DETC2009-87103

RELIABILITY PREDICTION METHODS:
A SURVEY AND SELECTION FOR MECHANICAL DESIGN-FOR-RELIABILITY

Zhaofeng Huang
Dept. of Aerospace and Mechanical Engineering
University of Southern California
Los Angeles, California 90089, USA
(818) 586-4794
zhaofeng@usc.edu

Yan Jin[*]
Dept. of Aerospace & Mechanical Engineering
University of Southern California
Los Angeles, California 90089, USA
(213) 740-9574
yjin@usc.edu

ABSTRACT

There are many reliability prediction methods applicable to mechanical systems design. This paper specifically discusses the methods of probability or failure rate generation for reliability prediction. The paper consists of three parts. The first part is to survey the methods. We survey five most frequently used failure probability generation methods: statistical frequency and modeling method, similarity and comparative assessment method, physics based failure modeling, Monte Carlo simulation, and expert elicitation. We discuss the technical rationale and scientific foundation of each method and illustrate them with application examples. The second part is to evaluate and compare the methods. We identify the following attributes for evaluating and ranking the methods: the closeness of the method to the design; the validity and fidelity of the prediction results; the extensiveness of the analysis effort involved and data needs; the applicability of the methods at different product life cycle stages; and the limitations and cautions of using the prediction results to assist design-for-reliability. The third part is to establish a selection framework from applicable methods based on the ranking result of the second part, to assist practical use of the methods for mechanical design-for-reliability.

Key Words: Reliability Prediction, Reliability Modeling, Design-For-Reliability (DFR), Statistical Methods, Similarity and Comparative Assessment Method, Physics Based Failure Modeling, Monte Carlo Simulation Modeling, Expert Elicitation

1   INTRODUCTION

Reliability has been considered as one of the key design parameters in many products. *Reliability is defined as the probability that a system or component performs its intended functions under a set of specified operation conditions for a specified period of time* [1-3]. The strong global competition environment has pushed many companies and government agencies to proactively address reliability issues of their products. To treat reliability as a design parameter, reliability consideration has to be incorporated into early stages of a design. To support this mission, the concept of design-for-reliability has been re-introduced and was defined in our previous papers as a *structured design methodology that guides design decision making with parametric reliability models to meet quantitative reliability requirements or goals during all design phases* [4-5].

Reliability modeling and prediction are the core tasks necessary to support design-for-reliability. Reliability modeling is referred as the collection of analytical modeling techniques that use engineering and mathematical principles to analyze reliability. Reliability prediction is the exercise of estimating and predicting the probability of success or failures of a part, component, sub-system or system. Reliability modeling and prediction go hand by hand as the modeling generates the analytical structure while prediction produces numerical reliability values. As one of the key modeling steps, the reliability modeling takes a set of probability values associated with its basic modeling elements, to derive the system, or

---

[*] Corresponding Author.

subsystem or component failure probability according to the specific modeling logic, structure and techniques. For example, a Fault Tree Analysis (FTA) model [6] takes probability inputs associated with each of its basic events to derive the probability of the occurrence of a system undesirable event according to the fault tree structure and Boolean algebra logic.

Various reliability modeling techniques can have different modeling logics, techniques and mathematical treatments. But there is one thing in common, that is all need a set of probability inputs associated with their basic modeling elements and key events, and then derive the system reliability or failure probability by following the modeling logics and associated mathematical equations. This set of probability inputs is usually obtained separately and off-line outside of the modeling boundary. For example, a quantitative Fault Tree Analysis requires to have probability inputs for all its basic events; an event tree analysis [7] requires to have probability inputs for its initiating events and pivotal events; a reliability block diagram requires to have probability inputs for all the blocks of the diagram.

It can be seen that obtaining this set of probability inputs is essential for the viability of the reliability modeling and prediction. It is also extremely important for the inputs to be correct and meaningful so we can avoid the situation of garbage-in and garbage-out. From the reliability discipline aspect, the generation of these probability inputs is part of the scope of the reliability prediction though the process of generating the probability or failure rate may involve some localized reliability modeling effort.

It has been observed that much more research has been conducted in the area of system reliability modeling, and probability net creation than in the area of generating basic probability or failure rate for the basic events of a reliability model. There has not been much research that systematically addresses how various methods of the probability input or failure rate generations are compared, and their roles and values in assisting mechanical design-for-reliability are studied. This paper focuses on surveying the widely used probability generating methods and techniques, categorizing them and analyzing the merits and the applicability of these techniques under the context of design-for-reliability for a reliability modeling. It should be emphasized that this paper is not about the system reliability modeling but about the generation of failure or fault probability, in some instance, the failure rate for a localized part or component.

The rest of the paper consists of three parts. The first part is to survey the methods. In Section 2, we survey five most frequently used failure probability generation methods: statistical frequency and modeling method, similarity and comparative assessment method, physics based failure modeling, Monte Carlo simulation, and expert elicitation. We discuss the technical rationale and scientific foundation of each

method and illustrate each with application examples. The second part is to evaluate and compare the methods presented in Section 3. We evaluate and rank the methods from the following attributes: the closeness of the method to the design; the validity and the fidelity of the prediction results; the extensiveness of the analysis effort involved and data needs; the applicability of the methods at different product life cycle stages. We pin-point the limitations of, and cautions for, using the prediction results. The third part, presented in Section 4, is to establish a selection framework of the methods based on the ranking results of the second part, to assist a practical application of the methods for design-for-reliability. We summarize our work and discuss potential future research activities in Section 5.

2 SURVEY OF PROBABILITY GENERATION METHODS

2.1 Statistical Frequency and Modeling Methods

Method description
The probability generation method based on the statistical frequency and modeling is the most intuitive and straightforward method. It is an empirical and data driven approach based on the statistical data collected from the product under the field use environment or controlled lab test conditions. The steps of the method include gathering the product data relevant to the events of interest, and analyzing the data using statistical and probability modeling techniques to predict the probability of the event occurrence. The simplest case is using the frequency of the binary events, success or failure from the product operating history, to predict the probability of the success or failure.

There are many probability models being used to model the probability prediction. Most reliability text books have one or more chapters discussing probability models for reliability applications [1-3, 8-14].

For discrete outcome data, Binomial, Geometric and Poisson probability distributions are the most frequently used probability distributions to predict an outcome probability. For continuous data, Exponential, Weibull, Normal, Log-normal, Extreme Value, Gamma, Beta, Uniform and Triangular distributions are the frequently used ones.

