to combine heterogeneous data and to give a visual representation of the relationships are used in this research project.

Of the problems that were identified during the modeling process, the choice which factors to include was the main issue. This issue relates to the flexibility of the model, the choice between general and specific factors and the size of the network. In this research project, this issue was resolved by using the type of network structure that was preferred by Philips Healthcare. For a feasibility study, this choice was not a problem, but in other applications the issue of which factors to include in the model can be a large barrier.

In literature, the steps to take to build a BBN seem easy, but to apply them in practice appeared a very difficult task in this research project.

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Abbreviations

ALM	Accelerated Life Models
BBN	Bayesian Belief Network
FEA	Finite Element Analysis
FMEA	Failure Mode and Effect Analysis
FR	Failure Rate
LCC	Life Cycle Cost
MR	Magnetic Resonance
MRI	Magnetic Resonance Imaging
MTBF	Mean Time Between Failure
NPT	Node Probability Table
Pdf	Probability Density Function
PoF	Physics of Failure
RGT	Reliability Growth Testing
SHELF	Sheffield Elicitation Framework

1 Introduction

The emerging technology has created a global economy. Due to this globalization, companies are able to market their products all over the world. On the one hand, this creates opportunities, on the other hand, it stimulates global competition. Due to the large global competition, the consumers demand with respect to delivery times, costs, quality and reliability have risen. "Today's manufacturers face intense global competition, pressure for shorter product-cycle times, stringent cost constraints, and higher customer expectations for quality and reliability" (Meeker and Escobar, 2004). As a result an increased pressure is put upon the reliability of the product.

The increasing attention for a Life Cycle Cost (LCC) approach is a second reason for the growing importance of reliability. Researchers have identified that operating and support costs are the most significant portion of the LCC and although operating and support costs are not only dependent on reliability, a significant part of the LCC is spent on maintenance alone. Since maintenance aims at preserving reliability, reliability has a major impact on the LCC. In this way, increasing the reliability decreases the LCC. Yates and Beaman (1995) show that 66% of the life cycle costs are already decided at the end of the concept phase (Figure 1.1). This indicates that if one wants to make design changes to improve the reliability and thus minimize the LCC, these changes should be made already before or in the concept phase. To be able to improve the reliability at this stage of the development, reliability predictions are needed at that time. For this reason, the reliability should already be predicted as early as possible. On the one hand, improving the reliability brings costs during development, and on the other hand, it saves costs later on. The challenge is to find a good balance between these costs.

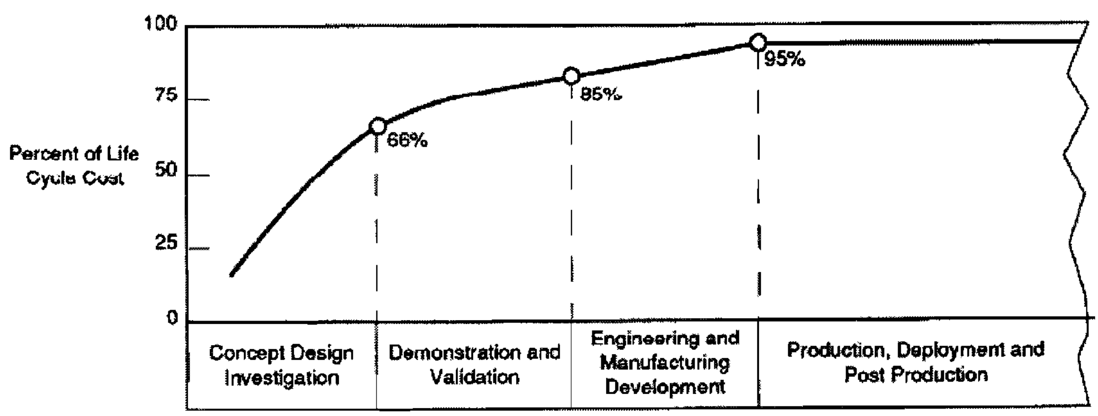


Figure 1.1. Over 65% of Life Cycle Cost (Inherent Reliability) is Determined by the End of the Concept Phase of Product Development (Yates and Beaman, 1995).

Next to the fact that the largest part of the costs is already decided in the early development phases, changes in the design also become more costly over time. The reliability should be predicted early enough in development to enable corrective action (Kerscher et al., 1998). Therefore, to save money and effort in the later stages of the development, a proactive approach should be adopted throughout the development cycle that immediately uses the information at the time it becomes available. Assessing the reliability at the time the product is in use is relatively easy, but to do this during the early development requires information that is scarcely available. As a result, prediction methods that are able to make predictions already early in the development rely on indirect as well as qualitative information about the reliability of the product. This indirect and qualitative information, however, increases the uncertainty of the reliability prediction. Therefore, when considering reliability prediction, it is important to not only take into account the reliability estimate, but also the uncertainty of this estimate.

1.1 Existing Reliability Prediction Methods

The first comprehensive reliability handbook, *TR1100* was developed in 1956 and the methods that were described in it were designed to predict the reliability of electronic equipment. "Refinements were made and it became a forerunner of *MIL-Hdbk-217*" (Wong, 1990). *MIL-Hdbk*-217 as well as its forerunner, *MIL-Std-217*, have been used for decades to predict the reliability of a product. "The main premise is that reliability depends on a Part-Count and Part-Stress approach, where the reliability of individual components determines the reliability of the system or product" (Economou, 2004). While adding more part types and parameters, this handbook evolved from the first version to version *217E*. At the mean time, companies like for example Bellcore were also trying to develop their own reliability prediction methods (*RPP*) (Wong, 1990). The main problem of MIL-base methods, as well as RPP, is that they rely on databases filled with field failure data and "since field failures depend mainly on design and application, these data are not representative of all cases" (Economou, 2004). As a result, predictions made with these methods have proven to be inaccurate.

Also qualitative methods have been advocated, such as *HALT/HASS*, or quantitative methods such as *Physics of Failure (PoF)*, *Accelerated Life Models (ALM)* and *Finite Element Analysis* (*FEA*) (Economou, 2004). HALT/HASS has the problem that to be able to perform accelerated tests, it needs a physical product, or prototype, as a result of which it can not be applied very early in the product development process.

Quantitative methods like PoF, ALM and FEA make use of simulation tools to determine the failure probability of a product or system. However, to be able to use these tools, the failure mechanisms must be known, together with some quantitative data concerning these failure mechanisms. Early during product development, these data are not available yet.

Another technique, developed in a military context, is *Reliability Growth Testing* (*RGT*). In this traditional context, a product was used to put on a test after it was developed, and could then be delivered to the customer with a demonstrated reliability. To be able to put the product to a test, a physical product is needed, either the finished product, or a prototype. The fact that these long-term tests required additional time as well as costs was accepted (Kerscher et al., 1998). In those days, the focus was more on the accuracy of the reliability estimate and tests were less constrained by time. However, in modern industrial settings, where manufacturers face a shorter time-to-market and higher customer expectations, this additional time and money are not available.

1.2 Criticism

According to Yadav et al. (2003) the reliability community only recently started realizing that the reliability prediction made by existing methods hardly matched with reality. These methods fail to provide the required accuracy, especially during the development phase. One of the problems of these methods is the use of wrong assumptions. The constant hazard rate, for example, "does not seem appropriate for any failure mechanism that can be attributed to fracture, fatigue, corrosion, and/or wear mechanism" (Yadav et al., 2003). Also "the assumption of independent failure mechanism is not realistic" (Yadav et al., 2003). However, Wong (1990) already questioned these methods in 1990. Additionally, Wong states that "many of the first-order effect factors are not explicitly included in the prediction methods" (Wong, 1990). And "the models were often simple approximations without scientific basis" (Wong, 1990).

Figure 1.2 illustrates how the reliability estimates deviate from the observed failure data. In this study, Mil-Hdbk-217B was used to predict the failure rates (FR) of several memory boards. From this figure it can be seen that not only do the predicted failure rates deviate from the observed failure rates, also only in three of the twelve cases the observed failure rate falls within the confidence interval of the predictions.

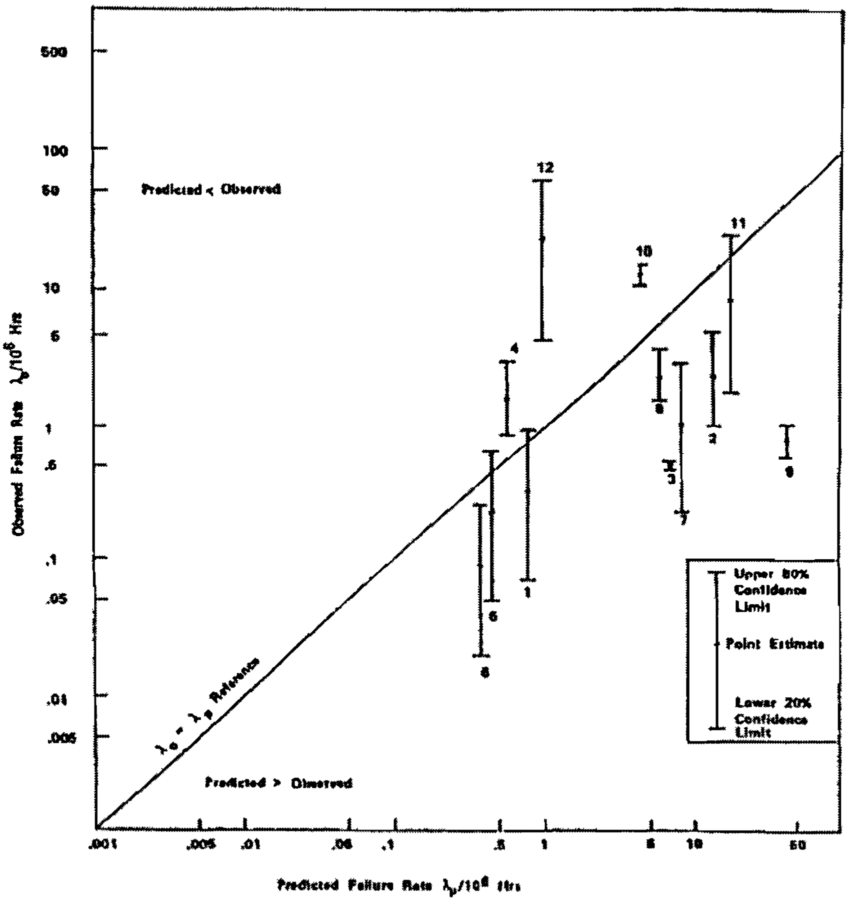


Figure 1.2. Observed vs. predicted failures with Mil-Hdbk-217B (Wong, 1990)

Although this figure stems from 1990, Economou (2004) and Yadav et al. (2003) repeat the opinion that the existing prediction methods are still far from accurate. Despite these accuracy problems, MIL-based predictions are still extensively used and required by many customers (Economou, 2004). Although much criticism has been written by researchers on the available reliability methods, still some prediction is needed early in the product development.

1.3 Research Problem

An increased pressure in put on the reliability of products and the reliability must be predicted already early during the product development process. Several reliability prediction methods exist, but they all have their drawbacks. MIL-based predictions rely on failure databases and because the actual failures depend the design and application, wrong assumptions are being made, resulting in inaccurate predictions. Qualitative methods need physical products, which are not available early during product development. Simulation methods need failure mechanisms, which can only be found with the use of a physical product.

Usually, the only information that is available early during product development are historical failure data on similar products and the opinion of experts. However, these expert opinions are qualitative and therefore hard to use in a model. More information becomes available later on in the product development when prototypes are tested. However, the reliability methods discussed in section 1.1 are not able to deal with the heterogeneity of all different incoming data.

An option would be to use other reliability prediction methods than the classical ones described above. An example of a reliability method that is becoming increasingly popular and will be used in this research project is the so-called Bayesian Belief Network (BBN) (Fenton and Neil, 2000; Neil et al., 2000; Neil et al., 2005).

1.4 Alternative of the Bayesian Belief Network

BBN's can be used to quantify the expert opinions and combine them with the already available historical failure data. Also, "BBN's model problems that involve uncertainty" (Neil et al., 2000). The promising prospect of being able to <u>combine heterogeneous data</u> and to <u>reason under uncertainty</u> was the reason to examine this specific reliability method in more detail. The name already indicates that BBN's are networks in which Bayesian probability theory is involved. "Although Bayesian probability theory has been around for a long time it is only since the 1980s that efficient algorithms (and tools to implement them) have been developed" (Neil et al., 2000). The word "belief" in the name of the method refers to the beliefs (in the form of expert opinions) on which the method is partially based.

In literature, applications of BBN's in practice are described. They mainly show the results of the modeling which are the model itself and the conclusions that are drawn from it. The focus is on proving that the use of the BBN worked well. However, the modeling process itself, and especially the encountered problems, are described minimally. To gain insight into the process of building a BBN in practice, in this project a BBN will be used to model the reliability of a module at Philips Healthcare. The result of this research project is not the BBN itself, but the insights gained from the process of constructing a BBN. For this reason, the whole process walkthrough of building a BBN is prioritized over the quality of each modeling step.

1.5 Report Structure

In the first half of this chapter, the research context, the reason to examine reliability prediction and in particular the use of BBN's in reliability prediction have been discussed. The company at which the research project was performed is Philips Healthcare. In chapter 2, the company introduction, Philips Healthcare and module that is modeled will be discussed.

BBN's were already introduced shortly in section 1.4, but will be discussed in more detail in the first part of the research project chapter, section 3.1. The theory on BBN's is explained more extensively because this is the methodology that will be used in the project. The process of building and using a BBN is done in three stages, namely the *problem structuring stage*, the *instantiation stage* and the *inference stage*. The research questions (section 3.2) and the research approach (section 3.3) are linked to these stages of the modeling process.

In the problem structuring stage the network structure is identified. Chapter 4 describes the execution of the activities within the problem structuring stage. The result of this stage is a network structure which is not quantified yet.

The quantification of the network is done in the instantiation stage. This stage of the modeling process is described in chapter 5. The relationships between the variables in the network must be quantified as well as the marginal probability density functions of the variables. When the network structure is quantified, the BBN is finished an can be used.

The third stage of the modeling process is the inference stage, which will be discussed in chapter 6. This is not really a stage of the building process, but of the use of the BBN. Evidence can be entered to update the network. In this research project, the inference stage is only used to "play" with the model, because no evidence was available to be entered.

Finally, in chapter 7, the project will be reviewed. The review gives an overview of the steps that were taken in this research project to built a BBN. The resulting model is reviewed and answers are given to the research questions. The answers to the research questions are discussed in the discussion section and the chapter will end with a conclusion on what was done and what was not during this research project.

2 Company Introduction

The company at which the project was executed is Philips Healthcare. This section starts with global information about Philips Healthcare and ends with the more specific description of the product that will be modeled.

