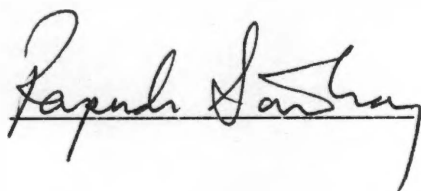


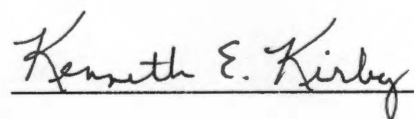
To the Graduate Council:

I am submitting herewith a thesis written by Thomas Brinly entitled "An Iterative Methodology For Reliability Prediction." I have examined the final paper copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Industrial Engineering.

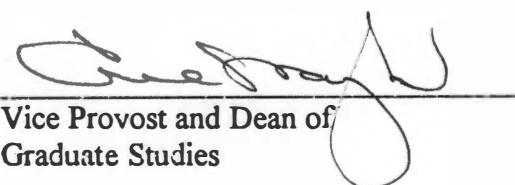

Hampton Liggett, Major Professor

We have read this thesis and
recommend its acceptance:





Acceptance for the Council:


Vice Provost and Dean of
Graduate Studies

An Iterative Methodology For Reliability Prediction

**A Thesis
Presented for the
Master of Science
Degree
The University of Tennessee Knoxville**

**Thomas Brinly
May 2002**

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Dedication

This thesis is dedicated to my parents, Robert W. and Ann G. Brinly for their never-ending support throughout my entire collegiate career, and my brother, Samuel, for his support, patience, inspiration, and humor.

Acknowledgements

I wish to thank the entire staff of the Industrial Engineering department for giving me the tools necessary to complete this endeavor. I thank my entire committee for their input and support, but most importantly, Dr. Liggett, without who's guidance, input, and advice this thesis would never have even begun.

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There was a support community of unbelievable proportions that got me through this, and I cannot begin to thank them all, but to everyone who encouraged and supported me, in whatever manner, thank you.

Abstract

While much research has focused on the development of reliability prediction methodologies for the electronics industry, far less work addresses the evaluation of mechanical rotating equipment. Structured prediction methodologies that consider and attempt to reduce the resource requirements of reliability prediction do not exist in this realm. Various prediction techniques to ascertain the failure rates of mechanical equipment are widely accepted and applied, each having different resource requirements and each inducing different degrees of uncertainty. A methodology is reported herein to assist the engineer in performing reliability prediction. This iterative framework utilizes simulation to evaluate the uncertainty of reliability prediction, and, in each iteration, identifies the critical components that have the greatest impact on the uncertainty of predicted reliability for the entire system. Non-critical components are not included in the more rigorous, and costly, subsequent iterations. Thus, the engineer is presented with a tool by which the resources consumed in reliability prediction may be reduced.

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Chapter I

Introduction

1.0 Introduction

Modern industry runs on equipment. In a perfect world, industry would never be handicapped by that equipment failing. Since there has yet to be the breakthrough development that leads to infinite lifetimes for equipment, the equipment will, at some point, fail. It is the job of the reliability engineer to minimize the frequency and effects of those failures. In order to do so, the reliability engineer must first predict the failures.

The significance of reliability prediction may be found in the standards of the two biggest original users of reliability prediction, the American Department of Defense (DoD) and the British Ministry of Defense (MoD). From United States military standards and handbooks:

Reliability prediction is an essential function in evaluating a design from concept through development and in controlling changes during production. Prediction provides a rational basis for design decisions such as the choice between alternative concepts, choice of part quality levels, derating to be applied, use of proven versus state-of-the-art techniques, and other factors. [13,iii]

“Reliability prediction provides the quantitative baseline needed to assess progress in reliability engineering. A prediction made of a proposed design may be used in several ways.” [14, 3-1]

The British MoD echoes that sentiment:

The principal purposes of a reliability prediction are:

- (a) to provide an early indication of the system's potential to meet the reliability requirement before practical data are available on the system in question [...]
- (b) to reveal aspects of the design which require particular attention to reliability or which present higher risks in relation to the achievement of the requirement;
- (c) to provide inputs to related project activities such as design reviews, design evaluation, trade-off studies, life cycle costing, logistics studies, safety analyses and apportionments. [2, 14-1]

These handbooks and standards represent some of the most well defined documentation of reliability procedures available. The fact that they place such a great importance on the prediction of the system reliability should establish the significance of that task.