Illustrative examples
Example 1: For the binary outcome data (success or failure), we have 5 failures among 100 independent and identical trials for a specific failure consequence of a component, the probability of the failures, p_f, is estimated to be $\hat{p}_f$ (with hat on top indicating an estimator of p_f), given by

$$\hat{p}_f = \frac{5}{100} = 0.05 \qquad (1)$$

Eq. (1) simply represents the frequency of the occurrences of the failure events among total trials. $\hat{p}_f$ is a point estimate of the failure probability p_f of the binomial distribution.

Example 2: For the continuous outcome data (time to failure), we have 10 time-to-failure data points for the part: 100 hours, 150 hours, 200 hours, 260 hours, 400 hours, 650 hours, 800 hours, 1100 hours, 1300 hours and 1800 hours. Assume the time to failure distribution is an exponential distribution with the distribution mean μ. From the exponential distribution modeling technique, the estimate of μ, denoted as $\hat{\mu}$, is given by

$$\hat{\mu} = \frac{100+150+200+260+400+650+800+1100+1300+1800}{10} \qquad (2)$$
$$= 676 \ Hours$$

Therefore, according to the accumulative distribution function (CDF) of the exponential distribution, the probability of failure, p_f, from the time zero to t hours, is predicted to be

$$\hat{p}_f = 1 - e^{-\frac{t}{\hat{\mu}}} \qquad (3)$$

For example, if we want to predict the probability of failure between zero and 500 hours, using Eq. (3), we obtain

$$\hat{p}_f(500) = 1 - e^{-\frac{500}{676}} = 0.52$$

Technical rationale and scientific foundation
The statistical frequency and modeling method is built on the frequency probability definition and the associated probability and statistical theories. The frequency probability definition states that the probability of an event is the proportion of times that it occurs if we conduct infinite number of repetitions. In real life, it is impossible to repeat the trials infinite times. Therefore, the probability and statistical estimation theory and modeling techniques come to play to predict the probability of the event occurrence as the illustrative examples have shown.

2.2 Similarity and Comparative Assessment Method

Method description
The similarity and comparative assessment method consists of two major steps. The first step is to collect failure probability or failure rate values on a set of standard parts as the comparison base. The second step is to conduct a comparative assessment and make adjustments by applying adjustment factors, called π factors, to the base set probability values to arrive at new failure probability values as the prediction for the new component. The adjustment factors are derived based on the comparisons of some parameters, such as severity of the operating environment, complexity of the design, manufacturing and assembly methods, quality level of the parts, and other factors considered to be relevant. The methods of deriving adjustment factors are based on some empirical data

with interpolation or extrapolation, or simple and approximate physical relationships.

The reliability prediction methods, based on the United States military standards, are basically similarity and comparative assessment method [15-16]. MIL-STD-756B [15] stated in its forward that "Reliability predictions are generally based on experience data from similar items, or their components, used in a same or similar manner." MIL-HDBK-217 [16] collected a baseline set of failure rates for standard electronic components such as resistors, capacitors, diodes and transistors then recommended various π factors as adjustment factors to obtain a new predicted failure rate for a specific application of certain component.

As the US military standards laid down the ground for this methodology, several software packages have been developed by commercial companies to implement the method, such as Relex [17], PRISM [18] and ITEM [19]. These software packages typically include the failure rate databases for a set of standard parts, and π factors for the user to adjust the baseline failure rate for a specific application. There have been failure rate books published to assist this effort such as NPRD [20] and EPRD [21].

Illustrative example
Example 3. This example is to predict the failure rate of various types of connections of two pieces of materials [16]. The failure rate model for a connection is calculated by

$$\lambda_p = \lambda_b \pi_E \qquad (4)$$

Here, λ_p represents the predicted failure rate for the connection being evaluated, λ_b represents the failure rate for a baseline standard connection type, and π_E represents an adjustment factor depending on the application environment. λ_b values are given by Table 1 for various types of standard connections. π_E values are given by Table 2 for various application environment conditions. Therefore, for a crimp type of connections used for missile flight, the connection failure rate is predicted to be $\lambda_p = \lambda_b \pi_E = 0.00026$ failures $/10^6$ hours x 9.0 = 0.00234 failures $/10^6$ hours.

Technical rationale and scientific foundation
The adequateness of the similarity and comparative assessment method relies on the extent of the similarity of the assessed parts to the standard parts in the archived databases, and the reasonableness of the adjustment factors. The similarity is often judged by the reliability analyst subjectively, based on the characteristics of the design, functionality, material selection, manufacturing and assembly, application environment, and supplier's capability. The reasonableness of the adjustment factors depend on how they are derived. They can be derived based on some physical scaling parameters, average failure

probability or failure rate ratios from the history of the part family, or expert suggestions. At the best, an adjustment factor approximates the average ratio between the failure rate of the predicted part and the failure rate of the standard part.

Table 1. Baseline Failure Rate (λ_b) for Standard Connections [16]

Connection Type	λ_b (baseline failure rate, failures/10^6 hours
Hand Solder, w/o Wrapping	0.0013
Hand Solder, w/Wrapping	0.000070
Crimp	0.00026
Weld	0.000015
Solderless Wrap	0.0000068
Clip Termination	0.00012
Reflow Solder	0.000069
Spring Contact	0.17
Terminal Block	0.062

Table 2. Failure Rate Adjustment Factor (π_E) for Different Application Environment [16]

Environment Descriptions	Failure Rate Adjustment Factor, π_E
G_B, Ground, Benign	1.0
G_F, Ground, Fixed	2.0
G_M, Ground, Mobile	7.0
N_S, Naval, Sheltered	4.0
N_U, Naval, Unsheltered	11.0
A_{IC}, Airborne, lnhabited, Cargo	4.0
A_{IF}, Airborne, Inhabited, Fighter	6.0
A_{UC}, Airborne, Uninhabited, Cargo	6.0
A_{UF}, Airborne, Uninhabited, Fighter	8.0
A_{RW}, Airborne, Rotary Winged	16.0
S_F, Space, Flight	0.5
M_F, Missile, Flight	9.0
M_L, Missile, Launch	24
C_L, Cannon, Launch	420

2.3 Physics Based Failure Modeling

Method description

The physics based failure modeling method is the most appealing method to the designers and engineering analysts since it is the closest to the engineering design. The physics based failure modeling comprises several steps. The first step is to understand the failure mechanisms of the component being analyzed such as crack initiation and propagation, corrosion, temperature effect on a component. The second step is to establish mathematical equations base on relevant physics principles and laws that relate all key engineering parameters together. The engineering parameters can include duty cycle environment parameters (temperatures, pressure, flow rate, dynamic loads, etc.) and material properties. The third step is to define the failure boundary in the multi-parameter domain of the math equations. The last step is to quantify the randomness

of the engineering parameters and calculate the failure probability which equates to the probability that the engineering parameter values fall within the failure domain.

