PREDICT: A Case Study, Using Fuzzy Logic

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SUMMARY & CONCLUSIONS

Los Alamos National Laboratory, Design For Reliability, Inc., and others, have worked together to develop PREDICT, a new methodology to characterize the reliability of a new product during its development program. Rather than conducting testing after hardware has been built, and developing statistical confidence bands around the results, this updating approach starts with an early reliability estimate characterized by large uncertainty, and then proceeds to reduce the uncertainty by folding in fresh information in a Bayesian framework. A considerable amount of knowledge is available at the beginning of a program in the form of expert judgment that helps to provide the initial estimate. This estimate is then continually updated as substantial and varied information becomes available during the course of the development program. This paper presents a case study of the application of PREDICT, including an example of the use of fuzzy logic, with the objective of further describing the methodology. PREDICT has been honored with an *R&D 100 Award* presented by R&D Magazine.

1. INTRODUCTION

A methodology has been developed to characterize the reliability of new products during development. PREDICT (Performance and Reliability Evaluation with Diverse Information Combination and Tracking) is an approach that has proven effective in evaluating systems ranging from automotive to national defense. Just as estimates of cost and program timing are critical factors to be known and monitored during program development, product reliability also needs to be addressed. The reliability estimate and the uncertainty of that estimate are an excellent way to provide this characterization. The PREDICT methodology involves combining information that ranges from qualitative, such as expert judgment, to quantitative, such as test data. It is possible to develop realistic reliability estimates at the beginning of a new product program, even though hardware is not available, because a considerable amount of knowledge exists in the experience base of engineers. This knowledge is elicited in the form of expert judgment. The process of estimating reliability proceeds throughout the entire development program, incorporating information from any available source (i.e., supplier, customer), about any level of the product (i.e., subsystem, component). The approach allows the early characterization of new product reliability prior to the availability of hardware, and it is updated as the design evolves. This allows the project team to "keep score" as they work through the program to design in reliability. The results may also be used to provide steerage to the project team with regard to how to drive reliability higher and/or reduce the uncertainty in reliability.

The challenge has been to develop a framework for this reliability characterization which is physically, logically, and mathematically sound. It must also be flexible enough to accommodate all of the diverse information that becomes available, and responsive enough to provide timely results which support the development process. The information updating approaches (such as those based on Bayes Theorem) are suggested as key methods directly applicable to this problem. This paper details a case study of the application of PREDICT to a new product development program. This work is an effort to further describe the methodology previously published by the same authors (Ref. 1, 2). In addition, it expands the case study described in Ref. 3 by including an example of the use of fuzzy logic. The methodology involves the elicitation and analysis of expert judgment, which is used to quantify the initial reliability estimate including uncertainty, and the Bayesian updating of the estimate that is applicable throughout the development program. The whole idea is to allow new project development teams to effectively address the reliability issue at the start of the project with the same focus that they traditionally place on timing, resources and other issues.

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1.1 *Notations*

R_i reliability characterization of a system , estimated at time step, i.

$f(R_i)$ probability distribution function of R_i, representing the uncertainty in system reliability.

λ failure rate for a component, subsystem or system (e.g., failures per vehicle per scaled unit of t (years)) and scale parameter of the Weibull distribution.

t time (in years in the examples).

β slope or shape parameter of the Weibull distribution.

R(t) reliability from a two-parameter Weibull distribution.

$\Gamma(n)$ gamma function, which is the $\int x^{(n-1)} e^{-x}\, dx$ from 0 to 1.

θ parameter of interest.

(a,b) two parameters of the beta distribution, sometimes referred to as the pseudo successes and pseudo failures, respectively.

p probability of success of a trial.

n number of tests.

(α, η) two parameters of the gamma distribution, sometimes referred to as the pseudo failures and pseudo total transformed test time, respectively.

s failures.