2.1 Philips Healthcare

To give an idea of the situation in which the method is applied, the context of the product under investigation will be discussed in this section, starting with background information on Philips Healthcare. The background information in this section is extracted from the Philips Healthcare website http://www.medical.philips.com.

Philips Healthcare is a global leader in diagnostic imaging systems, healthcare information technology solutions, and patient monitoring and cardiac devices. In Table 2.1, a number of other facts about Philips Healthcare are listed.

Table 2.1. Facts about Philips Healthcare

Headquarters	Andover, MA, USA and Best, the Netherlands
President and CEO	Steve Rusckowski
Employees	33,000 (27% of Philips total)
Sales and Services Operations	In more than 63 countries with more than 6,000 service technicians
Countries of Distribution	Over 100
Development and manufacturing sites	The Netherlands: Best and Heerlen. Germany: Hamburg and Böblingen. Finland: Helsinki. Israel: Haifa. USA: Bothell and Seattle, Washington; Reedsville and Philadelphia, Pennsylvania; Andover, Massachusetts; Latham, New York, Milpitas and Oxnard, California and Brisbane, California; Cleveland, Ohio; Chicago, Illinois; Madison and Pewaukee, Wisconsin; and Gainesville, Melbourne and Orlando, Florida.
Research and advanced development	At 22 Philips sites and over 40 medical and technical institutions worldwide
Affiliate Companies (Philips share):	Medquist (72%), Philips Medical Capital (40%), Trixell (24.5)

Philips Healthcare is involved in four businesses:

- *Imaging Systems* – This business consists of X-ray machines, CT, MR, Ultrasound and nuclear medicine imaging equipment, used to create images of various parts of the body in varied detail for radiologists and cardiologists.
- *Ultrasound and Monitoring Solutions* – This includes Ultrasound imaging, patient monitoring systems and cardiac systems.
- *Information* – This includes healthcare informatics and document services.
- *Customer Services* – This includes consultancy, clinical services, education, equipment financing, asset management and equipment maintenance and repair.

Within the business of *Imaging Systems*, the unit Magnetic Resonance (MR) is involved in Magnetic Resonance Imaging (MRI). This imaging technique is discussed in appendix A.

2.2 Module X

Due to confidentiality reasons name of the module that was modeled will not be used in this report. It will therefore be called "module X". Also its functions and components will be indicated with "function 1", "function 2", "component A", "component B", etcetera. The module is a small but critical part of a larger system which is being developed at the business unit MR. A description of the module and a list of the functions and components to which will be referred in this report can be found in the confidential appendix F.

Predicting the reliability of a product is most difficult when it is in the early stages of its development, because hardly any data are available yet. One of the advantages of BBN's is that they can overcome this problem by including expert opinion. Choosing a product that was still in the beginning of its development could help to fully cover all the aspects of constructing a BBN in practice. At the start of the project, module X was in the early stage of the development process and therefore it was chosen to be modeled during this research project.

Parallel to this research project at Philips Healthcare a Black Belt project was running, concerned with the reliability of module X. In this Black Belt project, classical reliability prediction methods were used. For information about module X, the Black Belt team had to be consulted first, to use the time of the development team as efficient as possible.

During this research project, three main experts were interviewed to gather information about module X. The reliability champion at MR, who is working fulltime on reliability improvement projects within MR, is referred to as the "reliability expert". The "product expert" is a hardware architect at MR and is responsible for the architecture of the larger system, of which module X is a part. As such, he is an expert on the module itself as well as on the function of the module within the larger system. The third expert is the "temperature expert". The temperature expert is occupied with temperature simulations and test for product development at MR.

3 Research Project

In section 1.4, a brief introduction was given of the advantages of BBN's. In section 3.1 of this chapter, BBN's are discussed more extensively. The aim of the project was to examine the methodology of building a BBN in practice. This methodology consists of three main stages, the *problem structuring stage*, the *instantiation stage* and the *inference stage*. The research questions (section 3.2) are therefore linked to these stages of the modeling process. The approach to applying the methodology of BBN's in order to answer the research questions was by doing a case study at Philips Healthcare. In section 3.3, the research approach of doing a case study is described.

3.1 Bayesian Belief Networks

BBN's are able to reason under uncertainty and to combine heterogeneous data, by quantifying the expert opinion and combine it with the already available historical failure data and other data that become available during the product development. The property of being able to reason under uncertainty is important because the aim of combining different types of data is not to reach a point estimate of the reliability, but to also monitor the uncertainty of the estimate.

The network consists of a number of quantified, causal relationships between discrete variables. Factors that directly or indirectly influence the reliability are included in the model and are represented by nodes. The statistical relationships between the variables are represented by arcs which connect the nodes. An advantage of the use of a network as opposed to the use of direct relationships (like in a regression model) is that it gives a better understanding of how the final reliability is derived. "The causal model is telling the story that is missing from the regression approach" (Fenton and Neil, 2000).

Another advantage of the dependencies among variables is that variables can also be estimated indirectly, via related variables. By using a network perspective, experts can specify the relationship between two variables in which they are knowledgeable, instead of having to specify the direct relation between the variable and the reliability. "BBN's enable reasoning under uncertainty and combine the advantages of an intuitive visual representation with a sound mathematical basis in Bayesian probability" (Neil et al., 2005). This reasoning under uncertainty is possible due to the Bayesian probability theory, which enables the combination of probability distributions. The mathematical basis makes it possible to not only generate reliability estimates, but also to investigate the impact of new evidence on the reliability estimate as well as the uncertainty of this estimate. "BBN's allow an injection of scientific rigor when the probability distributions associated with individual nodes are simply expert opinions" (Neil et al., 2005).

3.1.1 Child and Parent Nodes

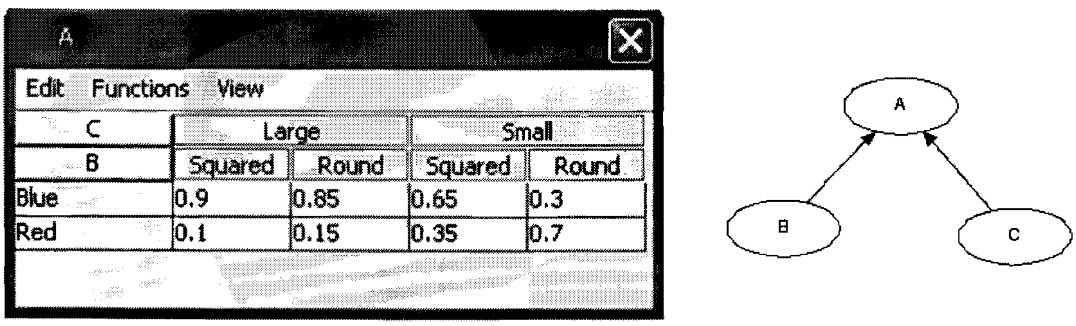
In Bayesian Networks, "child" and "parent" nodes are used to represent the variables that (in)directly influence the reliability. Several parent nodes can be connected to one child node, but one parent node can also point to several child nodes. The child node is influenced by its parents. The relationship between de child en the parent nodes is quantified. With the help of Bayesian probability theory it is possible to say something about the child node based on information on the parent nodes and the other way around. When these parent nodes also have other parent nodes themselves, a network arises. The probability distribution of the child node is calculated from the probability distributions of its parents in combination with the quantified relationship between the child and its parents. The probability distributions of the parents are calculated from the probability distributions of their parents again. For the nodes that do not have parents the modeller must quantify the distribution. These distributions are called marginal distributions, they are situated at the start of the "variable chain", and are the input for their child nodes.

The structure of the network is decided by the developer of the network in cooperation with product/process experts. All parent-child relations, which are represented by the arrows, can be causal or influential and are defined with the help of expert opinion and historical data. According to Fenton and Neil (2000), "regression models often lead to misunderstanding about cause and effect, because a correlation does not provide evidence of a causal relationship", which is why the causal nature of the relationships in the Bayesian network is so important.

In addition to the importance of the use of causal relationships between the nodes, close attention should also be paid to the direction of the relationship. When trying to influence the pdf estimate of a node, one should adjust the nodes that cause this estimate, and not the nodes that are affected by it.

3.1.2 Node Probability Tables

The conditional probabilities are stated in a so-called Node Probability Table (NPT). This NPT indicates the statistical relationship between the node corresponding to the NPT and its parents. In the table the probability of the variable being in each possible state is indicated, given the variable states of its parents. An example of a NPT is shown in Figure 3.1, for a fictive situation.



C	Large		Small	
B	Squared	Round	Squared	Round
Blue	0.9	0.85	0.65	0.3
Red	0.1	0.15	0.35	0.7

Figure 3.1. Example of a NPT

In the example given in Figure 3.1, the probability of variable **A** being in state *Blue*, given that the state of parent variable **C** is *Large* and the state of parent variable **B** is *Squared*, is 0.9. In this example the variables A, B and C each only have 2 possible states, but variables are allowed to have more. When the number of parents and possible states of the variables increases, the number of conditional probabilities that need to be specified grows exponentially.

3.1.3 Bayesian Updating

In the previous section, it is explained how the probability distributions of the variables in the network are related to each other as a result of the statistical relationships between them (represented by the arrows). The distributions that appear when the model is finished, but not yet "used" are called prior distributions. When quantitative information about the distribution of a variable becomes available, this can be entered into the network as evidence on this variable. As a result of the entering of this evidence, the prior distribution changes and is updated to a posterior distribution. Due to the statistical relationship of this variable with its childs and its parents, the probability distributions of these variables are also updated to posterior distributions. The child and parent nodes of these updated nodes will also be updated as a result of the change and that is how the incoming information is propagated through the whole network. In this way, the whole network is updated as a result of the new data that is entered at one variable.

3.1.4 Acyclic Graph

Each time when new evidence is entered into the network, the whole network is updated. However, each node is only updated once as a result of this specific evidence. The node structure is acyclic, which means that there is no directed path starting and ending at the same node. Therefore, each node can only be updated once per updating stage. When, for example, node A is updated, it can trigger the update of nodes B and C, but due to the acyclic nature of the structure, node A is not updated by B and C again.

3.1.5 Conditional Independence

The updating of the nodes is done using Bayesian probability theory. "The underlying theory of BBN's combines Bayesian probability theory and the notion of conditional independence to represent dependencies among variables" (Neil et al., 2005). Two variables A and B are conditionally independent on C if:

$$P(A \cap B \mid C) = P(A \mid C) \cdot P(B \mid C) \tag{3.7}$$

Variables A and B are independent given C. This can be illustrated by a small example. Two colleagues, Tom (A) and John (B), both travel to work by train (D). Tom finishes his journey by bike (C) while John takes the bus (E). The probability that Tom and John will be late partly depends on the train being delayed (see Figure 3.2).

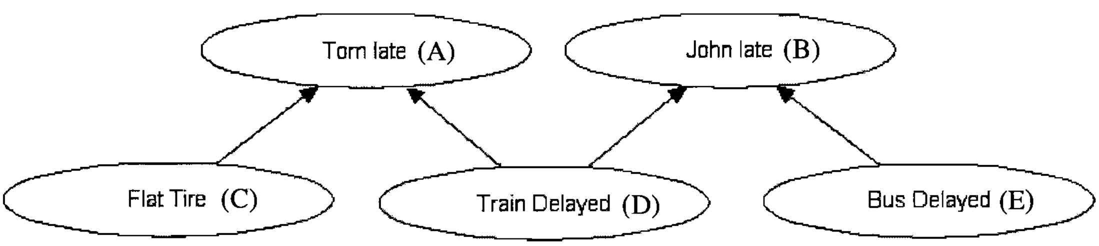


Figure 3.2. Example of conditional independence

If John is late, the probability of the train having been delayed increases. This may seem strange, because John does not cause the train to be delayed. Variable B is the effect and D the cause and not the other way around. However, if B has occurred, this is the effect of either cause D or the cause E. As a result, the probability of occurrence of both D and E increases. Because the increased probability of D does on its turn influence the probability of A, variables A and B are dependent. $P(A \cap B) \neq P(A) \cdot P(B)$ because $P(A)$ and $P(B)$ partially have the same cause. However, if D is known, information on variable B does not influence the probability of A anymore, so A and B are conditionally independent given D: $P(A \cap B \mid D) = P(A \mid D) \cdot P(B \mid D)$. From Figure 3.2 we can also see that C and E are conditionally independent given A *or* B *or* D. However, C and E are *not* conditionally independent given A *and* B.

3.1.6 Building Process

In the previous sections of this chapter, the most important aspects of BBN's have been discussed. In this section, the stages of the building process of a BBN will be clarified. The stages which are used in this report are the ones defined by Sigurdsson et al. (2001). These stages, the problem structuring, instantiation and inference stage were already mentioned in section 1.5 and are shown in Figure 3.3.

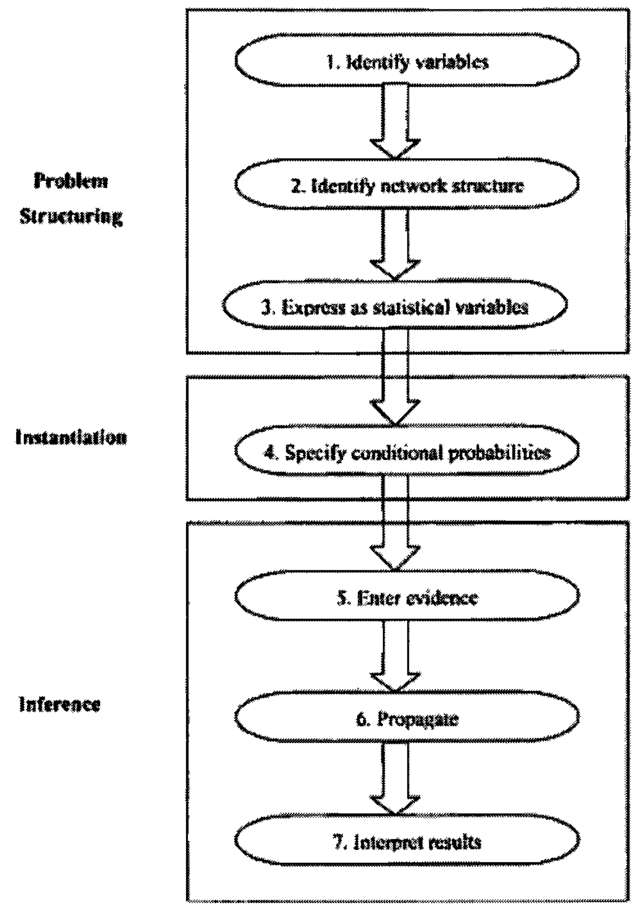


Figure 3.3. Flowchart showing the steps of building and using a BBN (Sigurdsson et al., 2001)

The first two steps, within the problem structuring stage, are the identification of the factors and the network structure. This is also pointed out by Kerscher et al. (1998), who state that "one of the first activities of an organized reliability program is the construction of a reliability logic flow diagram of the product under development" (Kerscher et al., 1998). "BBN's provide an alternative representation of fault trees and reliability block diagrams" and "they essentially provide a framework for graphically representing the logical relationships between variables and capturing the uncertainty in the dependency between these variables using conditional probabilities" (Sigurdsson et al., 2001). The third step of the problem structuring stage is expressing the statistical variables. The factors that have been identified in the first step must be expressed as statistical variables and the set of possible values should be specified in order to be able to define the statistical relationships between the variables. Note that the second and the third step can be interchanged, because they will probably need to be performed iteratively, before proceeding to the next stage. In this report, the variables will be referred to as factors, until they are expressed as statistical variables in the third step, since one could assume variables to be statistical by nature. In the first step, the factors are identified and in the third step the factors are specified as statistical variables.