The physics based failure modeling is the basic element and founding block for the probabilistic design analysis and reliability based design optimization (RBDO) [22-24]. There have been many research articles and textbooks published in this area, and software packages have been developed to support the effort [13-14, 22, 25-28]

Illustrative example

Example 4. In this example, the failure mode of a given part is structural break, and the failure mechanism is over load rupture. The strength of the part is a normal random variable with a mean value of 400 MPa and standard deviation of 70 MPa. The stress applied to the part is also a normal random variable with a mean value of 250 MPa and standard deviation of 100 MPa. We calculate the failure probability of the part due to over-loading. We denote μ_{stress} as the mean of stress, σ_{stress} as the standard deviation of the stress, $\mu_{strength}$ as the mean of strength, $\sigma_{strength}$ as the standard deviation of the strength. The stress random variable is represented by ST_{re} and the strength random variable is represented by ST_{rn}. The failure probability, P_f, is given by

$$P_f = \Pr obability(ST_{re} \geq ST_{rn}) \qquad (5)$$

Since both stress and strength variables are normally distributed, we can convert Eq. (5) to a standard normal distribution (with mean=0 and standard deviation =1) probability calculation as follows

$$
\begin{aligned}
p_f &= \Pr obability\left(\frac{ST_{re} - ST_{rn} - (\mu_{stress} - \mu_{strength})}{\sqrt{\sigma_{stress}^2 + \sigma_{strength}^2}} \geq \frac{-(\mu_{stress} - \mu_{strength})}{\sqrt{\sigma_{stress}^2 + \sigma_{strength}^2}} \right) \\
&= \Pr obability\left(Z \geq \frac{-(\mu_{stress} - \mu_{strength})}{\sqrt{\sigma_{stress}^2 + \sigma_{strength}^2}} \right) \\
&= \Pr obability\left(Z \geq \frac{-(250 - 400)}{\sqrt{100^2 + 70^2}} \right) \qquad (6) \\
&= \Pr obability(Z \geq 1.2288) = 0.11
\end{aligned}
$$

Here, Z represents the standard normal random variable with mean 0 and standard deviation 1. For the situations that the stress and strength random variables are subject to other types of distributions, Eq. (5) can be evaluated either by numerical approximation or Monte Carlo simulation.

Technical rationale and scientific foundation

The physics based failure modeling is founded on the stress and strength interference theory (SSIT) [29, 13]. SSIT basically

states that a failure occurs, when the stress, in general, exceeds or equals the strength. Mathematically, the theory presents the failure probability (P_f) of the component or the system as the probability that the stress exceeds or equals the strength: P_f = P(Stress $\geq$ Strength). Figure 1 illustrates SSIT for one dimensional stress and one dimensional strength case. Huang and Jin [4-5] extended the traditional mechanical stress and mechanical strength concepts to the conceptual stress and conceptual strength, developed the conceptual stress and conceptual strength interference theory (CSCSIT), and applied it to the conceptual and functional design. In many physics based failure modeling situations, the stress and strength interference equation involves multi stress and multi strength parameters and can be very complex. The failure probability only can be solved approximately or through a Monte Carlo simulation.
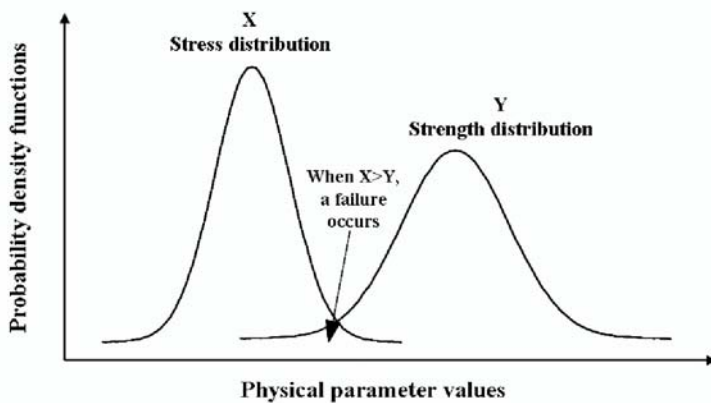

Figure 1. Stress and Strength Interference Diagram

2.4   Monte Carlo Simulation Modeling

Method description
The basic steps of a Monte Carlo simulation are as follows: 1) establish a system mathematical model based on physics principles and laws, and system concepts of operations, which contain various parameters and variables; 2) select a sub set of the parameters and variables as random variables and assign a probability distribution to each of the random variables; 3) sample random values from a pseudo-random number generator according to the probability distribution of the assignment as a representative value for that parameter or variable; and 4) plug the random values sampled from all random variables into the system math model to characterize the stochastic behavior of the system parameters interested.

We can classify the Monte Carlo simulations into several types according to what is being simulated. The first type is to simulate the physical behavior of the system being studied. One of the examples is to simulate the crack growth of a part due to environment factors, material properties and geometric variables. The second type is to use Monte Carlo simulation to find a probability solution in a complicated probabilistic equation with multi-parameter joint probability distributions.

One of the examples of this type is to determine a stress and strength interference probability as mentioned in the last section. The last type is to simulate the probability behavior for a pre-established probability net. One of the examples of this type is to simulate the probability propagation through a fault tree model with probability inputs defined for all its basic events. The first type overlaps the physics based failure modeling method. It basically simulates the physical behavior of the system, and counts the frequency of the failure occurrence during the simulation according to some pre-defined failure criteria. It usually requires much less intensive effort of the mathematical modeling than the physics failure based method since it avoids the explicit mathematical descriptions of all physical states, capturing instead the physical behavior and inter-relationships of individual variables as a result of the simulation. Therefore, it is more appealing in certain applications, especially in the case that analytical mathematical models are complicated and difficult to obtain and to solve. The second type can be considered as an extension of the physics failure based modeling since it helps determine the probability of the stress and strength interference which is the theoretical foundation of the physics based failure modeling. The third type is usually used for a system reliability modeling which is not what we discuss here for the failure probability generation of a localized part or component.