τ total transformed test time ($t_1^\beta + t_2^\beta + \ldots$)

2. OVERVIEW OF RELIABILITY UPDATING METHODOLOGY

The reliability logic flow diagram (reliability success tree) for the case study is shown as Figure 1. The base elements of the system, components A, B, C, and manufacturing process MP, are all examples taken from the authors' work on different systems. The sub-system SS and the overall system S are fictitious, and they are incorporated here for clarity so that all of the real world examples may be shown in the same case study. The organization of this "system" allows several aspects of PREDICT to be demonstrated in this case study, including:

1) the development of the appropriate prior distribution for a product component
2) the development of the appropriate prior distribution for a manufacturing process
3) the mechanism for dealing with manufacturing "spills"
4) the development of sub-system and system reliabilities at various times
5) how to perform "what if" studies, and
6) how to process updates at the component and manufacturing process level, using Bayesian and fuzzy logic methods.

The reliability of the product (including the manufacturing process) at any given point in time or at any given step in the overall development program is what has been referred to by the term reliability characterization. "Reliability characterization" includes both the functional calculation of the reliability (point estimate value) and the uncertainty (usually represented by a distribution function) that accompanies the reliability value.

Either the reliability calculation and/or its uncertainty distribution can change due to various changes in the development program (Ref. 4). Changes can occur in both the product design as well as the manufacturing process, which can affect the reliability value and/or its associated uncertainty.

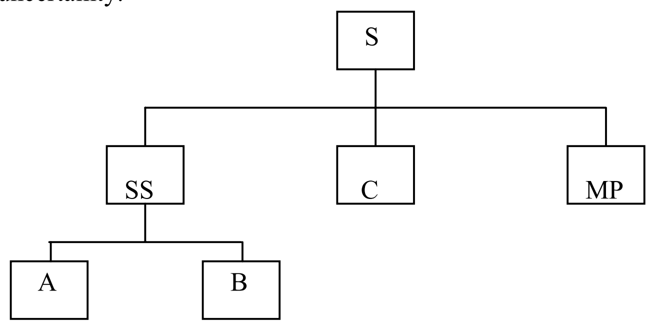

Figure 1. Case Study Reliability Success Tree Diagram

Once a change occurs anywhere in the development process, a new step (i) is designated and a new reliability, R_i, is calculated along with a new uncertainty distribution, $f(R_i)$. The tracking of these reliability snapshots over time is one method of monitoring how the changes in reliability are approaching the target value, as part of the validation effort.

At each reliability snapshot, gaps in the current state of knowledge become apparent, providing the project team with a rational basis for a strategy for deciding where to devote future testing and analysis resources (i.e. a reliability growth plan). In a proactive sense, "what if" analyses allow the project team to develop the optimal test/analysis and validation plan given existing constraints of hardware, facilities, schedule, etc. The power of these "what if" approximations results from understanding the potential impact of the test/analysis, and allowing the project team to judge the usefulness of the effort before it is started.

3. FRAMEWORK

One of the first activities of an organized reliability program is the construction of a reliability logic flow diagram (reliability success tree in this case study) representing the structure of the product under development. The framework of the reliability characterization involves selecting a mathematical model representing the failure properties of the elements in that diagram, making an initial estimate of the parameters identified in the model, and organizing a methodology for updating the model parameters as new information becomes available.

The concept of the "bathtub curve", in which a manufactured product's life span can be represented by infant mortality, useful life, and wearout, has a long history (Ref. 5). It is further suggested here that the "infant mortality" is mainly due to the latent defect sub-population generated during the manufacturing process, and the "useful life" portion is primarily due to latent design defects that manifest

Table 1. Expert Elicitation Results – Components (and related calculations)