In the second stage, the initiation, the conditional probabilities are specified. The conditional probabilities represent the causal statistical relationships between the variables. When the network structure is determined and the conditional probabilities are specified, the network is ready to be used, which will be done in the third stage. In this stage, the evidence will be entered and propagated through the network. Then, finally, the results must be interpreted, which can be done with the help of expert and developers.

The research questions, which will be discussed in the next section, are based on the modeling stages defined by Sigurdsson et al. (2001).

3.2 Research Questions

In theory, BBN's seem promising to overcome the problems of the more classical methods named in section 1.1. In the existing literature on BBN's, the main focus is placed on the benefits of the methodology. However, when applying the methodology in practice, problems will arise. The aim of this project was to identify these problems, so that they can be anticipated in the future. In section 3.1.6, three stages identified by Sigurdsson et al. (2001) are given which can be followed to build and use a BBN. These stages are the <u>problem structuring</u>, <u>instantiation</u> and the <u>inference</u> stage. The research questions that are discussed in this chapter are based on the problems arising in these stages. In the problem structuring stage, a Bayesian node structure is constructed. The first research question is dealing with the problems that occur during this stage. During the instantiation stage, the relationships within the node structure are quantified and this is what the second research question is based on. After the quantification, the network is finished and can be used, which is the third stage. The third stage is the inference stage, in which evidence is entered and propagated and the results are interpreted. Because the model is already finished at this point in time no problems are anticipated in this stage with respect to the building of the network, but more to the interpretation of the model. An issue that relates to the interpretation of the results is the validation of the model. The third research question focuses on validation, but has a lower priority than the first two research questions.

1. **What are the problems and risks encountered when constructing a <u>Bayesian node structure</u>?**

The product is still in the design phase of its development and as a result quantitative data on this product are scarcely available. The same holds for quantitative data on similar products, because it is the first generation of a new product. One of the benefits of BBN's is that they can be applied without quantitative data, already early during product development, by using expert opinions. However, if experts are the only information source, the development of the model becomes very dependent on this information source.

2. **What are the problems and risks when quantifying the <u>relationships</u> between the factors that determine the product reliability?**

The relationships between the variables in the BBN must be quantified. If no quantitative data are available on these relationships, the quantification must be done by experts. In the case of new products, the relationship between certain variables may be unknown to the experts. The fact that certain relationships are unknown to the experts can be represented by a large variance of the estimated probability distributions. A larger variation of a probability distribution is not a problem, because the network is perfectly capable of handling this uncertainty. However, it is not sure whether experts can say something quantitative about the relationships at all.

3. **How to validate the resulting Bayesian Network?**

When a model is finished, one normally wants to validate the model. In the case of a BBN which is applied to a product under development, there is hardly any evidence to validate the model with. Test data cannot be used to validate the model because they are incorporated in it. In a later stage, field data can be used to compare the reliability predicted by the model to the field reliability. Even then, the comparison does not say much, because the reliability following from the model evolves over time. Validation based on just a single reliability estimate from the model may therefore be too simple. The purpose of the BBN is to combine the available, up-to-date information, and as a result the accuracy of the predictions made using the BBN largely depends on the input data used. Therefore, the accuracy of the predictions are not a good measure of the performance of the methodology. What will be validated for this third research question is the way in which the BBN propagates the probability distributions of the variables. Independent of the question whether the BBN represents the reality, it can be examined whether the BBN propagates the probability distributions of the variables in the anticipated way.

3.3 Research Approach

The methodology that will be investigated in this project is the BBN. The research approach is the way in which this is done, which is by doing a case study at the business unit MR at Philips Healthcare. The software that will be used to model the BBN is AgenaRisk. For this master thesis project, the choice of a case study seems quite trivial, but when generalizing the results afterwards it remains important to keep in mind that the sample size is just one, because only one BBN was constructed.

The case study can be a useful tool in research, but it has also been criticized much in literature. One of the most important critics on the case study is that "built on a single case, it can with difficulty measure a theory's generality" (Hamel et al., 1993). The conclusions that follow from the application of the method can hardly be generalized because they largely depend on the specific context in which the method is applied. According to Hamel et al. (1993), another drawback of the case study is the problem of the subjectivity of the researcher. This subjectivity plays a role in every research, but is even larger when the researcher becomes a part of the research field himself. In that case he does not only add subjectivity by setting up the experiment and interpreting the results, but also by influencing the processes within the research field just as a result of his presence. As a result, "the case study became an exploratory investigation, a preliminary survey giving rise to a statistical study that could validate or eliminate a theory or general model" (Hamel et al., 1993).

In the case of this project the goal of the case study is not to 'give rise to a statistical study that could validate or eliminate a theory or general model,' because there is no theory or general model involved. Instead, the study will examine the applicability of a tool and as such, it will be a feasibility study. Foreman (1948) distinguishes case studies focused on development, resulting in a case history, and case studies that obtain a panoramic view of the present, which can be called photographic. The case study of this project focuses on the feasibility to develop a Bayesian Belief Network. The resulting model itself could be useful for Philips Healthcare, but not particularly for the study. What contributes more to the study is the way in which the model is developed. This is why this report describes the building process, following the different stages of the modeling process, instead of only describing the resulting model and its predictive performance.

This case study, concerning the construction of a BBN in practice follows the stages of the modeling process defined by Sigurdsson et al. (2001), described in section 3.1.6. The first stage in this modeling process is the problem structuring stage. The problem structuring stage will be discussed in the next chapter.

4 Problem Structuring

In the problem structuring stage, identified by Sigurdsson et al. (2001) in Figure 3.3, the network structure is made. The network structure consist of a number of variables which are connected by arrows. The arrows represent the causal relationships between the variables. In the problem structuring stage, these relationships are not quantified yet. When the variables and the relationships between them are quantified, the network is called a BBN. As long as the network is only qualitative in nature it is called a network structure.

Figure 4.1 shows the steps that have been followed in this research project during the problem structuring stage and the techniques that are used for each of the steps. In this research project, the main input to build the network structure was the opinion of the experts. However, also other information sources like the products functional requirement specifications and the results of an FMEA analysis were used, to use expert time as efficient as possible.

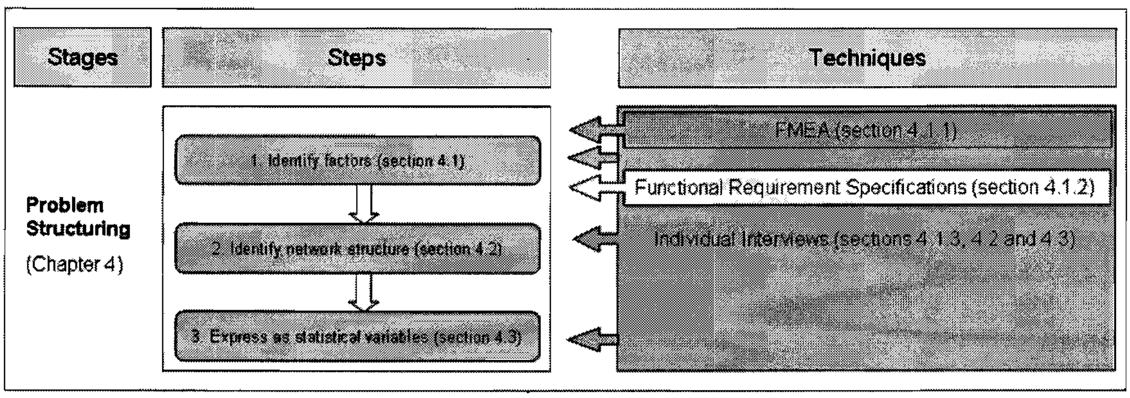


Figure 4.1. Techniques used in the problem structuring stage

Figure 4.1 also shows in which section of this chapter each step or technique is discussed. Section 4.1 describes the first modeling step within the problem structuring stage, namely the identification of the factors. An FMEA analysis, the functional requirement specifications and individual interviews were used to execute this step. The functional requirement specifications and the results of the FMEA were both used as input for the interviews. The second modeling step, the identification of the network structure will be discussed in section 4.2. and the third modeling step, in which the factors are expressed as statistical variables is described in section 4.3. As shown in Figure 4.1, step two and three of the problem structuring stage were also done by individual interviews. The interviews in the problem structuring stage were done with the reliability expert and the product expert, who were both introduced in section 2.2. The reliability expert decided the type of structure to use, while the product expert identified the factors within this type of structure.

In an interview with the reliability expert at MR, it became clear that Philips Healthcare preferred the network structure to be based on the functions of the product. The reliability expert defined the reliability of a product as *being able to fulfil its intended functions*. The product only fails if one or more of its functions fail. In this sense, the reliability of the product can be derived from the reliabilities of its (sub)functions. By using a functional structure, the model shows how the reliability of the module is influenced by its (sub)functions. "The causal model is telling the story that is missing from the regression approach" (Fenton and Neil, 2000). The reliability of the (sub-)functions depends on the components that execute these (sub-)functions. Therefore, also components were included as factors in the network. An example of a network structure based on the functions and components of a product is shown in Figure 4.2.

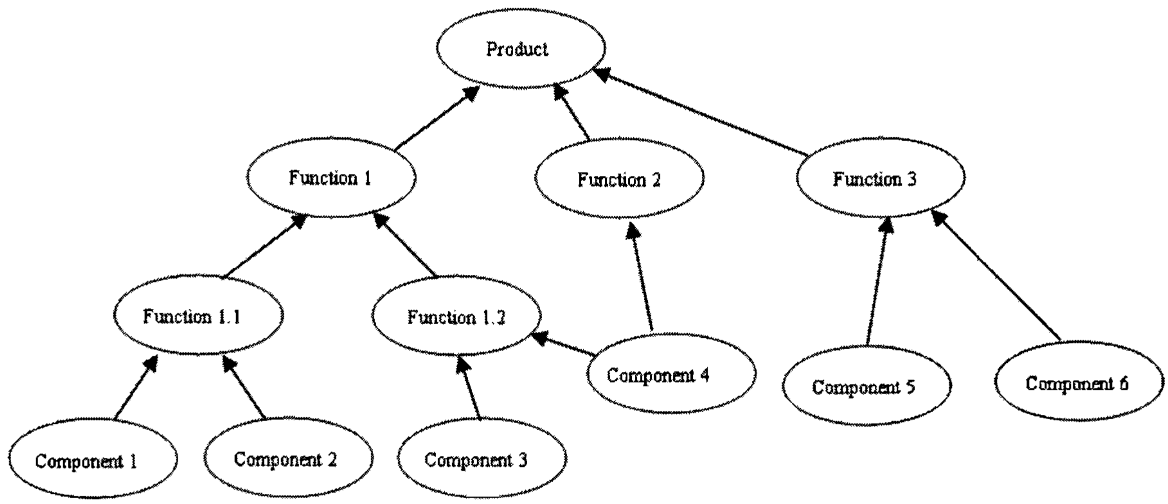


Figure 4.2. Example of a network structure based on functions

The choice to use the functions and components of module X as factors in the network structure was made during the factor identification (section 4.1) and the network structure identification (section 4.2). After a number of iterative loops of identifying factors, identifying the network structure, changing factors and changing the network structure, the decision was made to use the type of network structure of which an example is given in Figure 4.2. The first problem within the problem structuring stage was encountered here. Due to the large **flexibility of the model** is it difficult to decide what factors to use in the network. Besides the factors in Figure 4.2, other kinds of factors could be included, like the results of an FMEA, or more abstract factors like "the complexity" of the module of the "quality of testing". As a result of this large flexibility much effort was spend on examining the suitability of the alternatives.

4.1 Factor Identification

In their study, Sigurdsson et al. (2001) started with the engineers indicating which aspects of the system they felt could lead to a system failure. Concerns were indicated on the level that the expert is comfortable with, but it is also important to explore their sub-concerns, which influence the top-level concerns. In this graduation project, the experts had only very limited time available. Therefore a start was made with the identification of the factors using other information sources, to use the experts' time as efficient as possible. Because the module was still in the early stages of its development, there was only little information available about the product. The FMEA analysis and the requirement specifications were available and were therefore used to start the factor identification with. For the factor identification, an FMEA analysis, the functional requirement specifications and individual interviews were used.

4.1.1 FMEA Analysis

Shortly after the start of this master thesis project, a FMEA analysis was started. This analysis was part of the Black Belt project described in section 2.2. The results of this analysis can be found in appendix B.

The advantage of using the FMEA results as input for the BBN would be that the experts would no longer be necessary for the identification of the factors and a larger part of their time could be dedicated to the quantification of the model. However, since the complexity of the model increases with the number of nodes added to the model, including all failure modes and causes would result in a complex network. The more complex the model is, the longer the calculation times are and the more relationships must be quantified in the instantiation stage.

A way to decrease the number of nodes in the model is to only include the failure modes, and not the failure causes. Another option is to select the failure causes based on the values of their risk priority numbers (RPN's).

This is the second problem identified during the problem structuring stage; should the included factors be **generic or specific?** In literature, most studies (e.g. Neil et al., 2000; Fenton and Neil, 2000) use generic factors in their models for predicting the reliability, like the complexity of a product, the quality of testing or the effort spend on development. These factors can be used to predict and monitor the reliability, but are less useful for decision making during the development. Due to the generic nature of these factors, it is difficult to point out the exact improvement areas of the product.

Including many product specific factors, like the failure modes and causes of an FMEA, in the model increases the size of the model. Additionally, when problem areas identified by the BBN, such as failure causes, are solved, the network structure must be changed. Making the BBN more specific, increases the probability that the network structure must be changed as a result of changes in the product design. Monitoring the reliability of a product during its development is easier when only the numbers change while the network structure remains the same.

Although a large **size of the network** does not result in problems in the problem structuring stage yet, the instantiation stage and the inference stage are effected by it. This is the third problem identified in the problem structuring stage. Larger networks need more effort for their relationships to be quantified during the instantiation stage. In the inference stage, large networks result in larger calculation times and possibly calculation problems. These aspects must be taken into account when the network structure in constructed.

A start was being made with the construction of a network structure based on the FMEA results. Due to the large size of the resulting network, in combination with the large anticipated effort that would have to be spend on the quantification in the next step, and the preference of Philips Healthcare to explicitly include the module's functions in the network structure, the decision was made to use a network structure depicted in Figure 4.2.