Illustrative example
Example 5. In this example, the problem is to predict failure probability for a part with shared load sub-components. Suppose we have a part with two sub-components with a shared load. The part failure occurs when both sub-components fail. When both sub-components are working, each is subject to a mechanical load and the time to failure is characterized by a Weibull distribution with shape parameter 1.4, scale parameter 150 and location parameter 0. When one of the two sub-components fails, the other takes the full load, and the time to failure is accelerated which is characterized by a Weibull distribution with shape parameter 1.7, scale parameter 90 and location parameter 0. The required part operation time is 50 hours. What is the failure probability of the part ? We use the Monte Carlo simulation method to solve this problem.

We set up a Monte Carlo simulation framework as follows:
- Let t_1 be the time to failure for the first failed sub-component which is subject to the shared load time to failure Weibull distribution, denoted as Weib(1.4, 150, 0).
- Let t_2 be the time to failure for the second sub-component which is subject to the accelerated load time to failure Weibull distribution, denoted as Weib(1.7, 90, 0). This is the time on the second failed unit after the first one has failed and an equivalent consumed time on the second unit has been counted.

We then sample the random variable values for t_1 and t_2 respectively according to the assigned Weibull distributions,

and count the number of times that $t_1 + t_2 \leq 50$ as N. We ran the Monte Carlo simulation using the Crystal Ball simulation tool [50] and obtained N =1580 among 50,000 trials. Since either one of the two subcomponents can fail first, therefore the failure probability for the part is

$$p_f = \frac{2N}{Total\_trials} = \frac{2x1,580}{50,000} = 0.0632$$

Kececioglu [12] presented an exact formula which gives $P_f =$ 0.06199. Volovoi [30] used a Petri Net modeling method which gives P_f=0.06205.

Technical rationale and scientific foundation
The adequateness of the Monte Carlo simulation method relies on several factors. The first factor is the ability to correctly model the system behavior resembling the reality closely. The second factor is to correctly select random variables and assign proper probability distributions to them. The third factor is to simulate the random variables with adequate randomness through a sampling of a pseudo-random number generator. Marseguerra and Zio [31-32], Kennedy and Gentle [33], Rubinstein and Kroese [34], Johnsom [35] provided extensive discussions for the theory and applications of Monte Carlo simulations.

2.5 Expert Elicitation

Method description
Expert elicitation method can be considered as the most doable but the most controversial method for failure probability or failure rate generation. It is doable because experts exist in every field and expertise itself is a relative term so one can always obtain an expert's opinion on the probability of an event as well as the probability distribution of it. However, it is also very controversial because it is by nature subjective, and represents only a snapshot of the expert's state of knowledge at the time of solicitation [36]. It is considered a practice of quantifying the unquantifiable [37]. Despite the controversies surrounding the practice, it has been widely used in the design and management of large, complex engineering projects where the projects are often unique, the data about the similar products or projects are sparse or do not exist [38]. There have been many research efforts in the area of soliciting, quantifying, analyzing and using expert opinions. There have been attempts made to make the practice as scientific and logical as possible. Some representative works are O'Hagan et al. [38], Meyer and Brooker [39], Ayyub [40], Tetlock [37], as well as many research papers in the area of nuclear engineering risk assessment.

The basic steps of an expert elicitation on probability involve the following: 1) define the events of interest; 2) select experts; 3) train the experts on the elicitation methodology; 4) prepare and present elicitation questionnaire to the experts; 5) obtain questionnaire answers from the experts; 6) analyze and aggregate the elicited results; 7) confirm the results with the expert; and 8) use the results for a particular project. O'Hagan [38] and Meyer and Brooker [39] provided detailed descriptions of various elicitation processes and their variations as well as the reference materials.

Illustrative example
Example 6. A rocket engine design team was assessing reliability of a new component. The component was designed with a new design concept, new materials and new manufacturing processes therefore the history of similar functional components and data did not exist. An expert elicitation method was used to obtain the initial estimate of failure probability of the component during the conceptual design to assist the design-for-reliability effort and trade study. Three experts were surveyed separately and independently, and the most likeliest, worst and best case failure probability estimates were provided from each expert. The rationale of the estimates, including the experts' opinions on the challenges and concerns on the design complexity, material property uncertainty, analysis technique difficulties, and manufacturing process and supplier capability readiness, were documented. The data collected from the three experts were fitted to three truncated triangular distributions which were then aggregated to a single probability distribution representing the failure probability distribution of the component. This probability distribution was entered into a system reliability model to assist design-for-reliability and trade studies. It was noticed that in an industry integrated product team (IPT) setting, the rigor of the elicitation process is much less emphasized than the documentation of the assessment reasoning and rationales of the experts behind all numerical probability values. These rationales become a key data source for design-for-reliability and trade decisions, and also serve as an important data source for the reliability prediction update and verification.

Technical rationale and scientific foundation
The technical rationale and scientific foundation of the expert elicitation method resides in the psychology, organizational and human behavior study, human decision process, probability and statistics science, and system engineering. Psychology science, particularly in the areas of human judgment, logical reasoning and environment influence, provides the foundation for evaluating the validity and credibility of the experts' opinion [38-39, 41]. Decision process provides framework and detailed techniques for elicitation consistency and rationality [42-45]. Probability theory builds a scientific base for the interpretation of probability as personal belief [38, 46] and establishes Bayesian theorem and inference procedure. Probability and statistics theory and techniques provide many detailed treatments for the elicitation data aggregation and deduction [38-40,46]. System Engineering process and practice supplements the expert elicitation process development and applications [47].

6

3 EVALUATION AND COMPARISONS OF THE METHODS

There have been survey studies on reliability prediction methods and procedures for electronic components. Bowles [48] reviewed six prediction procedures for microelectronic devices, examined the assumptions behind each, and compared the prediction results for a computer component. All these six procedures assumed the constant failure rate for the device (the exponential failure rate model) and invoke the same type of math formula, i.e., a summation of baseline failure rate multiplied by adjustment factors for the failure rate calculation. Therefore all these procedures fall under the category of *Similarity and Comparative Assessment* method in our prediction method categorization. Denson [49] reviewed reliability prediction history and methodology evolvement focusing on electronic components, compared pros and cons of various methods including empirical based, physics failure based, and test data based.