Since the term reliability is often used in non-engineering terms, the inexperienced reader might have some uncertainty as to its application in the field of engineering. A common definition of reliability is the probability that a component or system will perform its intended function for a given set of conditions over a specified period of time. It is that probability that most, if not all, decisions regarding the reliability of a system are based upon. The problem lies in assigning a value to that probability. The most accurate method would obviously be to test the equipment under identical operating conditions and use that experience to estimate the probability of it failing. While accurate, the resources needed to perform such testing for all components in a system would quickly become prohibitive. Conversely, ballpark estimates, while

inexpensive to obtain, may not provide the engineer with sufficient precision to make a decision regarding the system.

The probability that equipment will fail is a function of the mean time between failures (MTBF) of the equipment. This value is the average time between failures of a repairable component. When dealing with non-repairable components, the appropriate term is mean time to failure (MTTF). The analysis presented herein will focus solely on non-repairable systems. As discussed by Kales, when discussing non-repairable systems where the analysis begins at time equal to 0, MTTF and MTBF may be used interchangeably. [10] Because of this, when citing other authors, the term MTTF is used, regardless of the notation in the cited source.

There has been a tremendous amount of effort dedicated to assigning values to the MTTF in the electronics industry. Reliability prediction itself was born out of the frequent failures of the electronic tubes used in the manned space program. [6, SP-321] Less common is the available literature and research regarding the reliability prediction of mechanical rotating equipment. A combination of the complexity of causes of failure and the more pressing requirements of electronics in aerospace and military industries have left the reliability engineer in less developed territory when dealing with the types of equipment commonly encountered in industrial environments.

The iterative methodology presented herein will aid the engineer not only in choosing from the commonly accepted component prediction techniques, but will also provide a manner by which to evaluate the uncertainty induced by the chosen technique. The procedure will also reduce the number of components requiring resource consuming analysis in each iteration.

1.1 Problem Statement

In order to make a decision based upon probabilistic analysis, a reliability engineer must obtain an estimate of the reliability of the component, sub-component, or system. Such estimates would be applied in most prescribed methods for comparing the reliability of equipment, and also in certain Reliability Centered Maintenance (RCM) and Streamlined RCM (SRCM) programs. Determining the reliability of the system hinges on providing numerical values for the MTTFs for the components and sub-components.

While there are methods to generate values for MTTFs, most procedures outline the use of the same method for every component in the system. While this is certain to ensure that all of the resulting predictions are thoroughly performed, these approaches require that each prediction be treated as equally important to the overall system reliability prediction. It would therefore be useful for an iterative algorithm to exist that would assist the engineer in selecting prediction methods and evaluating the uncertainty resulting from those selections in such a manner as to reduce required resources needed to perform the prediction phase of any reliability project.

1.2 Scope of Work

Since there are a number of established predictions methods, it would not be beneficial to attempt to duplicate that work. Instead, the current methods will be analyzed, and grouped into generic classifications for use in an iterative method. The strengths and weaknesses of the generic groups will be identified from literature and be used to develop a sequence of methods that will encompass the need for highly precise prediction, highly expedient prediction, or a combination of the two. Highly precise

predictions consume more resources, while highly expedient predictions are faster and cheaper, but typically result in much lower certainty.

In order to reduce the resources required for prediction, each iteration will require a method not only to determine the system reliability and its variance compared to a baseline, but also to identify the components whose predictions have the greatest impact on the system uncertainty. The analysis of the system reliability will be made using Monte Carlo simulation to choose values based upon the distributions of each component's prediction and inserting those values into the equation for system reliability. The impact of each component's prediction on the system reliability will be identified through sensitivity analysis.

This approach relies on two key prerequisites. The first, that a Failure Modes Effects Analysis (FMEA) has been performed to identify the components needing analysis. The second is that the engineer has identified both a minimum value (the lower limit) for the system reliability and a probability that the system's reliability will not fall below that lower limit.

The distributions used in this approach are those most commonly associated with the process industries. The primary focus of this methodology will deal with rotating equipment, although methods designed for electronics and static structures will not be excluded. This type of equipment has frequent industrial applications, and is less frequently discussed in literature.