The FMEA described earlier did not include any functions, but only failure modes and causes. However, Philips Healthcare's policy for the future is to start the FMEA analysis with defining the functional structure of the product and then identify the failure modes belonging to each of the functions. By basing the network structure of the BBN on the functional structure of the product, the BBN is also aligned with the intended structure of future FMEA's.

4.1.2 Functional Requirement Specifications

It was decided to base the network structure on the functions and the components of module X. The functions of the product were extracted from the functional specifications of the product. These are the following functions:

- Function 1
- Function 3
- Function 5.1
- Function 5.2
- Function 6.1.1
- Function 6.1.2
- Function 6.2.1
- Function 6.2.2
- Function 6.2.3
- Function 6.2.4
- Function 6.2.5
- Function 8
- Function 7
- Function 9

For confidentiality reasons, the real functions are not listed here. The functions to which is referred here can be found in the confidential appendix F. The numbering of the functions is based on the structure of the final BBN, which is why the function numbers may seem inconsistent.

4.1.3 Individual Interviews

Two interviews were executed with the product expert of module X. In literature, during the factor identification, more experts are interviewed either individually or in group sessions to combine their expertise (e.g. Sigurdsson et al., 2001). In this research project, only one expert was interviewed to identify the factors and structure them. The reason for interviewing only one expert was the limited amount of available time of the experts. Since this research project is a feasibility study, the priority was to make a network structure, and the quality of this modeling step had a lower priority.

The interviews had three purposes:

1. verify the functions which are extracted from the functional requirement specifications and the add other functions pointed out by the product expert.
2. identify the components that determine the reliabilities of the functions.
3. structure the functions and components in such a way that a network arises.

The third purpose concerns the second step of the problem structuring stage, the identification of the network structure (section 4.2). Since the modeling steps within the problem structuring stage were performed iteratively, the identification of the network structure was also done in the interviews.

The following functions were the result of the verification of the functions and the addition of other functions:

- Function 1
- **Function 1.1**
- **Function 1.2**
- **Function 2**
- Function 3
- **Function 4**
- **Function 5**
- Function 5.1
- Function 5.2
- **Function 6**
- **Function 6.1**
- Function 6.1.1
- Function 6.1.2
- **Function 6.2**
- Function 6.2.1
- Function 6.2.2
- Function 6.2.3
- Function 6.2.4
- Function 6.2.5
- Function 7
- Function 8

Function 9 was removed from the list of functions resulting from the functional requirement specifications, while the boldly written functions were added by the product expert. The components that were identified by the product expert to be influencing the reliability of these functions are listed below:

- Component A
- Component B
- Component C
- Component D
- Component E
- Component F
- Component G
- Component H
- Component I
- Component J
- Component K
- Component L
- Component M

The functions and components to which is referred here can be found in the confidential appendix F.

The functional requirement specifications of the module and individual interviews were used to identify the factors to be included in the network. The option to use the results of an FMEA analysis was explored, but refuted. The factors that were identified in this modeling step are listed in Table 4.1.

Table 4.1. Overview of the identified factors

	Interviews	
Functional Requirement Specifications	**Functions added by product expert**	**Components**
Function 1	Function 1.1	Component A
Function 3	Function 1.2	Component B
Function 5.1	Function 2	Component C
Function 5.2	Function 4	Component D
Function 6.1.1	Function 5	Component E
Function 6.1.2	Function 6	Component F
Function 6.2.1	Function 6.1	Component G
Function 6.2.2	Function 6.2	Component H
Function 6.2.3		Component I
Function 6.2.4		Component J
Function 6.2.5		Component K
Function 7		Component L
Function 8		Component M

In the next section, these factors are structured into a network. However, as argued before, the two steps of identifying the factors and the network structure were performed iteratively.

4.2 Network Structure Identification

The identification of the network structure is done at the same time as the identification of the factors during two interviews with a product expert. In the first interview a first draft network structure was made, which was verified and adapted during the second interview. The network structure is constructed using the factors identified in the previous section. This was done in the same way as has been done in literature, by asking the expert to indicate the qualitative causal relationships between the factors. Only in this research project only one expert was interviewed, instead of more experts in literature. Again, this choice was made based on the limited availability of the experts and the research project being a feasibility study. The interviews resulted in the network structure depicted in Figure 4.3 on the next page. This structure visualizes the relationships between the factors, but the relationships are not quantified yet.

The white top node, representing the reliability of module X, has a number of parents, representing the functions of the module. These functions have other (sub-)functions or components as their parents. The nodes representing functions are coloured blue, while the nodes representing components are yellow.

A problem that arose during the identification of the network structure was the fact that the NPT of a node, of which an example is displayed in Figure 3.1, grows exponentially with the number of so-called node states and the number of parents connected to this node. This problem of **large NPT's** is the fourth problem identified during the problem structuring stage. Fortunately, the NPT's do not all have to be filled manually, but expressions can be used to specify the relationships between the child and the parents nodes. However, when a expression is entered by the modeller, AgenaRisk translates this expression to a NPT. Calculations are made by using these NPT's. Growing NPT's increase the calculation time and can ultimately lead to calculation problems. For this reason, AgenaRisk advises the user to keep the number of parents of a node to a maximum of 3 to avoid memory issues. The problem of child nodes having too many parents was solved with the use of "dummy nodes", which is explained with the example in Figure 4.4.

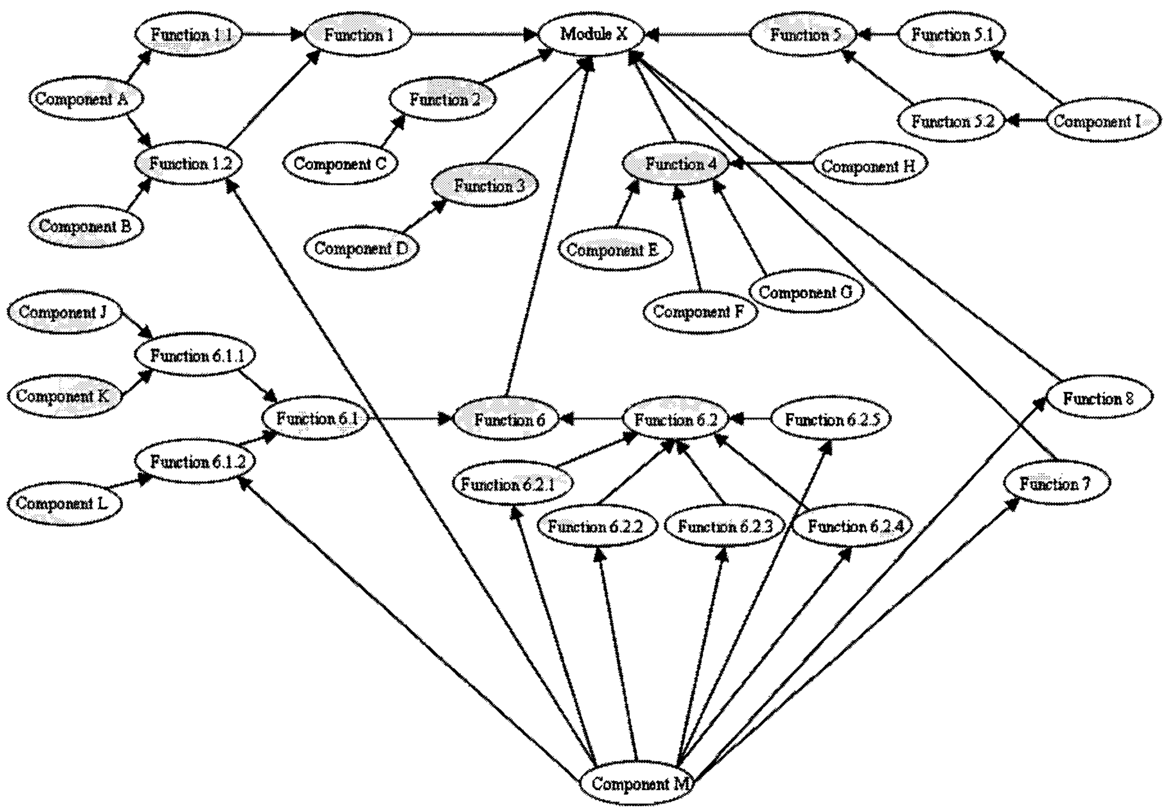


Figure 4.3. Network Structure

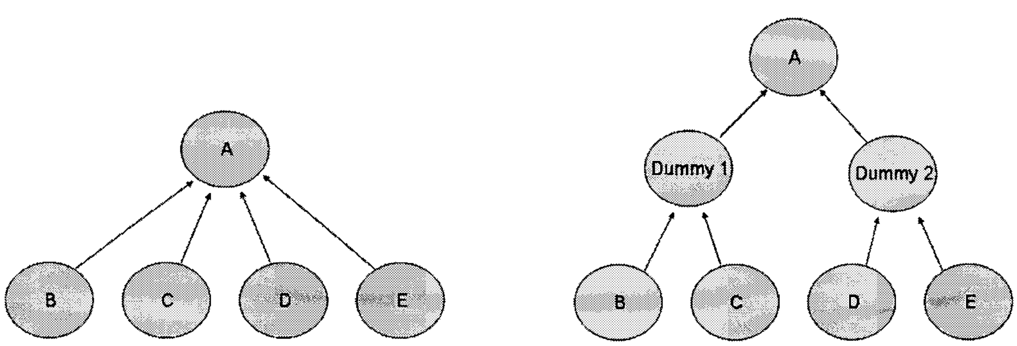


Figure 4.4. Example of the use of dummy nodes

Node A has parents B, C, D and E (see the left structure in Figure 4.4). Suppose all five variable have three node states, for example "high", "medium" or "low". The NPT at node A will contain $3^5 = 243$ cells. When two dummy nodes (with the same node states) are added to the structure as depicted in the right structure in Figure 4.4, the NPT at node A contains $3^3 = 27$ cells. The dummy nodes both also have NPT's of $3^3 = 27$ cells. The total number of cells in the example with dummy nodes is 81, which is one third of the number of cells in the NPT without the dummy nodes. When the number of node states increases, the effect of the dummy nodes will be even more apparent. In this way the dummy nodes help preventing the network from exploding. The addition of dummy nodes changes the relationships between the variables. For example, an interaction effect between the variables B and D can in the left structure in Figure 4.4 be modeled in the NPT of node A. In the right structure this interaction effect cannot be modeled anymore, because in none of the three NPT's variable B and D are both available. Whether dummy nodes can be added to the network without changing the relationships between the variables, depends on the quantification of the variables. Therefore, the dummy nodes were only added to the network after the next modeling stage, in which the relationships between the variables are quantified.

The result of the second step of the problem structuring stage is the network structure depicted in Figure 4.3. This structure consists of module X itself, the functions and sub-functions of the module and the components that influence these (sub-)functions. However, a function or component is not a statistical variable. In the next section, the factors that were identified in the first step and structured in the second step will be expressed as statistical variables. This is the third step of the problem structuring stage.

4.3 Statistical Variables

The third step of the problem structuring stage is expressing the identified factors as statistical variables. The factors which are identified in the first step are functions and components, without any numerical meaning. In the next stage, the instantiation stage, the factors and the relationships between them will be quantified. To be able to quantify the factors and the relationships, the variables must first be defined, which is done here.

This step is executed by doing interviews with both the reliability and the product expert. When talking about the reliability of functions, which is determined by the reliability of the components, the most logical choice would be to either use the Mean Time Between Failures (MTBF) or the Failure Rate (FR) as statistical variable. When constant FR's and the absence of interaction effects are assumed, the FR's of a number of components in series can be summed to calculate the FR of the chain, while this cannot be done with MTBF's. FR's are therefore easier to use for calculations. All variables in the network structure are expressed as the FR's of the functions and components.

Non-constant failure rates would cause difficulties with the quantification of the relationships. Interaction effects between the functions or components would require extra effort during the quantification of the relationships, but these effects could be added to the model afterwards. Since the research project is a feasibility study, the whole walkthrough of building a BBN is prioritized over the quality of each modeling step. For this reason, constant FR's and the absence of interaction effects were assumed.

When the factors are expressed as statistical variables, the problem structuring stage is finished. The result of this first stage of the modeling process is a network structure in which the factors are expressed as statistical variables, but which is not quantified yet. The resulting network structure is depicted in Figure 4.5.

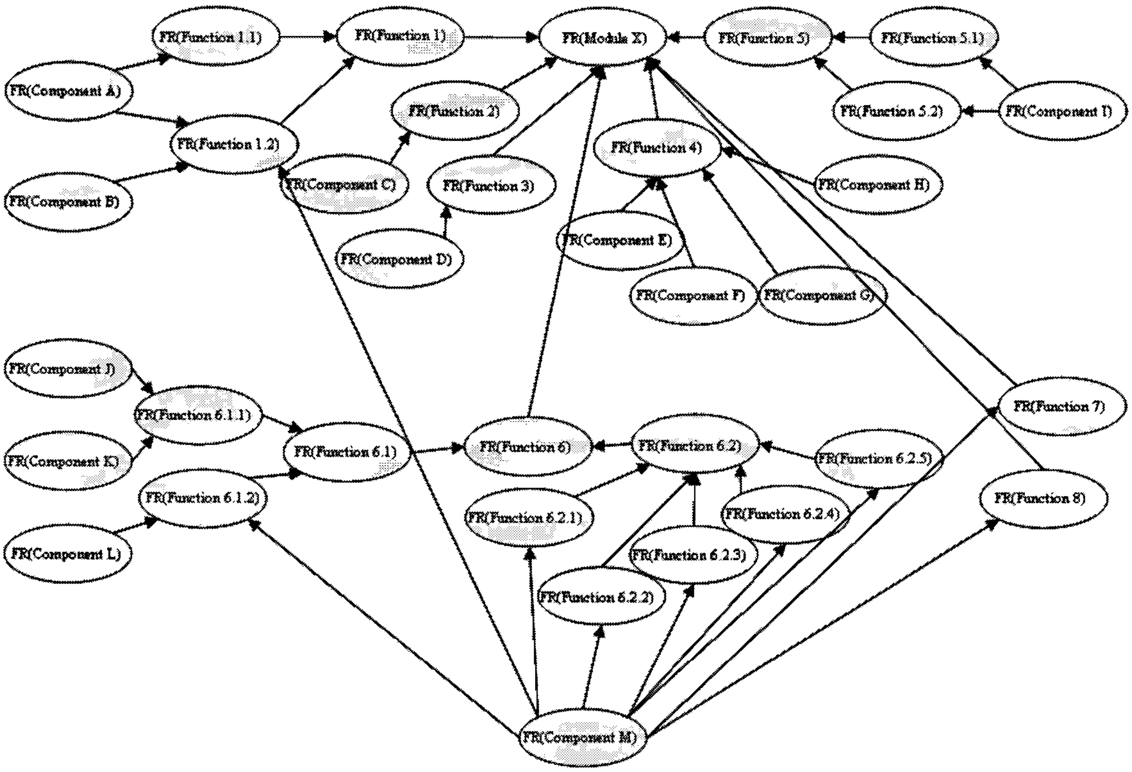


Figure 4.5. Network structure with factors expressed as statistical variables

5 Instantiation

In the problem structuring stage, the network structure has been identified. The second stage of the modeling process depicted in Figure 3.3 is the instantiation stage. In the instantiation stage, the relationships between the variables and the marginal distributions of the variables are quantified. Figure 5.1 shows the techniques that have been used during the instantiation stage.