	IPTV @ 12 MONTHS			Beta	R @ 12 MONTHS			FAILURE RATE - Lambda		
	BEST	MOST LIKELY	WORST		BEST	MOST LIKELY	WORST	BEST	MOST LIKELY	WORST
A	0.1	1.0	2.0	0.35	0.9999	0.999	0.998	0.0001	0.001	0.2002
B	0.5	1.5	30.0	0.35	0.9995	0.9985	0.97	0.0005	0.0015	0.03046
C	1.0	30.0	145.0	0.75	0.999	0.97	0.855	0.001	0.03046	0.15665

themselves over the life of the product. Identifying and addressing the latent defects in these sub-populations is the objective of a comprehensive design assurance program (Ref. 6). The final portion of the bathtub curve, wearout, is due to the failure mode(s) that dominate the design life of all of the manufactured product built to the intended design. A design assurance program is organized to identify these failure modes through test to failure, and mitigate their effects by driving their occurrence beyond useful life. For the purposes of this case study, any wearout failure modes are assumed to occur beyond useful life, and are not, therefore discussed here.

The two parameter Weibull may be used to model both the defect sub-population due to the product design, components A, B, and C in Figure 1, as well as the defect sub-population due to the manufacturing process, element MP in Figure 1 (Ref. 5).

The two-parameter Weibull expression for reliability is given in eq (1).

$$R(t) = \exp(-\lambda (t^{\beta})) \quad (1)$$

This version of the Weibull separates the two parameters and often simplifies the algebra and the subsequent Bayesian manipulations (Ref. 7). The challenge is to identify the two parameters; β (the slope), and λ (the failure rate per scaled unit of time) (Ref. 7). Section 4 describes the elicitation of expert judgment which is used to develop the initial (or prior information-based) estimate of the model parameters, and also describes the initial reliability characterization. Section 5 describes the use of Bayes Theorem to update the reliability characterization by updating the model parameters. Three examples of updates are provided. One describes reliability updating when the uncertainty associated with new information is best characterized using fuzzy logic methods, and in particular, membership functions.

4. EXPERT JUDGMENT AND THE INITIAL RELIABILITY CHARACTERIZATION

To obtain an initial overall reliability estimate, R_0, of the entire system S in the case study, estimates of component and manufacturing process reliabilities (with uncertainties) were elicited from teams of subject matter experts. Elicitation of expert judgment is described in detail in (Ref. 8). Table 1 lists the information developed for the product components A, B, and C. Specifically, the anticipated number of incidents per thousand vehicles (IPTV) were estimated at 12 months of field use. Estimates were made for the most likely situation, as well as the best possible and the worst case envisioned. An estimate was also made of the slope parameter, β (the decay rate of the failure rate in the Weibull formulation). No information was elicited for the subsystem SS, or the system S, whose reliabilities are defined by the logic flow diagram (Fig. 1), and the reliabilities of elements A, B, C, and MP.

Table 2 lists the information developed for the manufacturing process MP. Estimates were made for the most likely, best, and worst case measures of first time through defects, as well as the most likely amount of product generated with latent defects, measured in parts per million (PPM). Other information developed included estimates of the number and duration of spills (inspection failures) anticipated, and the expected location with regard to where the latent defect would manifest itself (percentage split between the next assembly plant or the field). Finally, an estimate was made regarding the anticipated time to failure that would be experienced if the latent defect were indeed fielded.

To develop component reliabilities for elements A, B, and C, the estimates for IPTV at 12 months (unreliability) were converted to failure rate estimates for λ using eq (1) and the estimate for β, also shown in Table 1. Curve fitting techniques were then used to transform the uncertainty expressed in the expert elicitations into distributional information for the failure rate, λ. Reliability estimates were then calculated in a simulation, sampling from the λ distribution. For component C, a distribution of reliability at 36 months (that point being of interest to the project team) was developed using a Monte Carlo simulation of eq (1) and

Table 2. Expert Elicitation Results – Manufacturing Process (and related calculations)