1.3 Anticipated Results

In order to minimize the number of components that require resource-consuming analysis, an iterative scheme will be developed whereby each component will be first evaluated by a simple, inexpensive method. Unless it is possible to obtain significant historical data without commitment of resources, the predictions garnered from this phase will most likely contain a great deal of uncertainty. The system reliability will be evaluated, compared to some established baseline, and the predictions of those components whose variance has a lesser effect on the system reliability will be deemed acceptable. Those components whose variance have a greater effect on the system reliability will require more rigorous, resource consuming prediction methods.

1.4 Organization

Appendix A.1 will provide readers who are unfamiliar with the concepts of reliability engineering with a short review of the fundamentals utilized in the remainder of the work. The second chapter will review the history of reliability prediction, evaluate currently accepted methods of prediction, and more specifically discuss the details of the problems identified in the problem statement. The iterative methodology developed to choose and evaluate prediction methods will be outlined in the third chapter. A sample problem will be solved in chapter 4 to provide insight into the use of the different prediction methods recommended. The conclusions reached, as well as a discussion of the limitations of the methodology and the potential for future work, will be presented in the fifth chapter.

Chapter II

Literature Review

2.1 History

Reliability prediction first became an area of interest as a result of post World War II technologies. While developing manned flight programs, the notoriously unreliable electronic tubes began to draw attention. Various studies and groups were commissioned to investigate this problem, and as a result, the Advisory Group on Reliability of Electronic Equipment (AGREE) was formed in the 1950s. [6] AGREE was to identify actions that would result in more reliable electronic equipment. It was during this time that reliability engineering as a discipline was conceived.

The 1950s would produce some significant steps in reliability engineering, as efforts were focused on improving the reliability of components through both design and testing. The first dedicated reliability programs were established, and statistical analyses were incorporated into reliability predictions. RCA's TR-1100, "Reliability Stress Analysis for Electronic Equipment," published in 1956 propagated the use of mathematical models in reliability prediction. [6] The first symposiums on reliability prediction were held during these times.

The 1960s would see a virtual explosion of research and publication in the area of reliability prediction. One of the most significant documents in reliability prediction, Military Handbook 217 "Reliability Prediction of Electronic Equipment" (MH-217), was first released in 1962 by the US Navy. MH-217 quickly eclipsed all other standards, partly due to its inclusiveness, and partly due to the defense contractors' forced adherence

to the standard. Also in 1962, the first symposium on physics of failure was held in Rome. The sponsoring agencies, Rome Air Development Center (RADC) and IIT Research Institute (IITRI) would both have major reliability prediction roles in the future. It was during this time period that two distinct groups of reliability engineers evolved, with the physics-of-failure engineers and scientists progressing towards improving equipment reliability, and the systems engineers predicting, testing, and specifying equipment reliability. [6]

In the 1970s, RADC took responsibility for the upkeep of MH-217, and in 1974 released the first revision (MH-217B). Many fundamentally sound models for reliability prediction were developed at this time, but were rejected by the users as being too cumbersome. Physics-of-failure suffered the same fate, requiring information that was simply not available to typical users, and as a consequence were left out of MH-217. Systems at this point were relatively simple, and the individual components were the primary focus. [6]

Integrated circuit (IC) technology forever changed reliability prediction in the 1980s. Industries began to develop their own models for more specific applications, with the automotive and telecommunications industries diverging from MH-217. MH-217 itself was updated frequently, the last occurrence being 1991 when MH-217F was released. ICs provided much more complex systems, and suddenly the individual components were no longer the limiting factor. The traditional approach of collecting field data and quantifying model factors based upon statistical analyses was no longer feasible. Up until this point, the standard measure of complexity had been the number of gates or transistors used. [6]

Since no preference had been established for either physics of failure or empirically based models, the debate rages on. The premises of lower system complexity that earlier models depended upon were no longer viable, and system-wide factors now dominate predictions. [7]

2.2 Current Methods

Ministry of Defense (MoD) DEF STAN 0041/3 identifies the preferred methods of reliability prediction: similar equipment method, extrapolation method, and generic parts method. While other prediction methods exist, their lack of common acceptance and use throughout industry has not yet warranted their inclusion here. [2] Conspicuously absent is a technique known as physics-of-failure. While a popular and effective technique in the electronics industry, publications regarding the application of this technique to mechanical rotating equipment are nonexistent.