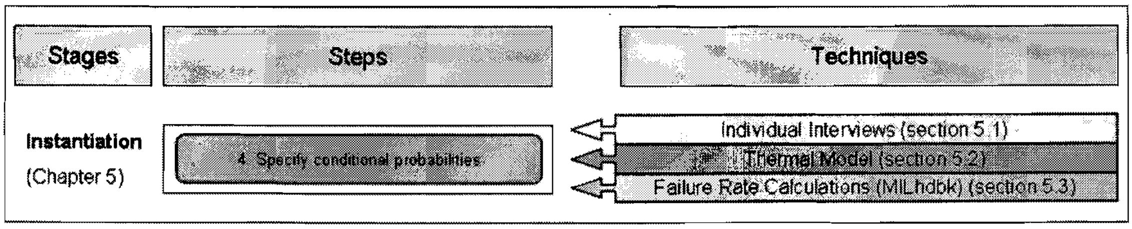


Figure 5.1. Techniques used in the instantiation stage

The quantification of the network structure consist of two main activities, namely the quantification of the relationships between the variables and the quantification of the marginal distributions of the variables. The relationship between a child node and its parent nodes is expressed in the NPT of the child node. The probability distribution of the child node is calculated from the combination of its NPT and the probability distributions of its parents. For the nodes which do not have parents, the probability distributions cannot be calculated like this. Therefore the probability distributions of the nodes without parents, which are the components in the network structure in Figure 4.5, will be expressed as marginal distributions.

The conditional probabilities can be specified in a number of ways, using different data sources. The relationships between the variables can for example be specified one by one using expert opinion, with the help of historical failure data or by using tools like MTBF calculation software. The planning was to use the "Sheffield Elicitation Framework" (SHELF) to specify the conditional probabilities. SHELF is a technique, which uses the combination of individual interviews and group sessions to quantify the conditional probabilities one by one using expert opinion. Since quantifying the relationships between the variables one by one and asking a group of experts to do this was too time consuming for the experts, an alternative strategy to represent the model as a series connection of components, was used. How this is done in explained in section 5.1.2. The marginal distributions of the variables are calculated using the software program BQR CARE (http://www.bqr.com). Additionally, a thermal model was built to determine the temperature values to be used as input for the calculations in BQR CARE.

5.1 Quantification of the Network Structure

In section 4.2, it was explained how the NPT of a node can explode as a function of the number of parents connected to this node and the number of node states. Since the relationships between the variables are expressed in the NPT's, the size of the NPT's was an important issue for determining how to quantify the relationships between the variables. This issue was discussed with the reliability expert.

5.1.1 Exploding NPT's

The FR's of the functions and components in the network are continuous distributions. However, for the calculations, AgenaRisk only uses discrete variables. Therefore, when defining a probability distribution for the FR, the distribution must be made discrete. This can be done manually, by making classes of FR-values, which are the node states, or by entering a continuous distribution and letting AgenaRisk make it discrete. Either way, the result is a discrete probability distribution with a number of possible value-ranges. The relationships between the variables are quantified using a NPT like the one depicted in Figure 3.1. In the example in Figure 3.1, node A has two node states and two parents each also having two node states, resulting in a NPT with 8 ($=2^3$) cells. In the network structure of this project, in Figure 4.5, for example a node with 3 node states and 3 parents with 8 node states each would have a NPT of $8^4 = 4096$ cells. Making the product experts quantify all relationships manually would thus be unfeasible.

Known relationships can also be quantified using formulas. In the case of the network structure chosen for module X, the relationship between the reliability of the components and the reliability of the product is known and can be represented by a series connection, which is explained in the next section. The relationships between the variables can therefore be derived from this alternative representation, which is also clarified in the next section.

5.1.2 Series Connection

In the case of the network structure for module X all of the components are critical. This means that if one of the components fails, all the functions connected to this component fail, as well as the total system. In the situation of a series connection, depicted in Figure 5.2, the FR of the module is equal to the sum of FR's of its components.

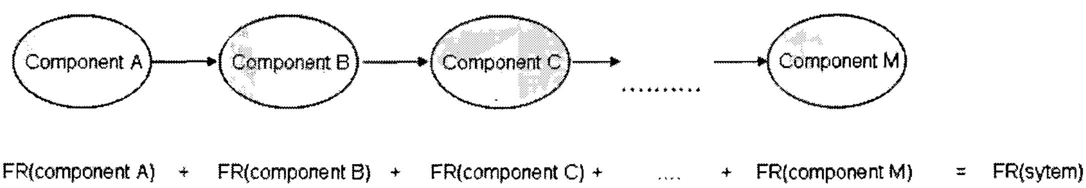


Figure 5.2. Series connection of the components A-M

The FR of a function in the network is the sum of the FR's of all components that are connected to this function, as (grand)parent nodes. These relationships can be modeled and expressed in formulas, so that the NPT's do not have to be filled in manually. Therefore, if the FR's of the components are elicited, all of the other FR's will be calculated by AgenaRisk. By deciding to use a series connection, it is assumed that all components included in the BBN are critical. This assumption is supported by the reliability expert at MR.

If interaction effects between components would be present, a failing component could lead to a failure in another component. In that case, the FR of the system would no longer be the sum of the FR's of the components. Therefore, summing the FR's of the components to calculate the FR of the module, suggests that there would be no interaction effects present. However, interactions could be added to the network later, by adding relationships between components or by manually defining the NPT's of the nodes at which interaction effects are anticipated. In this research project, interaction effects were not added to the model due to time constraints.

The FR's of the components were calculated using BQR CARE. Experts indicated to have no clue at all about the FR's of the components, which is the reason that this calculation software was used. These calculations will be discussed in more detail in section 5.3. One of the input parameters of the calculations with this software is the temperature of the components. To find out what temperatures to use in the calculations, the temperature expert was consulted. In cooperation with this expert, a simplified thermal model was constructed, to determine the temperatures of the components in the network structure. This thermal model will be clarified in the next section.

5.2 Thermal Model

One of the main input parameters of the FR calculations is the components temperature. It must be noted that the static temperature is concerned here. For a number of parts, the static temperatures were simulated by the temperature expert, independent of this research project. The temperatures resulting from the simulations were the mean temperatures. Additionally the mean value of the heat generated by each of the parts is available. The mean temperatures could be used as input for the FR calculations. Entering the temperature of a component in BQR CARE results in exactly one estimate of the FR of the component, which can be entered as its marginal distribution in the BBN.

However, since this research project is a feasibility study, it is preferred to use marginal distributions with variations larger than zero, instead of point estimates. BBN's are able to reason under uncertainty, but without variation in the BBN, there is no uncertainty in the model at all. To receive a FR distribution with variation from the FR calculations, the input parameters must be varied.

When the temperature distributions of the components are known, they can be translated to FR distributions with the help of the BQR CARE. The purpose of the thermal model was to simulate the temperature distributions of the components. The mean temperatures were already available, but they will be translated to temperature distributions using the thermal model.

The temperature within the module rises when it is turned on, because heat is generated within the parts. According to the temperature expert, there will be variation in the temperatures caused by variations in the heat that is generated at the parts. The mean temperatures of the parts are known from the temperature simulations run by the temperature expert earlier. The purpose of the thermal model is to <u>translate the variation in the heat generated by the parts to a variation in the temperatures</u>.

The parts on which the temperature simulation data were available were the parts that generate the heat. However, the parts that generate the heat are not the same as the components used in the network structure, since not all components are included in the BBN and not all parts were included in the simulations. The temperature simulations were done by the temperature expert to try to find the extreme temperatures. The components in the network structure do not all generate heat themselves and are therefore not all included in the temperature simulations. These temperature simulations were done independent of this research project and to do them again using the components of the network structure would require too much effort from the temperature expert.

Only the parts on which the temperature simulations were performed are included in the simplified thermal model, since they are the only parts on which thermal information is available. To indicate the difference between the part/components in the thermal model and the BBN, the use of the word "parts" refers to the thermal model, while "components" are used in the BBN. The differences and overlap between the parts and the components will be discussed in section 5.2.3.

5.2.1 Construction of the Model

When heat is generated at certain parts, other parts which do not generate heat themselves, also warm up since the heat transfers through and between the different surfaces. The heat that is generated at a certain part is transferred to the board to which this part is connected. The heat of the board is transferred to the shelf of module X. Finally, the heat of the shelf is transferred to the surrounding of the module. How well the heat is transferred depends on the thermal resistance (Rth):

$Rth = \Delta T / \Phi$

In which Rth is the thermal resistance (in W), ΔT the temperature difference over a surface (in C°), and Φ the heat transfer through the surface (in C° / W). The model is depicted in Figure 5.3.

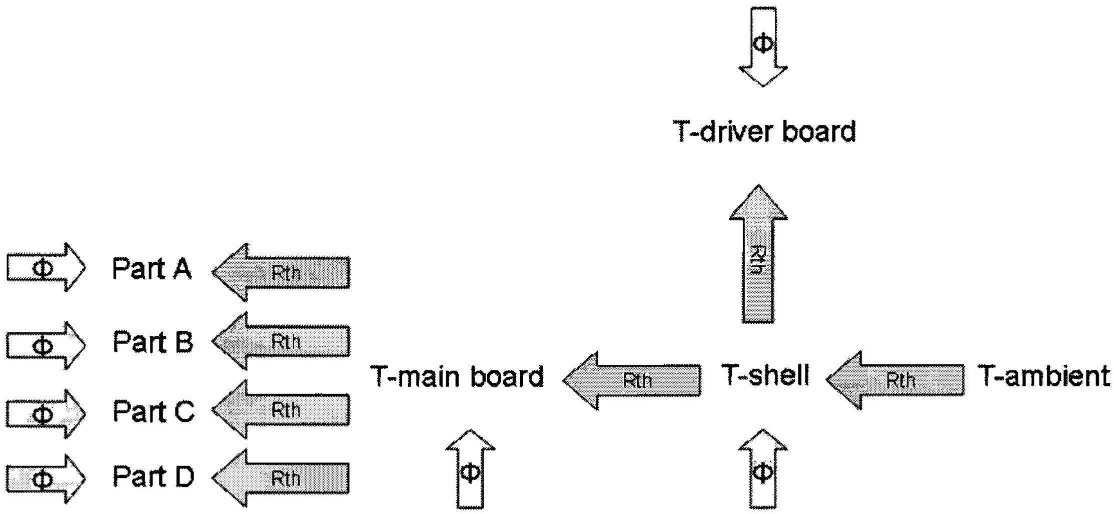


Figure 5.3. Simplified thermal model

In Figure 5.3, the heat that is transferred (Φ) between "part A" and the "main board" is equal to the heat generated by the part A. The heat that is transferred from the main board to the "shelf" is equal to the total heat generated by the parts on the main board. The thermal resistances are working in a direction opposite to the direction of the heat transfers.

Using the model depicted in Figure 5.3 the following steps are executed:

1. Calculation of the all the values of Rth with the values of Φ and ΔT which are known.
2. Fix the Rth's at the calculated values.
3. Vary the values of Φ to examine the impact on the temperatures.

With this simplified model, the impact of the variation in the heat that is generated by the parts on the temperatures of the parts can be calculated.

The mean heat that is generated by each of the parts is known. The variation in the heat generated by the parts was predicted by the temperature expert. He estimated that the generated heat for each part was normally distributed, with 5% and 95% intervals at -30% and +30% of the mean (μ). The estimated probability distribution is depicted in Figure 5.4.

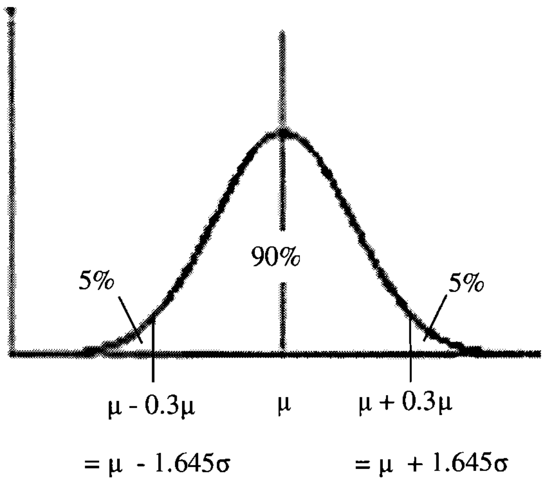


Figure 5.4. Estimated probability density function of the generated heats

In a standard normal distribution, $P(Z \leq -1.645) = 0.05$, indicating that $P(x \leq \mu - 1.645\sigma) = 0.05$. Similarly $P(Z \leq 1.645) = 0.95$, indicating that $P(x \leq \mu + 1.645\sigma) = 0.95$. The estimation of the expert can be translated to a normal distribution with mean μ and standard deviation σ by solving the following equations:

$\mu - 0.3\mu = \mu - 1.645\sigma$ and $\mu + 0.3\mu = \mu + 1.645\sigma$

$\sigma = 0.3\,\mu / 1.645$

This results in a number of distributions of the generated heats with a given μ and $\sigma = (0.3\mu)/1.645$. The probability distributions estimated here by the temperature expert are used as input values in the thermal model.

5.2.2 Temperature Distributions in the Thermal Model

Knowing the distributions of the generated heat of the parts in the simplified thermal model, does however not automatically result in the temperature distributions of these parts. Since a change in the generated heat of one part also influences the temperatures of other parts, the temperature of each part is a function of the heat generated by all other parts. To derive the temperature distributions from the probability distributions of Φ, simulations were used. It would have also been possible to explicitly include the thermal model in the BBN. The reason that this was not done is that the results of the thermal model are used as input for the FR calculations. When modeling the thermal model explicitly in the BBN, the calculations done by BQR CARE would also have to be modeled in the BBN. This would have made the BBN far more complex.

10,000 simulations were run, resulting in the same amount of temperature values for each part in the thermal model. The resulting temperatures were rounded to integers. In Table 5.1, the resulting temperature distributions of the different parts within the thermal model are given.