	FIRST TIME THROUGH			PPM	SPILL	SPILL	SPILL	LOCATION		
	BEST	MOST LIKELY	WORST	MOST LIKELY	FREQ	TIME	%	PLANT	FIELD	MILES
MP	1%	2%	5%	2000	10 / year	8 hours	0.042	10%	90%	4,000

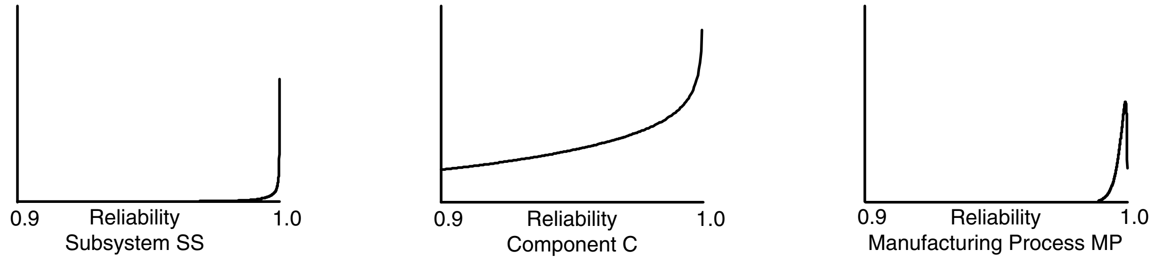

Figure 2. Reliability Distributions at 36 Months

distributions for λ, as shown in Figure 2. Reliability distributions for components A and B were also calculated in a similar manor. Just as Monte Carlo simulations were used to develop the reliability characterizations for elements A, B, and C, they are also used to propagate the reliability characterizations through to subsystem SS (made up of components A and B in series), as shown in Figure 2. The same technique may be used to propagate the reliability characterizations through to the system level, S, as shown in Figure 3. Note also in Figure 3 that the calculation of reliability distributions at various times is also straight forward using eq (1).

With regard to element MP, curve fitting techniques were again used to transform the uncertainty expressed in the expert elicitations regarding first time through defects, as shown in Table 2. That distribution was also scaled to represent the distribution of generated defects, the most likely value of which (in PPM) is also shown in Table 2.

The manufacturing process impact on product reliability is represented by a distribution made up of samples from both of the aforementioned distributions. The proportion of each distribution is determined by the estimate of "spill", or the period during which process inspections are not functioning as intended. The spill percentage is calculated from the estimate of the frequency of spills and their estimated duration, as shown in Table 2.

The β and λ parameters for the defect subpopulation generated by this manufacturing process are calculated from eq (1), and the estimates (Table 2) of failed product at time zero, and the length of time at which the entire subpopulation is estimated to have failed (two equations in two unknowns).

The impact of the manufacturing process on product reliability, at 36 months in this case study, is again developed using eq (1) and Monte Carlo techniques, and is shown in Figure 2. This information is then available for further analysis, in the same form as the reliability information developed for components A, B, and C.

5. DESCRIPTION OF UPDATING METHODOLOGY

Pooling data from different sources or of different types (e.g. tests, process capability studies, engineering judgment) is usually done with methods that combine the distribution functions associated with the various information sources. Bayes Theorem offers one mechanism for such combination. Bayesian pooling combines information with the following structure: the existing information (data) forms a distribution, called the likelihood. That likelihood distribution is formed from the data/information symbolized by the random variable, x, and it has characteristics (i.e. parameters), such as a mean. That parameter(s) is not considered a fixed quantity but instead, has its own probability distribution, called the prior. The prior is combined with the likelihood using Bayes Theorem to form the resulting or posterior distribution. Bayes Theorem is used to calculate the posterior distribution, $g(\theta|x)$, from the likelihood distribution, $f(x|\theta)$ as shown in eq (2).

$$g(\theta|x) = [f(x|\theta)\, g(\theta)] \,/ \int f(x|\theta)\, g(\theta)\, d\theta \qquad (2)$$

where $g(\theta)$ is the prior distribution on the parameter of interest, θ. Bayesian combination is often referred to as an updating process, where new information is combined with existing information. Simulation methods are often used to accomplish this Bayesian combination, as well as combine or propagate uncertainties (represented as distribution functions) through the logic flow diagram (Ref. 9, 10, 11). This is the approach taken with this case study. It should be noted that updating can be done by combination methods other than Bayes Theorem (Ref. 8).