In this paper, we evaluate and compare the prediction methods by focusing on assisting mechanical design-for-reliability. As we have defined in Section 1, the *design-for-reliability is a structured design methodology that guides design decision making with parametric reliability models to meet quantitative reliability requirements or goals during all design phases*. As such, failure probability or failure rate prediction data have to be closely related to, or better linked with, or best to be generated from and evolved along with the design synthesis and analysis model development. Thereby reliability modeling can be truly formulated in parallel with the design synthesis and design analysis models, and design-for-reliability decisions can be an integral part of the design decisions. Such parallel reliability model development and integrated reliability decision-making fundamentally change the way of currently prevailing reliability modeling practices as a post-design assessment tool. Based on these considerations, we evaluate and compare the five prediction methods surveyed in Section 2 from the following five attributes: 1) the closeness of the method to the design; 2) the validity of the prediction results; 3) the fidelity of the results; 4) the extensiveness of the analysis effort involved and data needs; 5) the applicability of the methods at different design and development stages. We also discuss the limitations and cautions of using the prediction results to assist design-for-reliability.

1) Closeness of the method to the design

We define the closeness of a reliability prediction method to the design as the extent to which the reliability prediction data generation process is connected with the design synthesis and design analysis process. According to this definition, we consider the physics based failure modeling and the Monte Carlo simulation method are the closest among the five prediction methods. This is because these two methods use the same data sources as in design, such as physics principles and laws, and system concepts of operations, to derive reliability prediction data. Among the rest three methods (statistical frequency and modeling, similarity and comparative assessment, expert elicitation), the expert elicitation is potentially the most closest to the design since whatever data and knowledge extracted from the experts should have lot of relevance to the design at hand due to the experts' expertise. The statistical frequency and modeling method is purely an empirical data driven method which does not explicitly relate to the design synthesis and design analysis. The similarity and comparative assessment method starts with a set of empirical data from similar products then adds an adjustment step to arrive new probability prediction. Therefore, it can be the least closest to the design. We summarize the ranking assessment in Table 3 with the score 1 as the closest to the design (the most desirable).

2). Validity of the prediction results

We define the validity of a model or prediction as its truthfulness. In reliability prediction discipline, we probably never know the true failure probability values. Therefore, we pursue the soundness of the prediction process that can potentially produce prediction values close to the truth. The statistical frequency and modeling method should be ranked number 1, for the reason that the empirical data, unbiased collected from the product under the field usage environment, truly reflects the intended design conditions. It also implicitly includes the system interaction, interface and human error related failures which are likely to be ignored by other methods. The physics based failure modeling and Monte Carlo simulation modeling methods usually only predict inherent reliability of the product. The filed usage and manufacturing introduced failure causes, such as human and process errors, are often not counted in these methods. The expert elicitation method has potential to count both inherent and filed usage failure causes, but after all, the result from the method only represents a snap shot of the expert knowledge and judgment. The validity of the results from the similarity and comparative assessment method depends on the nature of the "similarity" and soundness of the adjustment factors applied. We should point out that all methods are valid to some extent. The ranking assessment is a relative comparison on the methods. We assign the validity ranking scores in Table 4 with 1 as the highest validity for the method (the most desirable)

3). Fidelity of the prediction results

We define the fidelity as the roughness of the prediction details. The physics based failure modeling and Monte Carlo simulation modeling methods involve detailed physics laws and corresponding parametric equations. The statistical frequency and modeling method is basically built upon the field empirical data which are usually collected with intensive data collection and documentation effort. The similarity and comparative assessment method involves similarity analysis and adjustment factor derivation. The expert elicitation method involves an expert elicitation process that can range from very formal to an ad-hoc process. Both similarity and comparative assessment

Table 3. Ranking of Closeness of the Reliability Prediction Methods to Design

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Closeness to the design	4	5	1	1	3

method and expert elicitation method can have varying degree of fidelity. Based on the above discussion, we assign the fidelity ranking scores in Table 5 with 1 as the highest fidelity (the most desirable).

4). Extensiveness of the analysis effort involved and data needs

The expert elicitation method collects expert opinion data then aggregates them using statistical and probability modeling to arrive the prediction. Relatively speaking, it requires the least mount of analysis and data. We assign the ranking score 1. The similarity and comparative assessment applies a set of pre-developed adjustment factors to the baseline similarity data set to arrive new prediction. We rank it after the expert elicitation method. The statistical frequency and modeling method is built on analyzing the field data using statistical and probability models so we rank it next. The physics based failure modeling and Monte Carlo simulation modeling methods involve detailed physics failure modeling, and parametric model development and quantification. Therefore they are the most extensive from the analysis effort and data need perspective. We summarize the ranking assessment for this attribute in Table 6 with 1 as the least extensive (the most desirable).

5). Applicability of the methods at different product life cycle stages

We examine the applicability of the reliability prediction methods at the different design and development stages of a product, particularly, conceptual design, embodiment design, detailed design, manufacturing and testing (lab testing, prototype testing and field testing), and field usage. Not all reliability prediction methods are applicable at every stage of a product design and development. For example, during a conceptual design, the statistical frequency and modeling method is not applicable because the field empirical data do not exist at that time. Table 7 summarizes the applicability of the reliability prediction methods. In several places, we use "partially" to indicate the method is partially applicable depending on the data available and the approach taken. For the statistical frequency and modeling method, we designate "partially" applicable at the stage of manufacturing and testing for some data obtained at that stage can be considered applicable for the empirical statistical data quantification. For the physics based failure modeling and Monte Carlo simulation method, we consider they are "partially" applicable at the conceptual design stage since function structure design data may provide the modeling possibility, even though the form

Table 4. Ranking of Validity of the Prediction Results

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Validity of prediction results	1	4	2	2	4

Table 5. Ranking of Fidelity of the Prediction Results

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Fidelity of prediction results	1	4	1	1	4

Table 6. Ranking of Extensiveness of the Analysis Effort and Data Needs

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Extensiveness of the Analysis Effort and Data Needs	3	2	4	4	1

structure data do not exist at that time. For the expert elicitation method, we consider it is "partially" applicable during the manufacturing, testing and field usage for the reason that it gradually loses its usefulness when the field test data become available.