2.2.1 Similar Equipment Method

The most accurate data for prediction is based upon similar equipment operating under similar conditions. Often this data is available in-house, and therefore comes with less uncertainty due to variance in operating conditions, but is based upon fewer failures, and therefore less statistically certain. [2] When comparing equipment to determine if similarity exists, the design similarities, manufacturing similarities, and operational environment and load similarities are taken into account. When dealing with equipment whose design is based upon older, but still similar equipment, the small differences can be isolated and evaluated for effect on the equipment's anticipated reliability. [15]

2.2.2 Extrapolation of Tests and Trials

Reliability estimations can be inferred from specific testing of equipment. These tests should mimic as closely as possible actual design details, duty cycle, operating environment, failure definition, and other operating conditions. Data gleaned from this method should be handled with due diligence because of the inherent uncertainties induced when extrapolating data outside of test conditions. [2]

2.2.3 Generic Parts Method

The generic parts method relies on the principle that the reliability of a component can be estimated through a base failure rate multiplied by various factors to account for operating conditions. This method allows for a quick and easily applied analysis of any system in which the equipment configurations are known, and interdependence is low. Since this method is the least self-explanatory, there has been a greater amount of publication concerning it than the other two methods. The widely accepted US MIL-HDBK-217F provides such a process for electronic equipment. The initial efforts in this area for non-electronic equipment were spearheaded by US Rome Air Development Center, although sources can now be found in a wide variety of industrial and military publications. [2]

The Institute of Mechanical Engineer's Guides for the Process Industries publication *The Reliability of Mechanical Systems* offers a clear review of the use of generic parts method and its subsequent data sources for non-electronic equipment. [5]

Generic parts count reliability prediction relies upon the premise that the overall reliability of the system is a function of the number of components in the system and the reliability of those components. The failure rates for many such components can be

found in published databases. IMechE summarized 22 such databases, 19 of which provide data for rotating equipment. [5] The summaries are included in Appendix A.2. Obviously, the accuracy of any prediction is related to the quality of the data it is based upon. Since very few mechanical components are identical, there will be many cases when “closest fit” data or anecdotal estimation must be used to obtain values for the reliability of components. Other sources of data are from the manufacturer or historical data from similar applications. [5]

The general form of the models is

$$\lambda_{xA} = \lambda_o (K_1 \times K_2 \times \dots \times K_n) \times p(A)$$

where λ_{xA} is the predicted failure rate for equipment X in failure mode A, λ_o is the overall Failure Rate for equipment types similar to X, K_i is the stress factor for stress I, and $p(A)$ is the proportion of failures in modes A.

A simplified model for global reliability

$$\lambda_{xA} = \lambda_o \times K_1 \times K_2 \times p(A)$$

where K_1 represents the stress factor for the overall environment and K_2 is the stress factor based on the component nominal rating stress. Tables 1 and 2 [5] show recommended values for K_1 and K_2 . Where sample data is available, confidence limits can be set. Bloch and Geitner also provide a method of predicting the reliability of turbomachinery, then, more specifically centrifugal pumps. This method is an example of the use of publicly available data and modification of it by the application of factors. For turbomachinery, a series of *reliability factors* are used. These factors include: type of equipment, equipment size, number of bearings in train, start-up time, maximum pressures, maximum temperature, coupling, coupling support, starting frequency, piping

Table 1: Environmental stress factors (K_1)

General Environmental Conditions	K_1
Ideal, static conditions	0.1
Vibration free, controlled environment	0.5
General-purpose, ground-based	1
Ship, sheltered	1.5
Ship, exposed	2
Road	3
Rail	4
Air	10
Missile	100

Table 2: Rating Stress Factors (K_2)

Percentage of component nominal rating	K_2
140	4
120	2
100	1
80	0.6
60	0.3
40	0.2
20	0.1

strains, pipe supports, expansion joints, foundation rigidity, vibration, vibration insulation, operators, maintenance personnel, and maintenance facilities. When the values are assigned based upon experience and industrial knowledge, the sum result can be compared with that of another piece of machinery to determine the best choice. [1]

For centrifugal pumps, three factors are identified: speed (in RPM), impeller diameter, and flow rate. The reliability index is the product of these three and may be used to compare different pump options. [1]

2.3 Comparison and Evaluation of Methods

The similar equipment method cannot be used for equipment being placed in a new environment, or new equipment. Additionally, smaller companies are less likely to have this data available, and thus more likely to develop a habit of using generic parts count methods. However, the proliferation of sources of reliability data increase the likelihood of finding data based upon similar equipment. DEF STAN 00-41/3 and MIL-STD-756B identify this method as preferred whenever possible.