Three example updates may serve to illustrate these principles. First, note that there is considerable uncertainty around component C (Fig. 2) which is reflected in system S (Fig. 3). The design team chose to redesign component C to increase the reliability of the part. After the changes the team estimated that the new design would most likely result in an

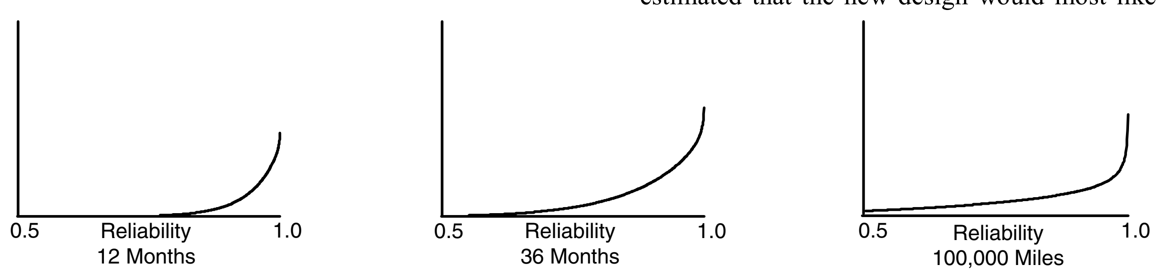

Figure 3. System S Reliability Distributions

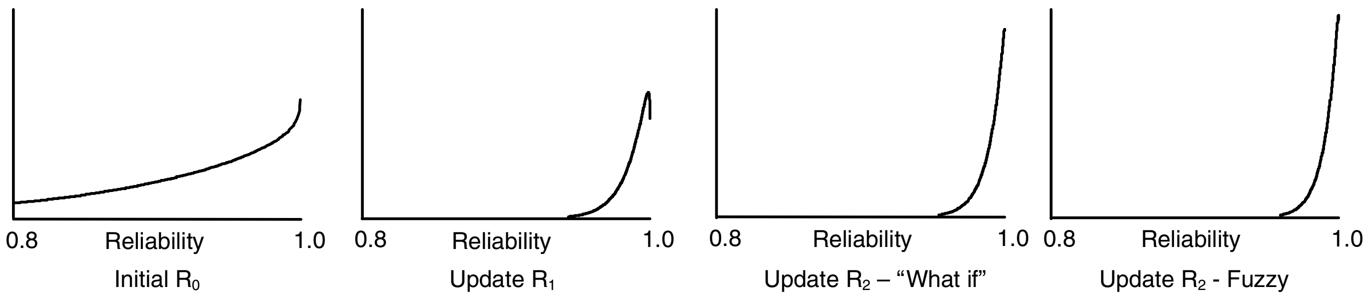

Figure 4. System S Reliability Distributions – 36 Months

experience of 1.00 IPTV after 12 months of field use, and the same value of β (the Weibull slope). Likewise, the best and worst cases were estimated at 0.01 and 10 IPTV, respectively. This resulted in a new prior distribution of λ (the failure rate) for component C (substituted for the old), and is one of the simplest updates possible. The resulting reliability characterizations for component C and the system S at 36 months of field use were calculated as described in Section 4.

system S is component B (note the extended "tail" in the distribution of subsystem SS in Figure 2, and the data in Table 1). That particular design team proposed to conduct a significant test of the part because of the uncertainty of its performance. They asked how much reduction in uncertainty would occur "if" a test of 38 samples were conducted for 185,000 miles, resulting in zero failures. This data would serve as the likelihood in Bayes Theorem. Because the data