6). Limitations and cautions of using the prediction results to assist design-for-reliability

Uncertainty of the prediction
Uncertainty is naturally embedded in the prediction process and results. Uncertainty can be classified in three basic types which are aleatory uncertainty, epistemic uncertainty, and uncertainty due to human error [22]. We have observed that in most practical application situations, uncertainty is often not addressed to the satisfaction of theoretically required rigor. The detailed treatment of uncertainty is beyond the scope of this paper. However, as minimal, the existence of uncertainty needs to be aware and cautions have to be taken for using the reliability prediction results for design decision making.

System failure definition and local failure probability generation
As mentioned in Section 1, we focus on the generation of failure probability for a localized part or component. These failure probabilities are then fed to a system reliability model to calculate a system failure probability. From the reliability definition given in Section 1, we interpret that all failures are functional failures. Now we apparently have a paradox. On one hand, a system reliability model requires probability inputs from local part or component to address system functional failure probability. On the other hand, the development of local part failure probability is often carried out without the information and knowledge of the relevant system functional failures and associated complexity. This limitation needs to be aware of, and the best effort of understanding the system reliability modeling needs should be made when generating local part failure probability inputs.

Prediction results versus prediction process
Execution of the prediction process is more important than obtaining the prediction results. This is because the prediction results are static while the prediction process can be dynamic and be evolving along with design progression. Design-for-reliability, design trades, and design optimization may constantly require the update of failure probability inputs. Therefore, more emphasis should be put on establishing a sound prediction process than just obtaining prediction results for one time use.

Analysis results versus analysis assumptions
All analysis involves assumptions. The assumptions behind the reliability prediction often provide more insights than the result itself for understanding how the prediction results are derived and how valid the result is. Key assumptions need to be documented and constantly updated to reflect design knowledge and status.

4   A FRAMEWORK FOR SELECTION OF APPLICABLE PREDICTION METHODS

In this section, we develop a selection framework to assist practical use of the reliability prediction methods. The selection framework uses the ranking results on the prediction methods presented in the last section. It applies a set of customized preference weighting factors to the comparison attributes, to assist the selection of an applicable prediction method for a specific application. We first present the selection framework then provide an example to illustrate its use.

4.1   A Framework for Prediction Method Selection

In Section 3, we ranked the five prediction methods for each of the 4 comparison attributes: the closeness of the method to the design; the validity of the prediction results; the fidelity of the results; and the extensiveness of the analysis effort involved and data needs. Notice that we didn't rank the applicability of the methods presented in Table 7 since we feel as a candidate method of the selection, it has to be applicable to the product life cycle stage at hand. Therefore, before we apply the selection framework, we have to screen out the methods that are not applicable. Combining the ranking results from Table 3 to Table 6, we obtain Table 8. Ranked values are from 1 to 5, with 1 being the most desirable and 5 being the least desirable.

Table 7. Applicability of the Methods at Different Design and Development Stages

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Conceptual design	No	Yes	Partially	Partially	Yes
Embodiment design	No	Yes	Yes	Yes	Yes
Detailed design	No	Yes	Yes	Yes	Yes
Manufacturing and testing	Partially	Yes	Yes	Yes	Partially
Field usage	Yes	Yes	Yes	Yes	Partially

9

We can present the content of Table 8 in a spider-web diagram (Figure 2) to visualize the comparisons of the usefulness of the methods. The larger the area that is covered by the method, the better the method is. The diagram also provides a convenient way to spot the area the method covers that match our preferred attributes. For example, if the preference is the closeness to design, we would like to use the method which can cover a large area near the "Closeness to design" label. For this case, we would select either physics based modeling or Monte Carlo simulation method.

Though the spider-web diagram provides useful information, it treats all attributes equally. In real applications, we may prefer some attributes more than the others. Let's examine the four attributes we have used. The closeness of the method to the design is essential to support the design-for-reliability. The validity and the fidelity are about data quality. The extensiveness of the analysis effort and data needs directly relates to the analysis cost. Every project that needs reliability prediction may have own emphasis on these attributes. Before the prediction task is executed, we can let the project team assign a fraction to each of the four attributes with a higher fraction indicating a more emphasis. All fractions are added up to 100%. For example, we can assign 25% to each of the four attributes, indicating the four attributes are equally important which is the case in Figure 2. Another example is to assign 100% to the closeness to the design and 0% to the rest, indicating we want everything possible to relate the reliability prediction to the design. We then multiply the fraction by the corresponding ranking score for that method and sum all products for each method to get a weighted ranking value for that method. Table 9 presents an example of the weighted ranking evaluation. The weighted ranking score of 2.4 in Table 9 for the statistical frequency and modeling method is calculated from 2.4 = 40% x 4 + 25% x 1 + 25% x 1 + 10% x 3. Note that the smaller the weighted ranking value, the more preferred the method. Therefore, the physics based model or Monte Carlo simulation method is preferred when the weighting fraction values (40%, 25%, 25%, 10%) are given, since these two methods have the smallest ranking value (1.6) among 5 methods.

Table 8. Rankings of Reliability Prediction Methods for the Comparison Attributes

	Statistical Frequency and Modeling Method	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Closeness to the design	4	5	1	1	3
Validity of prediction results	1	4	2	2	4
Fidelity of prediction results	1	4	1	1	4
Extensiveness of the analysis effort and data needs	3	2	4	4	1

Table 9. Sample Evaluation of Weighted Ranking Scores for Five Prediction Methods

Comparison Attributes	% weighting factor	Statistical Frequency & Modeling	Similarity & Comparative Assessment	Physics Based Modeling	Monte Carlo Simulation	Expert Elicitation
Closeness to the design	40%	4	5	1	1	3
Validity of prediction results	25%	1	4	2	2	4
Fidelity of prediction results	25%	1	4	1	1	4
Extensiveness of the analysis effort and data needs	10%	3	2	4	4	1
Weighted ranking		2.4	4.2	1.6	1.6	3.3

Table 10. Weighted Rankings of Four Prediction Methods for Sub-team 1

Comparison features	% weighting factor	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Closeness to the design	40%	5	1	1	3
Validity of prediction results	10%	4	2	2	4
Fidelity of prediction results	5%	4	1	1	4
Extensiveness of the analysis effort and data needs	45%	2	4	4	1
Weighted ranking		3.5	2.5	2.5	2.3