Table 5.1. Probabilities of the parts operating at a temperature T

T	Main PCB	Part M	Part D	Part J	Part K	PCB Middle	Shelf
60							0.0002
61							0.0006
62							0.0025
63						0.0005	0.0086
64						0.0003	0.0258
65						0.0022	0.0601
66	0.0001					0.0046	0.1084
67	0.0001					0.0109	0.16
68	0.0003			0.0002	0.0002	0.03	0.1902
69	0.0017		0.0002	0.0002	0.0002	0.0543	0.1737
70	0.0044	0.0001	0.0002	0.0007	0.0009	0.0849	0.1312
71	0.0125	0.0001	0.0002	0.0021	0.0022	0.1239	0.0782
72	0.0259	0.0002	0.0011	0.0067	0.0058	0.153	0.0402
73	0.0486	0.001	0.0036	0.0147	0.0161	0.1472	0.0138
74	0.0758	0.0017	0.0069	0.0311	0.03	0.1406	0.0052
75	0.1153	0.0051	0.0144	0.0516	0.055	0.1069	0.0013
76	0.1415	0.0101	0.0267	0.0831	0.0792	0.0732	
77	0.1496	0.0172	0.0433	0.1182	0.1165	0.0365	
78	0.1382	0.0309	0.0658	0.1334	0.1405	0.0184	
79	0.114	0.0448	0.0839	0.1468	0.1426	0.0086	
80	0.0765	0.062	0.1126	0.1312	0.1351	0.003	
81	0.0512	0.0841	0.1283	0.1092	0.1025	0.0008	
82	0.0248	0.0991	0.1252	0.0729	0.0787	0.0002	
83	0.0113	0.1114	0.1132	0.0524	0.0468		
84	0.0056	0.1173	0.0935	0.0248	0.0267		
85	0,0022	0,1106	0,0706	0,0115	0,0133		
86	0,0004	0,0915	0,0459	0,0065	0,005		
87		0,071	0,0329	0,002	0,0021		
88		0,0504	0,0177	0,0005	0,0005		
89		0,0403	0,0081	0,0002	0,0001		
90		0,0232	0,0033				
91		0,014	0,0017				
92		0,0079	0,0007				
93		0,0029					
94		0,0022					
95		0,0007					
96		0					
97		0,0002					

The results in Table 5.1 are shown graphically in Figure 5.5.

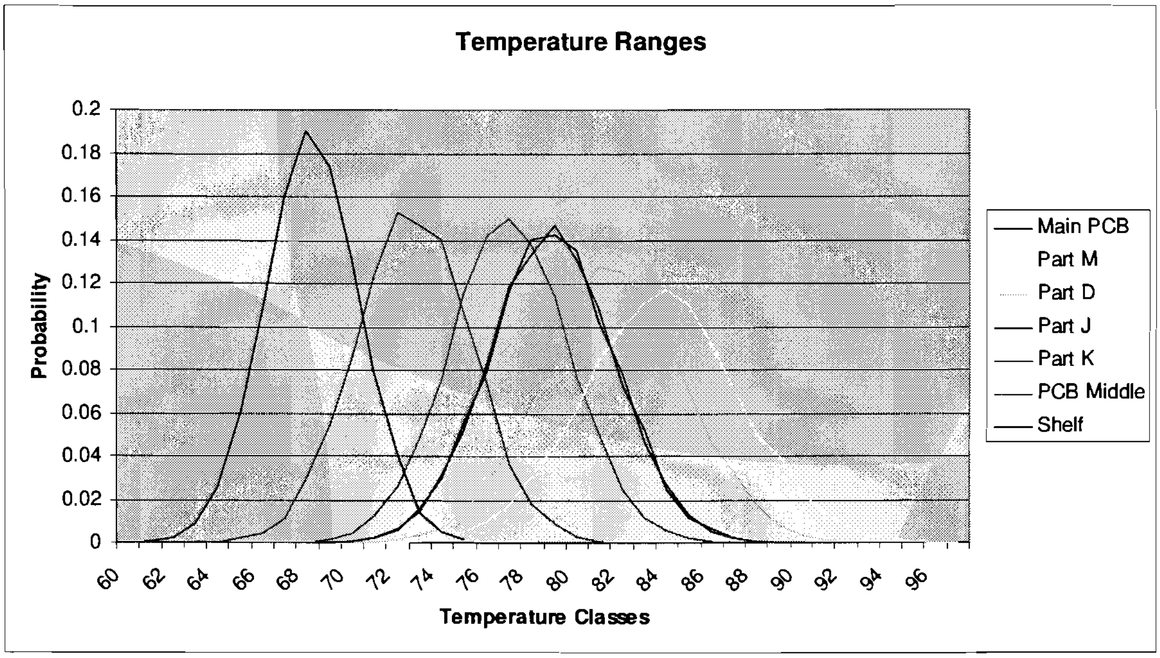


Figure 5.5. Temperature distributions of the parts in the thermal model

The temperature values in Table 5.1 were used as the input parameters for the FR calculations.

5.2.3 Temperatures of the Components

Temperature simulations were performed independently of this research project by the temperature expert. Since the parts included in these simulations are the only ones on which thermal information was available, only these parts were included in the simplified thermal model, in Figure 5.3. However, these are not the same parts as the components included in the BBN. This means that the parts from the thermal model must be linked to the components in the BBN to determine what temperatures to use in the FR calculations of the components. Of the components that were included in the thermal model the temperatures are given in Table 5.1. The components that were not included in the thermal model are all situated on the "main PCB". Since there are no alternative temperature estimates available for these components, the temperatures of the "main PCB" will be used for the FR calculations of the components that are included in the thermal model. In Table 5.2, the temperatures of the parts in the top row are used as input for the FR calculations of the components underneath them. It shows that six of the components can be linked to the parts directly and the others (in the left column) are linked to the "main PCB".

Table 5.2. Link between the thermal model and the BBN

Main PCB	Part M	Part D	Part J	Part K	PCB Middle	Shelf
Component B	Component M	Component D	Component J	Component K	Component A	Component I
Component C						
Component E						
Component F						
Component G						
Component H						
Component L						

5.3 FR Calculations

With exception of component M, The FR's of the components included in the BBN were all calculated using BQR CARE. The component M is developed by Philips Healthcare and is therefore not included in the library used by BQR CARE. For component M, its supplier provided the formula with which the FR can be calculated as a function of the temperature. The calculations of the FR of component M are discussed in section 5.3.2.

5.3.1 In BQR CARE

The calculations of the FR of all the components, except component M, were done using BQR CARE. This software calculates the FR's based on Mil-Hdbk217F and assumes constant FR's. In the introduction to this project, it was argued that these predictions are far from accurate, partly because of the wrong assumption of constant FR's. Still these calculations were used as quantitative input for the BBN. The reason for this is that experts indicate that they have no clue at all what the FR of the components could be and that the predictions based on Mil-Hdbk217F were the most accurate in that case.

The fact that a prediction method was used that was refuted earlier, is specific for this project. However, it does show that early during the product development, inaccurate quantitative information is still better than having no information at all. The advantage of using the Mil-Hdbk217F calculations only as an input for the BBN is that the values of the FR's can be updated when new, more accurate, information becomes available.

One of the input parameters of these calculations was the operating temperature of the component. While varying the temperature, the rest of the parameters were fixed at the Philips Healthcare default values. Since every temperature input resulted in one FR output for each component, the temperatures in Table 5.1 were entered one by one, to calculate the resulting FR's. This was done for all temperatures that a component can reach, according to Table 5.1. Part of the results of the calculations are shown in Table 5.3.

Table 5.3. FR's (in failures per 10^6 hours) for a range of operating temperatures

Temperature	60	61	62	63	64	65	66	67	68
Components J & K							15,600	16,200	16,800
Component L							0,049	0,051	0,053
Component D									12,403
Component C							1,707	1,803	1,903
Component B							11,547	12,078	12,631
Components E, F, G & H							1,916	2,004	2,096
Component A				3,259	3,352	3,449	3,549	3,652	3,759
Component I	1,465	1,482	1,498	1,514	1,531	1,548	1,564	1,581	1,599

Table 5.3, which links the temperatures to the FR's of the components, shows part of the FR's of the components in the BBN, resulting from the calculations. The failure rates are given in failures per 10^6 hours. This table does not show all temperatures, but shows how the temperatures and the FR's of the components are linked. The total table shows the FR's of the components for temperatures up to 92°C and is depicted in appendix C.

Table 5.1 shows the probabilities of the parts in the thermal model having a certain temperature. Table 5.2 shows which of these temperature probabilities can be applied to the components included in the BBN. In Table 5.3, the FR's are given for the temperature ranges in Table 5.1. When these three tables are combined, the probability of a component in the BBN having a certain FR, can be determined. For one of the components, component L, this is shown in Table 5.4, for part of the temperature range. The FR probabilities for the total temperature range, and of the other components, are given in appendix D.

Table 5.4. Failure Rate probabilities of component L

Component L								
Temperature	66	67	68	69	70	71	72	73
Failure Rate	0,0487	0,0507	0,0529	0,0551	0,0573	0,0597	0,0622	0,0647
Probability	0,0001	0,0001	0,0003	0,0017	0,0044	0,0125	0,0259	0,0486

5.3.2 Supplier Data for Component M

Component M is developed by Philips Healthcare and as a result it is not included in the library used by BQR CARE. Therefore, to determine the FR for this component, data from the supplier were used. The supplier provided the formula to be used for the estimation of the FR of component M. In this formula, which can be found in appendix E, the FR is calculated as a function of the temperature. The probability distribution of FR's of component M can therefore be determined in the same way as it has been done for the other components. Only for component M, the formula provided by the supplier was used to calculate the FR's. The calculated FR's for part of the temperature range of component M given in Table 5.1 are shown in Table 5.5. The FR's for the total temperature range of component M can be found in appendix D.

Table 5.5. Failure Rate probabilities of component M

Component M								
Temperature	70	71	72	73	74	75	76	77
Failure Rate	0,2332	0,2499	0,2676	0,2864	0,3064	0,3277	0,3504	0,3745
Probability	0,0001	0,0001	0,0002	0,0010	0,0017	0,0051	0,0101	0,0172

The tables containing the probability distributions of the FR's for each of the components are used for entering the marginal distributions in the BBN. This is discussed in more detail in the next section.

What steps are taken until here in this chapter to arrive at the FR probabilities of the components is depicted in Figure 5.6.

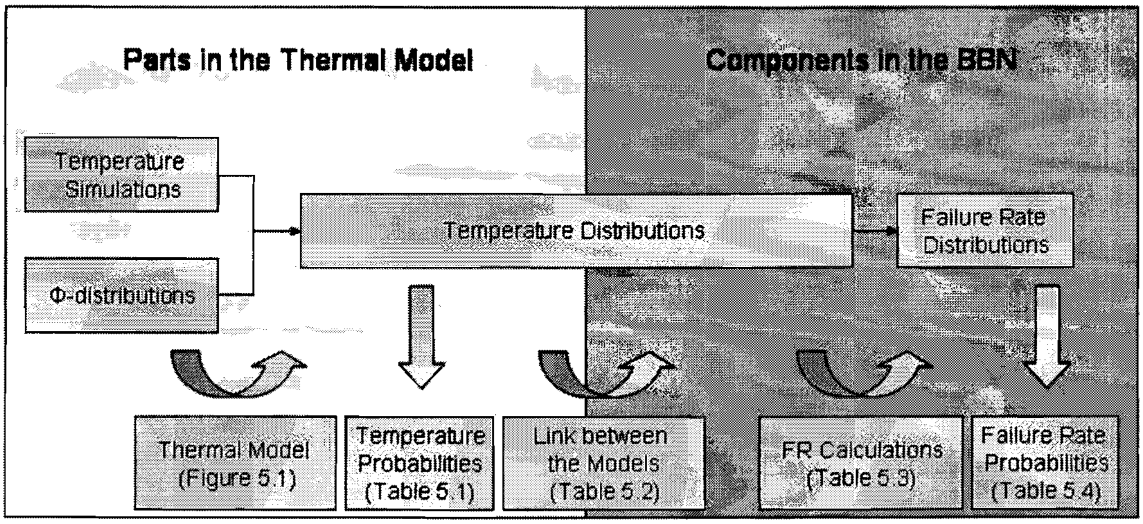


Figure 5.6. Overview of the steps towards the Failure Rate probabilities

Figure 5.6 also shows the relationship between the steps that are taken and the resulting tables and figures. The steps taken in the yellow part on the left are related to the parts which are included in the thermal model. In table 5.2, the link is made between the parts in the thermal model and the components included in the BBN. The steps on the green part on the right are related to the components. The next step is the implementation of the results in the BBN.

5.4 Implementation in the BBN

The probability distributions of the FR's of the components must be entered into the network and the relationships between the variables, which were determined in section 5.1.2, must also be specified in the model.

5.4.1 Marginal Distributions

To start with the marginal probability distributions of the FR's of the components, the FR's must be translated into classes of FR's to be able to enter them into the network. The results of the simulations done with the thermal model were rounded to integers. This means for example that the probability of component M being 71°C (see Table 5.5) is actually the probability of it being between 70.5°C and 71.5°C, which makes it a temperature class. When FR classes are made accordingly, the lower bound of the FR class is defined as the mean of the FR belonging to 71°C and the FR belonging to 70°C. Consequently, the upper bound is defined as the mean of the FR belonging to 71°C and the FR belonging to 72°C. To link the probability of the temperature classes to the probability of the FR classes, the assumption of a linear relationship between the temperature and the FR must be made.

Figure 5.7 shows the relationship between the temperature and the FR's of the components resulting from the FR calculations. From Figure 5.7, it can be seen that the relationship is not linear, but the relationship approaches linearity and given the small interval between the two temperatures over which linearity is assumed, these FR classes will be used.

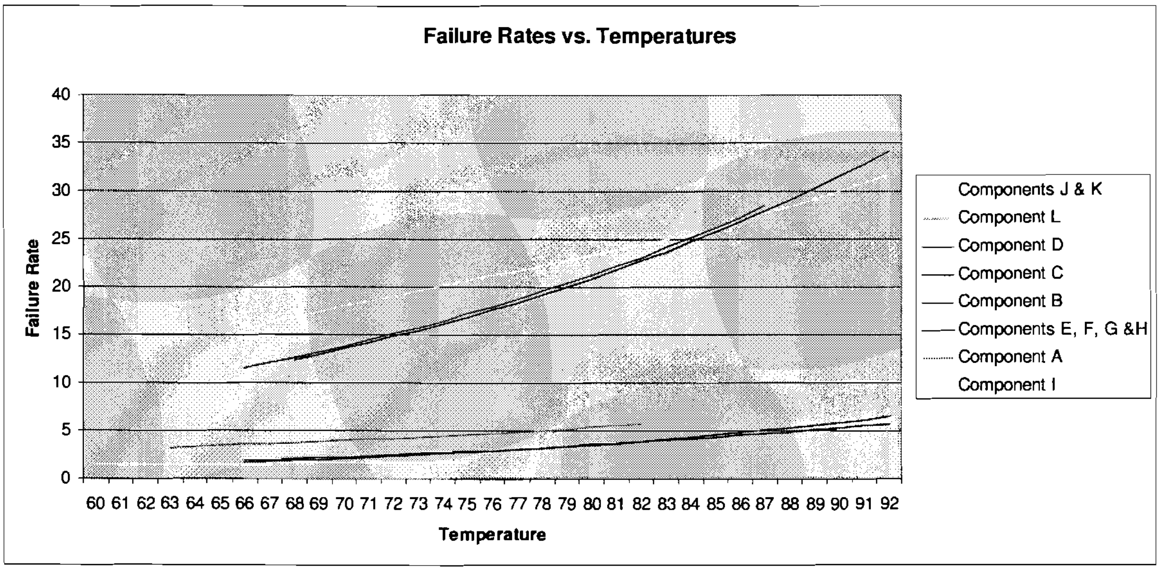


Figure 5.7. Relationship between the temperature and the failure rate

For each of the components, the FR classes were defined manually in AgenaRisk. Also, for the components, the probability of each class was specified manually in AgenaRisk. The FR classes that were used for each of the components can be found in appendix D.