Table 3. "If Then" Rules for Mapping Knowledge to Reliability

MEMBERSHIP FUNCTION	**IF** ANTICIPATED PROBLEMS ARE	**THEN** RELIABILITY IS	MEMBERSHIP FUNCTION
a	Very small	Excellent	A
b	Okay	Nominal	B
c	Moderate	Poor	C
d	Large	Unacceptable	D
e	Extremely large	Ridiculous	E

The initial reliability distribution for the system S (R_0) and the resulting distribution after this first update (R_1) are shown in Figure 4 (at 36 months). Note the reduction in uncertainty and the obvious improvement in estimated reliability.

A second update is illustrative of the Bayesian methodology as a tool for planning tests by asking "what if" questions. The logical place for further improvement of

would be in the form of failures per total time on test, it could be used as a likelihood with a conjugate prior distribution for λ and combined using a Monte Carlo simulation as further described in Ref. 2. The resulting posterior distribution of λ would then be used to calculate the reliability distribution at 36 months. The same simulation would propagate the reliability characterization to the subsystem SS and the system

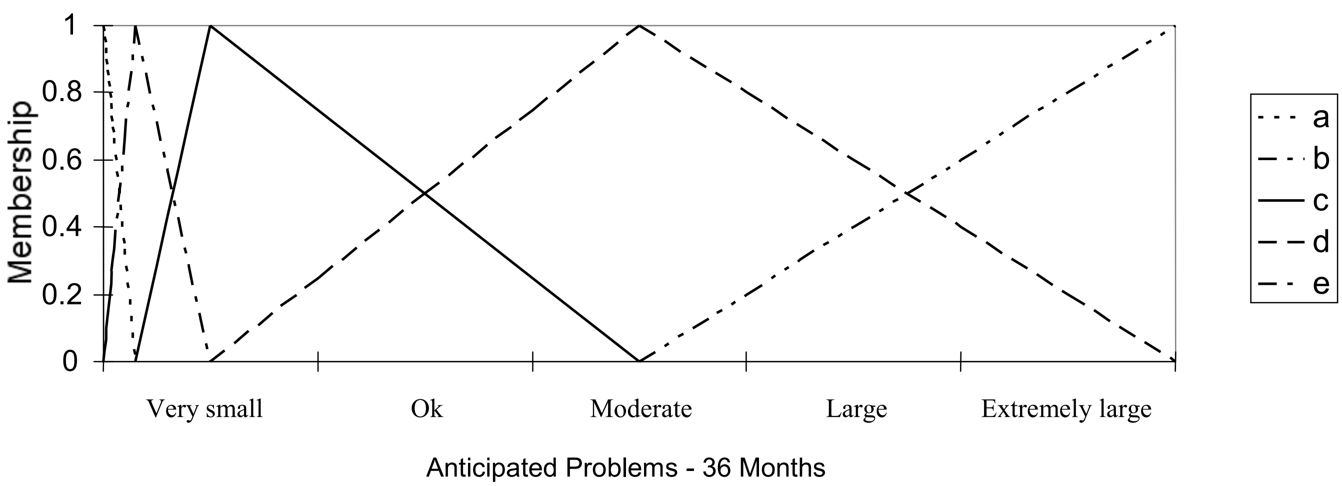

Figure 5. Anticipated Problems Membership Functions

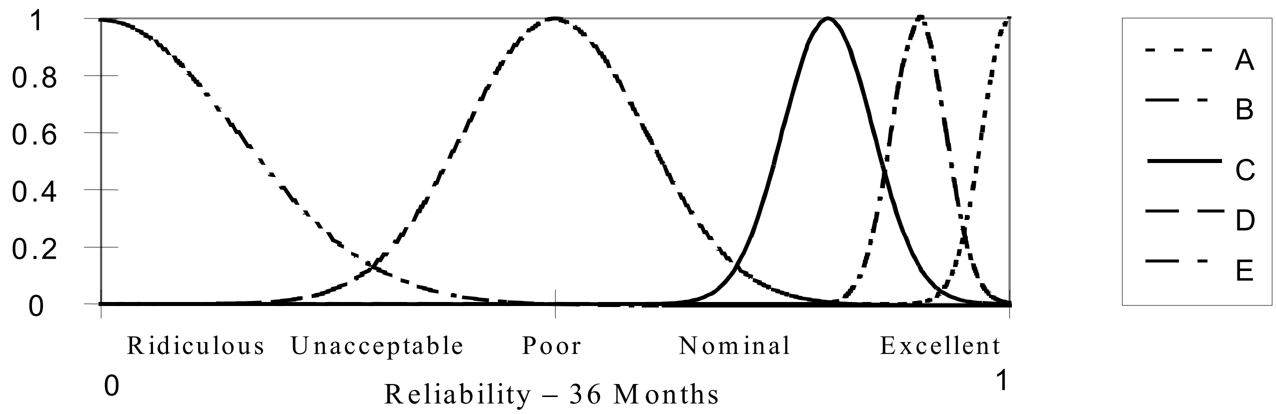

Figure 6. Reliability Membership Functions

S, as described above. The result of running such a simulation for this proposed test is shown as the second update (R_2 – "What if") in Figure 4. Note that the median reliability improves slightly, but the uncertainty is reduced substantially, and this attribute causes an overall significant improvement in reliability, making the actual planning and running of the test a viable option.

For a third updating example, suppose the focus is again on component B. But this time new information becomes available from the engineering judgment of the supplier who provides component B. The supplier's continued development of the component brings to light some issues not considered in the team's judgments used to formulate the prior, yet the prior information is still relevant for inclusion into the analysis. The new information also represents the supplier's different way of modeling the component's reliability and involves uncertainties that are less quantitative in nature. The supplier does not wish to think in terms of the Weibull model in eq. (1), but