Table 11. Weighted Rankings of Four Prediction Methods for Sub-team 2

Comparison features	% weighting factor	Similarity and Comparative Assessment Method	Physics Based Failure Modeling	Monte Carlo Simulation Modeling	Expert Elicitation
Closeness to the design	60%	5	1	1	3
Validity of prediction results	5%	4	2	2	4
Fidelity of prediction results	5%	4	1	1	4
Extensiveness of the analysis effort and data needs	30%	2	4	4	1
Weighted ranking		4.0	2.0	2.0	2.5

4.2 An Illustrative Example of Using Selection Framework

A rocket engine design team is conceptually designing a new rocket with several complicated components such as turbopump, combustion chamber and controller. Reliability is one of the most important programmatic requirements therefore design-for-reliability is highly emphasized. The reliability prediction task is one of the necessary tasks to support trade study and design-for-reliability decisions. However, the project team is also harshly constrained by the budget and schedule. The team's reliability engineers have built a system reliability model which incorporated design data and information but needs failure probability inputs for various components to compute the system reliability. The team has to decide what prediction method(s) should be used to obtain the failure probability for these components. Since the design is at conceptual design stage, the statistical frequency method can not be used. The team has to select methods among the other four methods. To be consistently executing the reliability prediction tasks among several sub-teams to meet the program needs, the design team chooses to use the selection framework described in the previous section for the prediction method selection. Sub-team 1 considers the closeness to the design is important but wants to make sure the task can be executed within cost and schedule constraints. The team also feels the validity and fidelity of the results are not essential during the conceptual design stage. Therefore, the weighting fractions are assigned to be (40%, 10%, 5%, 45%) for the closeness to the design, validity, fidelity and extensiveness of the analysis effort respectively. Based on the weighting fractions and the ranking values in Table 8, Table 10 presents the weighted rankings of the four methods. The result of Table 10 indicates that the expert elicitation method is a preferred choice to meet the design team's needs and constraints, since it has the lowest (best) ranking score.

For Sub-team 2, the components being designed are completely new. The team wants to have reliability prediction fully utilize design data for addressing potential failure mode and cause concern. So the team assigns the weighting fractions to be5%, 5%, 30%). Table 11 presents the weighted rankings for the four applicable methods which show the physics based failure
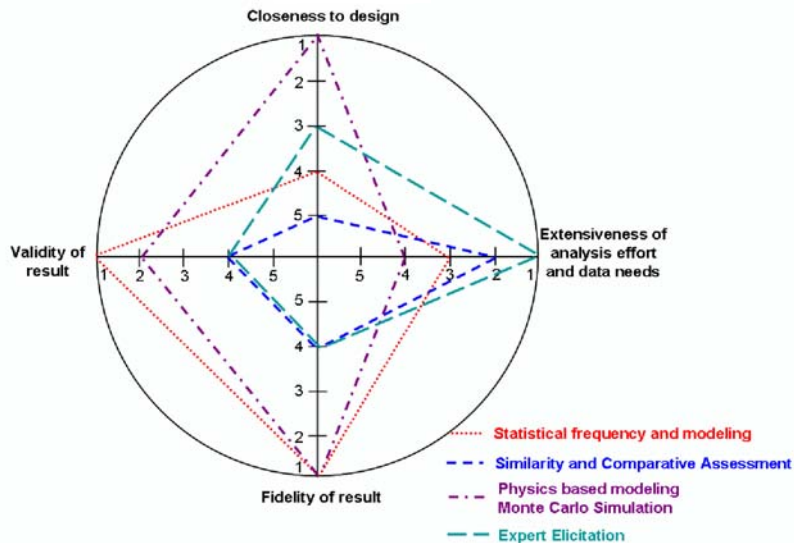
Figure 2: Reliability Prediction Method Evaluation Diagram

modeling and the Monte Carlo method rank the best. Therefore, the team decides to use a combination of the physics based failure modeling and Monte Carlo method as the choice for the reliability prediction.

4.3 Discussion

The ranking of the prediction methods and the selection framework provide useful insights about how in a practical situation we can use the prediction methods to best execute a prediction task that meets the project needs and constraints. The selection framework also provides guidance for consistently selecting the prediction methods based on the design team's technical and economical considerations. The selection framework can be applied to each individual prediction task within a design project since the ranking and economical considerations can be different for each prediction task. Besides, in reality, when we perform a reliability prediction, we may use more than one method, or create a hybrid method with mixed elements from some or all of the five methods to increase the method merit. In this case, some probability and statistical techniques, such as Bayesian theorem, can be used to help aggregate the data generated from various methods.

5 SUMMARY AND CONCLUDING REMARKS

We surveyed five reliability prediction methods for a component or part failure probability prediction applicable for the mechanical design system, i.e., statistical frequency and modeling method, similarity and comparative assessment method, physics based failure modeling, Monte Carlo simulation, and expert elicitation. Every method has its own unique approach, technical and scientific rationales behind.

These methods also have their own pros and cons relative to the comparison attributes identified, namely, the closeness to the design, the validity and the fidelity of the prediction results, the extensiveness of the analysis effort involved and data needs. We discussed uniqueness of the methods and presented the rankings of the methods in the comparison space characterized by the attributes. Based on these attributes and rankings, we developed a selection framework that can guide the selection of the prediction methods for a practical application for a mechanical design system.

There are research opportunities to improve the reliability prediction methods to better support design-for-reliability. One area of further research is to develop a hybrid method that integrates the existing methods which can provide better merits and better fit to the design needs and project constraints. Another research direction is to develop an integrated prediction method that can evolve in parallel with design iteration and embed itself within the design synthesis and design analysis process to support design decision and optimization. Finally, a prediction process and the prediction results have to be viably validated and verified that is largely an open research question.