5.4.2 Relationships between Variables

In the previous section, the marginal distributions of the components were modeled in AgenaRisk. In section 5.1.2, it was argued that a series connection could be used as a model. The FR of the module is equal to the sum of FR's of its components. The FR of a function in the network is the sum of the FR's of all components that are connected to this function, which is depicted in Figure 5.8.

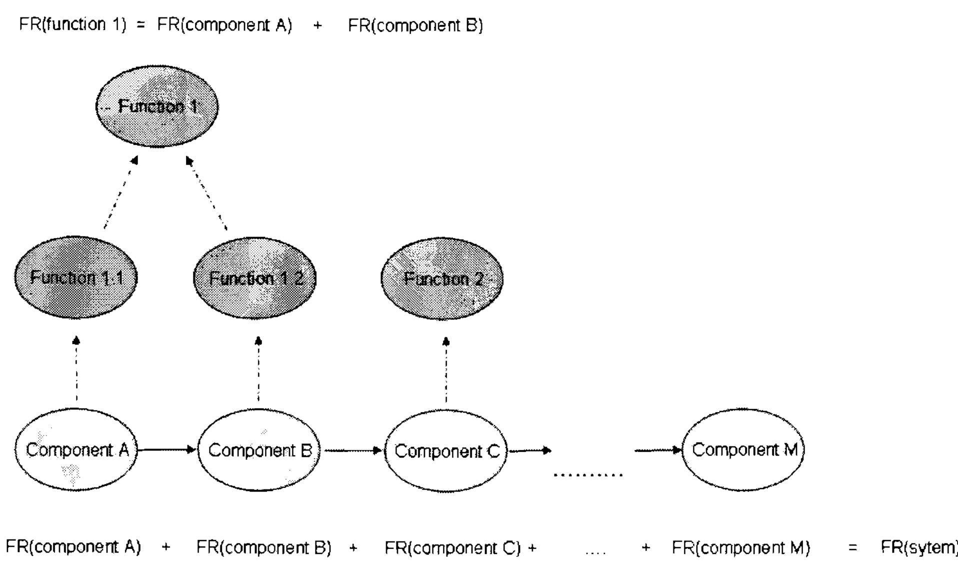


Figure 5.8. Series connection of the components influencing the functions

The FR's of the functions are calculated by taking the sum of the FR's of the parents. This can be modeled in AgenaRisk by summing the probability distributions of the parents in the arithmetic expression of the NPT, which is shown in Figure 5.9. When the two parents are summed in the arithmetic expression this means that the variables, being the FR's, are summed and not the probabilities.

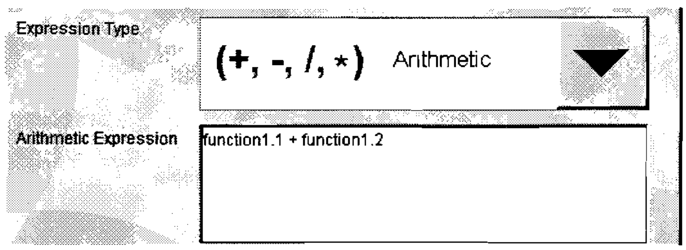


Figure 5.9. Sum of the FR's specified in the arithmetic expression

The FR of a function is not always equal to the FR's of its parents. This can be illustrated with the help of the network structure depicted in Figure 5.10.

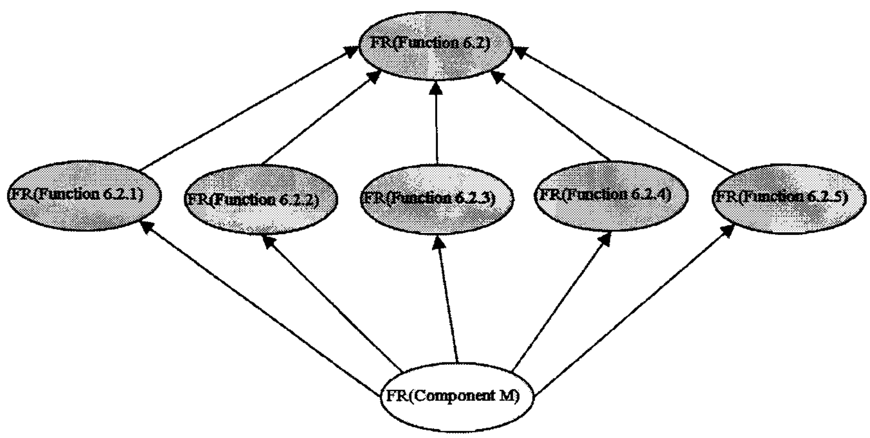


Figure 5.10. Part of the network structure

Component M has six child nodes. In the arithmetic expression of each of these childs, depicted in Figure 5.11, it is defined that the probability distribution of the variable is equal to the probability distribution of its parent, component M.

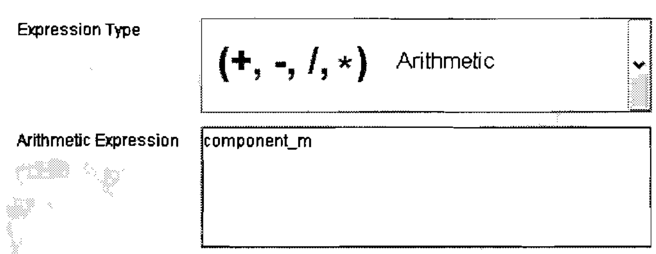


Figure 5.11. Arithmetic expression used for the child nodes of component M

These six nodes together have one child, namely function 6.2. Although not connected directly, function 6.2 has only one component on which it is dependent, which is component M. As a result, the FR of function 6.2 must be equal the FR of any of its parents, instead of being equal to the sum of them. The probability distribution of function 6.2 can not be expressed as a function of component M, because they are not connected directly. Therefore, the probability distribution of function 6.2 was chosen to be defined as being equal to the probability distribution of function 6.2.1. The choice of function 6.2.1 was random. The six nodes in the previous example must always be the same, because they are all equal to the same parent, so linking their child to only one of them should not be a problem. This will be tested in the next stage, the inference stage. During the instantiation stage, the relationships between the variables in the network structure were quantified. The result of the instantiation stage is the quantified BBN depicted in Figure 5.12, which is ready to be used in the next chapter.

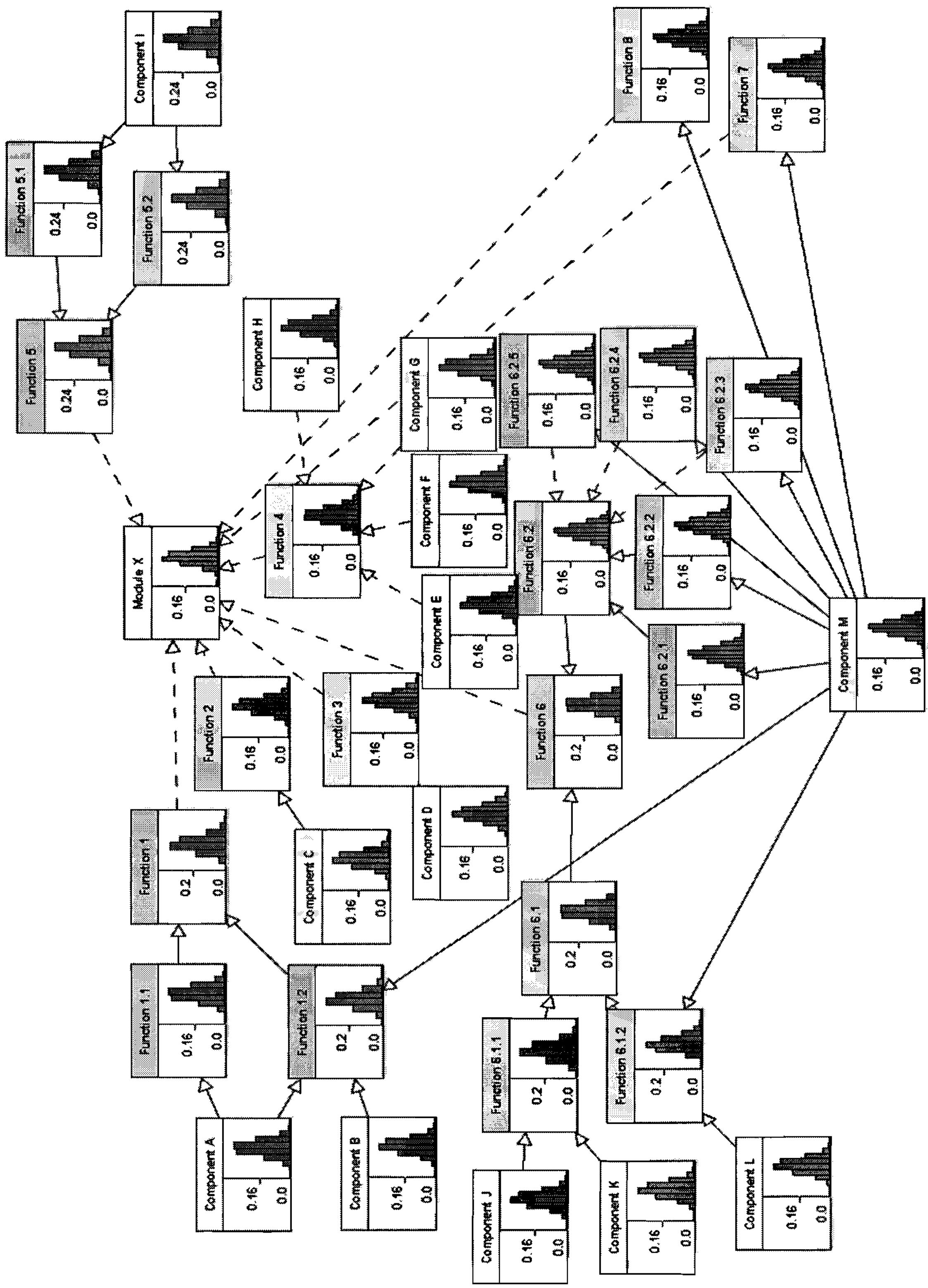


Figure 5.12. Final BBN resulting from the instantiation stage

6 Inference

The third stage is the inference stage. The BBN was finished during the instantiation stage and is ready to be used in the inference stage. The steps within this stage, described by Sigurdsson et al. (2001) are the *entering of evidence*, the *propagation* and the *interpretation of the results*, which is also depicted in Figure 6.1.

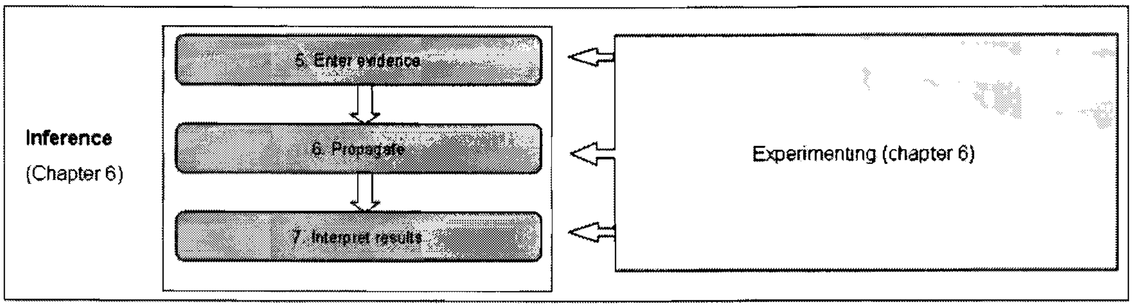


Figure 6.1. Activities during the inference stage

In this research project, no evidence was available to be entered. Therefore, in the inference stage three experiments will be conducted to test whether the propagation of the probability distributions through the BBN complies to the expectations.

6.1 Updating the FR of a Function

In section 5.4.2, the specification of the relationships between the variables in AgenaRisk is discussed. One of the issues identified there was that function 6.2 has six parents, that all have the same FR distribution (Figure 5.12). The reason is that these six FR's are all equal to the FR of their common parent, component M. Because these distributions are all equal, the FR distribution of function 6.2 was linked to only one of the nodes, namely function 6.2.1. If the FR distributions of these six nodes are all equal to the distribution of component M, it should not matter on which node the FR distribution of function 6.2 is based. When the FR distribution of component M is updated, this will indeed not be a problem. However, the question is what happens if one of the nodes, other than the 6.2.1 node, is updated. The function 6.2 is not defined as a function of the other five nodes, so it could be that the six nodes will not contain the same distributions anymore.

When testing this scenario in AgenaRisk, it shows that the nodes are updated correctly. Updating any of the functions 6.2.1, 6.2.2, 6.2.3, 6.2.4 and 6.2.5 updates component M. Since the FR distribution of these functions is defined as being equal to the FR distribution of component M, the FR distribution of component M is updated to be equal to the FR distribution of the updated function. As a result of the update of component M, its other child nodes are updated. The conclusion is that the BBN reacts in the preferred way here.

6.2 Checking the Mean FR's Calculated by the BBN

The relationships between the variables in the BBN are expressed as sums of their parents. The variables are expressed as discrete variables, which could cause bias in the summations. Therefore it is checked here whether the mean values of the FR's calculated by AgenaRisk comply with the manually calculated FR's.

AgenaRisk calculated a mean FR of 112.3 failures per 10^6 hours for module X. Calculating the FR of module X manually results in 109.08 failures per 10^6 hours, which is difference of 2.9%. At all nodes in the BBN, the calculations by AgenaRisk deviate from the manual calculations. The reason for the differences can be explained by the fact that AgenaRisk calculates with the FR classes, instead of with the exact FR values. This can be clarified by Figure 6.2:

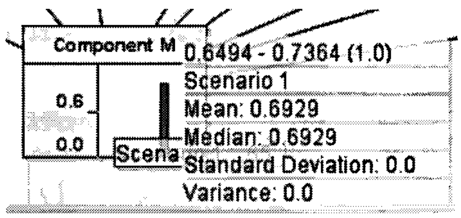


Figure 6.2. Numerical values of component M

In Figure 6.2 evidence has been entered at component M that it's FR is 0.65. One of the node states of component M is the FR class "0.6494 - 0.7364", depicted in the top row of Figure 6.2. Component M has a chance of 1 of being in this node state, since the evidence indicates that the FR is 0.65. Although the exact value of the FR of component M is 0.65, the mean value of the FR class is calculated by taking the average value of the boundaries of the class, which is 0.7364 – 0.6494) / 2 = 0.6929. Since the FR of component M is within this FR class for sure, the mean FR of component M is also calculated by AgenaRisk to be 0.6929 (third row in Figure 6.2). When evidence is entered that the FR of component M is 0.73, the numerical values in Figure 6.2 remain exactly the same, since the FR of component M is still in the same FR class with a probability of 1.