instead formulates "if then" rules that directly map his feeling of the design into reliability. For example, "if" anticipated problems are very small, "then" reliability is very good. Table 3 illustrates such a rule base. The uncertainties associated with using verbal descriptions can be quantified using methods from fuzzy logic based on Zadeh's fuzzy set theory (Ref. 12). Membership functions (Figures 5 and 6) provide the quantification mechanism for both linguistic terms and reliability descriptors at 36 months.

Specifically, the triangular membership functions in Figure 5 are for five levels (a-e) of verbal descriptions corresponding to the linguistic terms shown in Table 3 {very small, okay, moderate, large and extremely large}. Similarly, the normal appearing membership functions in Figure 6 indicate the five levels (A-E) for reliability corresponding to the additional linguistic terms in Table 3 {excellent, nominal, poor, unacceptable, ridiculous}. The reliability membership functions are normal distributions without a scale factor such that they range from 0 to 1 for membership values. Five rules (Table 3) define mapping of the supplier's feeling of the design into reliability: if anticipated problems are very small (a), then reliability is excellent (A), and so on. It should be noted that the "if then" rules and membership functions may apply to many different components or be specific to one component / process.

The supplier tells us that the range of anticipated problems with component B at 36 months varies from almost none to very small, such that in the worst case they have membership of 0.67 in (a) and 0.33 in (b). Using the rules, the defined anticipated problem membership values are mapped into reliability level (A) with a weight of 0.67 and reliability level (B) with a weight of 0.33. In fuzzy control system methods, the membership functions for reliability levels (A) and (B) are combined based on the weights 0.67 and 0.33. This combined membership function is reduced to a single value (in this case the median) in a process called "defuzzification." The resulting reliability in this case is 0.98. Reliabilities for the lower limit and most likely values of anticipated problems were similarly calculated to form the basis of an uncertainty distribution for characterizing reliability for component B.