6 BIBLIOGRAPHY

[1] Ireson, G.W, C.F. Commbs, and R. Moss (1995),"Handbook of Reliability Engineering and Management," John Wiley & Sons, Inc., New York
[2] Department of Defense (1980), "MIL-STD-785 Reliability Program for System and Equipment Development and Production," Washington D.C.
[3] O'Connor, D.T. (2002), "Practical Reliability Engineering," John Wiley & Sons
[4] Huang, Z., and Jin, Y. (2008), "Conceptual Stress and Conceptual Strength for Functional Design-For-Reliability," ASME IDETC 2008-49347, New York, NY
[5] Huang, Z., and Jin, Y. (2008), "Extension of Stress and Strength Interference Theory for Conceptual Design-For-Reliability," Submitted to ASME Journal of Mechanical Design
[6] NASA (2002), "Fault Tree Handbook with Aerospace Applications," NASA, Washington D.C
[7] NASA (2002), "Probabilistic Risk Assessment Procedures Guide for NASA Managers and Practitioners," NASA, Washington D.C
[8] Lloyd, K.D. and M. Lipow (1984), "Reliability Management, Methods, and Mathematics," ASQ, Milwaukee
[9] Bain, L.J. and M. Englehardt (1991), "Statistical Analysis of Reliability and Life-Testing Models," Marcel Dekker, Inc.
[10] Nelson, W. (2004), "Applied Life Data Analysis," John Wiley & Sons
[11] Lawless, J.F. (2003), "Statistical Models and Methods for Lifetime data," John Wiley & Sons, New York

[12] Kececioglu, D. (2002), "Reliability Engineering Handbook," Volume 1 & 2, DEStech Publications, Lancaster, Pennsylvania

[13] Kapur, C.K. and L.R. Lamberson (1983), "Reliability in Engineering Design," Marcel Dekker, New York

[14] Dhillon, B.D. (1999), "Design Reliability: Fundamentals and Applications," CRC Press, Boca Raton, Florida

[15] Department of Defense (1982), "MIL-STD-756 Reliability Modeling and Prediction," Washington D.C.

[16] Department of Defense (1991), "MIL-HDBK-217F Reliability Prediction of Electronic Equipment," Washington, DC

[17] Relex (2008), "Relex Software User Manual," Relex Software Copmpany, Greensburg PA

[18] SRC (2003) "PRISM User Manual," System Reliability Center, Rome, NY

[19] ITEM (2007), "ITEM ToolKit User Manual," ITEM Software, Anaheim, CA

[20] RAC (1995), "Electronic Parts Reliability Data," Reliability Analysis center, Rome, NY

[21] RAC (1995), "Nonelectronic Parts Reliability Data (NPRD95)," Reliability Analysis center, Rome, NY

[22] Nikolaidis, E., D.M. Ghiocel and S. Singhal (2005), "Engineering Design Reliability Handbook," CPC Press, London

[23] Augusti, G., A. Baratta and F. Casciati (1984), "Probabilistic Methods in Structural Engineering," Chapman and Hall, London

[24] Haugen, E.B. (1980),"Probabilistic Mechanical Design," John Wiley & Sons

[25] Hall, P.L. and Strutt, J.E. (2003), "Probabilistic physics-of-failure models for component reliabilities using Monte Carlo simulation and Weibull analysis: a parametric study," Reliability Engineering and System Safety, Vol. 80, Number 3, June 2003, Elsevier

[26] White, M. (2008), "Microelectronics Reliability: Physics-of-Failure Based Modeling and Lifetime Evaluation," Jet Propulsion Laboratory, CA

[27] Petch, M. and A. Dasgupta (1995), "Physics-of-failure: an approach to reliable product development," International Integrated reliability Workshop, IEEE

[28] Petch, M., A. Dasgupta, B. Donald and C. T. Leonard (1990), "The reliability physics approach to failure prediction modeling," Quality and Reliability Engineering International, Vol. 6, Issue 4, Sep/Oct 1990

[29] Disney, R.L., N.J. Sheth and C. Lipson (1968), "The Determination of the Probability of Failure by Stress/Strength Interference Theory, "Proceedings of Annual Symposium on Reliability, 1968, pp. 417-422

[30] Volovoi, V. (2006), "Stochastic Petri Nets Modeling Using SPN@," Annual Reliability and Maintainability Symposium, 2006

[31] Marseguerra, M. and E. Zio (2002), "Basics of the Monte Carlo Methods with Applications to System Reliability," LiLoLe-Verlag GmBH (Pbl. Co Ltd.)

[32] Marseguerra, M. and E. Zio (2008), "Monte-Carlo Sampling and Simulation for Application to R&M," Annual Reliability and maintainability Symposium, 2008

[33] Kennedy, W.J. and Gentle, J.E. (1980), "Statistical Computing," Marcel Dekker, New York

[34] Rubinstein, R.Y. and D.P. Kroese (2008), "Simulation and The Monte Carlo Method,", John Wiley and Sons, New York

[35] Johnsom, M.E., (1987), "Multivariate Statistical Simulation," John Wiley and Sons, New York

[36] Keeney, R.L. and D. von Windterfeldt (1989), "On the Uses of Expert Judgment on Complex Technical Problems," IEEE Transaction on Engineering management, Vol 36, 1989, p83-p86

[37] Tetlock, P.E. (2005), "Expert Political Judgment: How Good Is It? How Do We Know?" Princeton University Press, Princeton New Jersey

[38] O'Hagan, A., et al. (2006), "Uncertain Judgments: Eliciting Experts' Probabilities," John Wiley & Sons

[39] Meyer, A.A. and J.M. Brooker (1991), "Eliciting and Analyzing Expert Judgment: A Practical Guide," Academic Press, London, UK

[40] Ayyub, B.M. (2001), "Elicitation of Expert Opinions for Uncertainty and Risks," CRC Press, Boca Raton, Florida

[41] Plous, S. (1993), "The Psychology of Judgment and Decision Making," McGraw-Hill, New York

[42] Raiffa, H. (1968), "Decision Analysis: Introductory Lectures on Choices Under Uncertainty," Addison-Wesley, Massachusetts

[43] Raiffa, H. (1969), "Preferences for Multi-Attributed Alternatives," Rand Corporation, Santa Monica, CA

[44] Keeney, R.L. and H. Raffa (1976), "Decisions with Multiple Objectives: Preferences and Value Tradeoffs," John Wiley, NY

[45] Ullman, D.G. (2001), "12 Steps to Robust Decisions," Trafford Publishing, Victoria, Canada

[46] Winkler, R.L. (2003), "An Introduction to Bayesian Inference and Decision," Probabilistic Publishing, Gainesville, FL

[47] Bedfore,T., J. Quigley and L. Walls (2006), "Expert Elicitation for Reliable System Design," Statistical Science, 2006 Vol. 21, No. 4, 428–450

[48] Bowles, J. 1992, "A Survey of Reliability Prediction Procedures for Microelectronic Devices," IEEE Transaction on Reliability," Vol. 41, No. 1, March 1992

[49] Denson, W. (1998), "The History of Reliability Prediction," IEEE Transaction on Reliability, Vol. 47, No. 3, Sep. 1998

[50] Decisioneering (2001), "Crystal Ball User Manual," Decisionnering, Denver, Colorado