When the probability distributions of child nodes are calculated from the probability distributions of their parents, again the classes are used for the calculations. Each time that a calculation is done at a node, the results are allocated to the FR classes defined in this node. Since AgenaRisk does not differentiate between low and high values in a class, this causes **bias in the probability distributions**.

Interestingly, in the BBN that was built for this research project the calculated mean values of the FR's calculated by AgenaRisk were higher than the mean values calculated manually at all nodes. Unfortunately, I do not have an explanation for this effect.

6.3 Updating Other Nodes

Knowing that the mean values of the FR's can differ from the anticipated values, it was tested how the mean value of the FR of module X reacted to evidence entered at other nodes. Entering a FR value higher than the mean FR value at this node, should result in a higher mean value of the FR of module X. When entering a FR value lower than the mean FR value at a node, this should result in a lower mean FR value of module X. Although the impact of the evidence largely depended on the node where the evidence was entered, the model did react in the anticipated way. Increasing the mean FR value at any of the nodes, resulted in an increased mean FR value of module X. Similarly, decreasing the mean FR value at any of the nodes, resulted in a decreased mean FR value of module X.

The inference stage, three experiments were performed to examine the propagation of the probability distributions through the BBN. For these experiments, fictive evidence was used. The most interesting finding resulting from these experiments is that the FR of a child node, expressed as sum of the FR's of its parents, is biased. Summing the FR's of the parents manually leads to a different FR. To find out whether this is the result of the use of the methodology as a "summation machine", or that this bias is also present when using other expressions could be a topic for future research.

7 Review, Discussion and Conclusions

In this chapter, first the research project will be reviewed (section 7.1). The review starts with an overview of what has been done during the research project and a description of the resulting BBN. Then, the research questions are answered one by one shortly. The answers to the research question are discussed in section 7.2 and the conclusion of the total research project is given in section 7.3.

7.1 Review

Following three building stages identified by Sigurdsson et al. (2001), a BBN was built and used during this research project. In the chapters 4-6 the execution of the steps within these modeling stage was discussed, each chapter containing one modeling stage. Figure 7.1 shows an overview of what was done during the research project and which techniques were used.

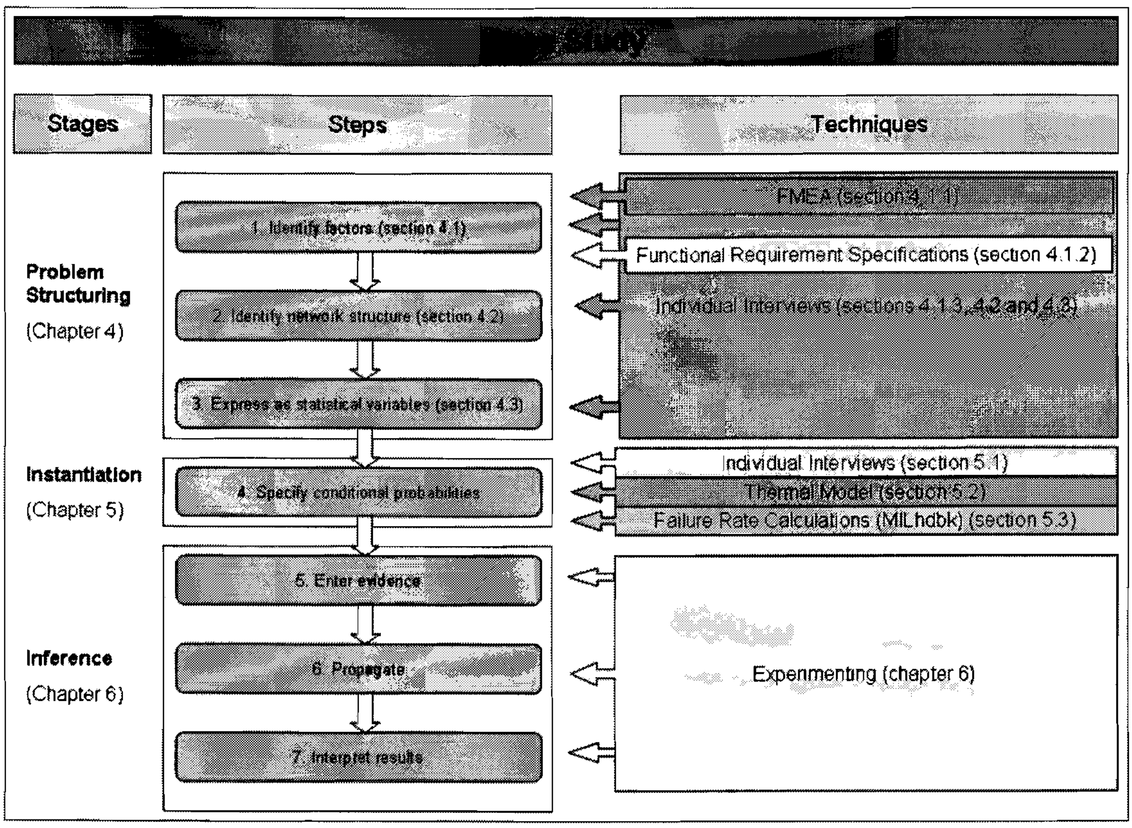


Figure 7.1. Overview of the techniques used in each of the modeling stages

The research approach to the total research project was a case study. The methodology of BBN's was applied in practice at Philips Healthcare. Within the case study, the modeling stages on the left of Figure 7.1 were followed, each stage containing a number of steps. The techniques which were used during the modeling stages were discussed in this report.

One of the results of the modeling process described in Figure 7.1 is a BBN. The relationships between the FR's of the module, its functions and the components, were derived from an alternative representation of the structure, namely a series connection. However, by not only including the components in the network, but also the functions, the functional structure is visualized in a BBN. As a result, one can derive from the model which functions are critical and which are not.

By including uncertainties in the FR's, the resulting reliability of the module is not given as a point estimate of the FR, but as a probability density function of the FR. Additionally, by entering evidence on the FR's of the components or the FR's of the functions, the estimated mean FR as well as the uncertainty of this estimate can be monitored.

Expert opinion is incorporated in the model in two ways. First, for the identification of the network structure the expert opinion of the reliability expert and the product expert is used, although this was only qualitative information. Second, for the quantification of the marginal probabilities of the components, a thermal model was built in cooperation with the temperature expert. The probability density function of one of the input parameters of this thermal model, the applied heat of the components, was also estimated by the temperature expert.

In important part that is missing in the BBN are the interaction effects. Although BBN's are specialized in modeling interaction effects, the interaction effects are not included in the BBN of this research project, because the relationships in this BBN are specified as the sums of the FR's of the components.

The model itself is only one part of the results, the other part are the findings during the modeling process. For each of the modeling stages a research question was defined in section 3.2. In the coming three sections the findings within the modeling stages will be listed per research question. The identified problems will be discussed in more detail in section 7.2.

7.1.1 Research Question 1

What are the problems and risks encountered when constructing a Bayesian node structure?

This research question concerns the problem structuring stage. The main issues that were experienced in this stage were the following:

- Flexibility of the model
- Generic or specific
- Size of the network
- Exploding NPT's (resulting from a large number of parents)

7.1.2 Research Question 2

What are the problems and risks when quantifying the relationships between the factors that determine the product reliability?

This research question concerns the instantiation stage. The main issues that were experienced in this stage were the following:

- Exploding NPT's (resulting from large number of node states)

7.1.3 Research Question 3

How to validate the resulting Bayesian Network?

The third research question, about the validation of the BBN, was added with a lower priority than the first two research questions. The attempts to validate the model were by experimenting with it. This does not validate the predictive ability of the model, but it can help examining whether the model propagates the probability distributions in the way it is expected to, which is done in the inference stage. The main issue that was experienced during this stage was the following:

- Bias in the probability distributions

7.2 Discussion

7.2.1 Flexibility of the Model

In the BBN, practically any factors can be included, as long as they can be quantified. One the one hand, this is a advantage of BBN's compared to other methodologies, which are more prescriptive. However, on the other hand, this large flexibility increases the freedom of choice. The task of identifying the factors that influence the reliability of the RX4 directly or indirectly becomes a very difficult task if these factors can be anything. Especially when the modeller is not familiar with the product, and the product expert is not familiar with the methodology of BBN, it is difficult to capture the right factors. This issue is not the result of this specific research project, but will also be apparent in other projects, where the influencing factors must be identified.

7.2.2 Generic or Specific

The choice to use generic or specific factors in the network relates to the previous issue in section 7.2.1, because it results from the large choice of factors to be included. In literature, most studies (e.g. Neil et al., 2000; Fenton and Neil, 2000) use generic factors in their models for predicting the reliability, like the complexity of a product, the quality of testing or the effort spend on development. These factors can be used to predict and monitor the reliability, but are less useful for decision making during the development. Due to the generic nature of these factors, it is difficult to point out the exact improvement areas of the product. A product engineer, for example, wants to know what part of the product causes reliability issues, instead of knowing that the bad reliability is mainly causes by the complexity.

Examples of specific factors are failure modes and failure causes identified during an FMEA. The advantage of including these specific factors in the network is that trouble areas can be identified easier. As a result, the network can for example be used during development for prioritizing improvement actions. A disadvantage of including specific factors is that by adding specific factors, the model becomes more detailed which increases the size of the network. Additionally, when problem areas identified by the BBN, such as failure causes, are solved, the network structure must be changed. Making the BBN more specific, increases the probability that the network structure must be changed as a result of changes in the product design. Monitoring the reliability of a product during its development is easier when only the numbers change while the network structure remains the same.

The choice to use generic of specific factors will also be an issue in other applications of BBN's, because in any research context, there are always generic as well as specific aspects of the situation which is modeled.

7.2.3 Size of the Network

In the previous section, it was mentioned that with increasing the detail of the network, also the size increases. Although a large size does not result in problems in the problem structuring stage yet, the instantiation stage and the inference stage are effected by it. Larger networks also need more effort for their relationships to be quantified during the instantiation stage. In the inference stage, large networks result in larger calculation times and possibly calculation problems. These aspects must be taken into account when the network structure in constructed. In this research project, the problem of the quantification of the relationships in a large size network, was solved by using an alternative representation of the relationships between the variables, namely a series connection. However, when interaction effects between the variables are taken into account, the relationships between the variables are not so obvious and more time and effort must be spend on the quantification. Increasing the size of the network would then significantly increase the effort to be spend.

7.2.4 Exploding NPT's

In Figure 3.1, an example was given of the NPT of a node with two parent nodes and each of the three nodes having two node states. This results in a node probability table of $2^3 = 8$ cells. To be able to predict the reliability accurately, the number of states of the variables must be more than the two in the example. If the three nodes would all have ten node states, the NPT would contain $10^3 = 1000$ cells. Every time that a parent is added to this node, the number of cells is multiplied by the number of node states of this parent. Fortunately, the cells do not all have to be filled manually, but expressions can be used to specify the relationships between the child and the parents nodes. However, when a expression is entered by the modeller, AgenaRisk translates this expression to a NPT. Calculations are made by using these NPT's. Growing NPT's increase the calculation time and can ultimately lead to calculation problems. This is why AgenaRisk advises the user to keep the maximum number of parents to three. In this research project a number of nodes had to be added to the network to be able to keep the maximum number of parents to three.

The problem of NPT's getting very large, resulting in long calculation times or calculation problems, will also occur in other research contexts. In a smaller networks, this problem will occur less because the total number of nodes is smaller.

7.2.5 Bias in the Calculated Probability Distributions

The FR's of the functions and module X are expressed as the sum of the FR's of the components influencing them. However, the mean FR values calculated by AgenaRisk deviate from the mean FR values calculated manually (up to 2% of the manually calculated values). The reason for the differences can be explained by the fact that AgenaRisk calculates with the FR classes, instead of with the exact FR values. When the probability distributions of child nodes are calculated from the probability distributions of their parents, the classes are used for the calculations. Each time that a calculation is done at a node, the results are allocated to the FR classes defined in this node. Since AgenaRisk does not differentiate between low and high values in a class, this causes bias in the probability distributions. In the BBN that was built for this research project the mean values of the FR's calculated by AgenaRisk were higher than the mean values calculated manually at all nodes. Unfortunately, I do not have an explanation for this effect.

Whether this problem can be solved by expressing the relationships between the variables in a different way is a topic for future research.

7.3 Conclusions

A Bayesian Belief Network was constructed for this research project. The network was structured as a BBN, although the relationships between the variables were derived from a series connection of components. However, in contrast to the representation of a series connection, the BBN also gives insight in the influences of the components on the functions of the product by visualizing the functional structure. Bayesian statistics were used, as a result of the uncertainties incorporated in the model. Additionally, also expert opinion is included in the model. What is missing in the BBN resulting from this research project is are the interaction effects between variables. By using AgenaRisk as a "summation machine", the full functionality of the methodology is not used.

For Philips Healthcare, the main benefit of the project is the functional structure. The structure is a visualization of the relationships between the module, its functions and its components. Another benefit are the insights gained from this project. By closely monitoring the project, Philips Healthcare has seen the application of the BBN and could decide to apply it again, either for the same, or for a different purpose.

The goal of the case study for the research project was to gain experience with the application of BBN's in practice and to identify problems during the different modeling stages. A network structure was built and problems were identified during the problem structuring stage. In the instantiation stage, the decision was taken to use a series connection to derive the relationships between the variables. This resulted in a quantified BBN, but the step of specifying the conditional probabilities by eliciting expert opinion became unnecessary, because the relationships became trivial in the series connection. Since the elicitation of expert opinion to quantify the conditional probabilities is an important step in the construction BBN's described in literature, the absence of this step is a drawback of this project.

Although the possibility of BBN's to model interactions between variables is not included in the model, the benefits of being able to reason under uncertainty, to combine heterogeneous data and to give a visual representation of the relationships are used in this research project.

Of the problems that were identified during the modeling process, the choice which factors to include was the main issue. This issue relates to the flexibility of the model, the choice between general and specific factors and the size of the network. In this research project, this issue was resolved by using the type of network structure that was preferred by Philips Healthcare. For a feasibility study, this choice was not a problem, but in other applications the issue of which factors to include in the model can be a large barrier.

In literature, the steps to take to build a BBN seem easy, but to apply them in practice appeared a very difficult task in this research project.

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