To update component B in light of the new information from the supplier, the question becomes how to combine the supplier's fuzzy generated reliability uncertainty distribution with the probability distribution function formulated from the team's prior information. It can be shown that Bayes Theorem is again useful in a theoretical sense for solving this problem because membership functions can be treated as likelihoods (Ref. 13, chapter 2). Therefore, the new information from the supplier's rules and fuzzy membership functions can be used to form a likelihood distribution function for reliability that may be combined with the reliability distribution function provided by the team's prior information.

The supplier's fuzzy generated reliability uncertainty distribution was used as the likelihood for the Bayesian updating of the prior. The change in reliability of component B after this update is similar to that of the previous update for the proposed 38 tests, and is shown as the third update (R_2 – Fuzzy) in Figure 4. The uncertainty after the fuzzy update is reduced, while the median remains essentially the same. The similarity between the results of the "what if" update and the fuzzy update is noteworthy because it illustrates the fact that information of any type (test, judgment, computer simulation) can be valuable in achieving the goals of reducing uncertainty and improving reliability.

Although the use of fuzzy logic may be quite helpful in applications where only qualitative information is available, direct updates using quantitative data are always possible as described in Ref. 3. In addition, useful approximations exist that are helpful for planning purposes involving potential component tests and manufacturing process capability studies. These are also described in detail in Ref. 3.

Characterizing with large uncertainty the initial reliability of a new product under development, and then working to reduce that uncertainty has been found to be a culturally acceptable way to address the reliability issue. The PREDICT methodology may prove useful in facilitating this approach. The methodology is flexible enough to integrate information at various stages of product development, including the asking of "what if" questions. Also, as has been shown, updates of various types are possible, including information that is fuzzy in nature. If application of this methodology further assists a project team in successfully including the reliability issue earlier in its day to day activities involving performance, cost, and timeliness, it will prove to be a powerful additional tool in the development of a high reliability product.

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Dr. Booker received her Bachelor of Science degree in Meteorology / Engineering, her Master of Statistics and Ph.D. in Statistics, all from Texas A&M University. Her recent research and development efforts have been in the areas of statistical reliability, information integration methods, and analysis of expert opinion. During her career, she has co-authored two books: one on Eliciting and Analyzing Expert Judgment: A Practical Guide, reprinted by SIAM in 2001, and another on Fuzzy Logic and Probability to appear in 2001. She was Group Leader of the Statistics Group from 1992-1998. In 1995, she received the H.O. Hartley award for service to the Statistics profession. In 1999, she was honored as a Fellow of the American Statistical Association and received the prestigious *R&D 100 Award* for the development of the PREDICT methodology.

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Mr. Kerscher is President of Design For Reliability, Inc. Prior to that he held several positions at Delphi Systems and General Motors Corp. He received his Bachelor of Science degree in Electrical Engineering from General Motors Institute and his Master of Science degree in Engineering from the Massachusetts Institute of Technology. He is a Certified Reliability Engineer, holds three patents, and has been elected a member of Tau Beta Pi. In December, 1998 he received his second masters degree in Reliability Engineering from the University of Maryland. In 1999 he received the prestigious *R&D 100 Award* presented by R&D Magazine for reliability activities in conjunction with the Los Alamos National Laboratory. He has delivered papers on reliability / assurance at the Reliability and Maintainability Symposium, European Safety and Reliability Conference, Institute of Environmental Sciences, Reliability Engineering and Management Institute, Spring Research Conference, Product Engineering Technology Conference, Pennsylvania State University Quality Assurance Seminar Series, and the SAE International Congress and Exposition. He has also served as a panel member in these various forums. A member of ASQC, SAE and SRE, Bill has chaired several committees and served as Treasurer, Vice-Chairman, and Chairman of the Mid-Michigan Section of the Society of Automotive Engineers.

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