While trials and tests can provide an insight into equipment behavior under conditions similar to the operating environment, there are two key drawbacks. Any tests require extrapolation to the operating environment, inducing uncertainty. More significantly, the cost of performing these tests in a manner to reduce that uncertainty can be prohibitive. The financial costs are merely a portion of the resource consumed, as industrial equipments' typical longevity requires a testing time much longer than the time frame generally given for the prediction phase of a project. Because of this, tests and trials are the method of last resort, typically only applied in systems whose consequences of failure, be they monetary, safety or environmental; or system which have little historical reference.

The generic parts count method is an efficient bypass of expensive tests, but induces an unwelcome uncertainty into the prediction. Data should be found that requires the fewest and most certain multipliers. Such data will be encountered in situation where the equipment was not similar enough for the application of the similar equipment method. Since this method does provide information without the commitment required in the testing method, it can be used in situations where variability is not such a high

concern. Because there is inherent variability in the use of the generic parts count method, some type of sensitivity analysis must be performed before accepting the system reliability results.

2.4 Prediction Organization Methods

The military sources give some help in organizing the system prediction. DEF STAN 00-41/3 gives a list of the preferential order of the three groups of prediction techniques, but states that a typical equipment prediction will employ data from all three. [2] The US military standard for reliability prediction only specifies the use of the similar equipment method and generic parts count method, although the use of the similar equipment method is preferred. [15]

While the MoD document mentions the presence of uncertainties resulting from the prediction methods, no manner by which to analyze the uncertainty is offered. The DoD document procedure completely ignores the uncertainties induced by the prediction techniques it identifies. Additionally, neither of the procedures laid out by the MoD or DoD takes into account that the prediction of some components will be more important than others. Because of this, all components will be treated equally, consuming resources that could be diverted elsewhere.

Coit addresses some of the issues of importance in *System Reliability Prediction Prioritization Strategy*. Company-specific field data, accelerated life test results, physics of failure models, publicly available data and empirical models are identified as potential sources of component reliability predictions. Company-specific field data, while the most similar to actual operating conditions, often suffers because of a low number of failures, resulting in a high statistical uncertainty. Accelerated life testing requires

extrapolation from test conditions to the operational environment, inducing both statistical and additional uncertainty. Publicly available data has a low degree of statistical uncertainty because of the high number of failures the estimates are based upon, but a high degree of uncertainty resulting from the lack of knowledge of operational and environmental conditions. Empirical methods (which predict a constant failure rate) and physics-of-failure models (which produce time-dependant failure rates) induce uncertainty due to the fundamental differences in the models. [4]

System prediction as an iterative scheme is discussed, as well as prioritization of prediction activities. The preliminary prediction is performed using previous data or other mechanisms, and as more detailed information evolves, components predictions are updated or replaced. When this method is employed, there will be instances where the uncertainty associated with component predictions will have a negligible effect on the overall system reliability prediction. This is often exhibited in redundant configurations. In these cases, no further resources need to be expended to estimate the component predictions. Conversely, when the uncertainty associated with the component predictions has a large effect on the overall system reliability, more analysis must be performed. [4]

The Reliability Prediction Prioritization Index is introduced as a function of the variance of the component's prediction and the corresponding effect on the system's prediction. This is calculated for every component in the system. Using Pareto Analysis, the indices are ranked to determine a group by which the largest benefit can be made by the smallest assignment of resources. There are four cases where the ranking is overridden. These are

1. Failure Modes and Effects Analysis (FMEA) classifies the component in the highest (most severe) class.
2. Component technology is unproven and has yet to be demonstrated in fielded systems.
3. Component is in a redundant configuration and the effect of common cause failures is believed to be significant.
4. Other system or operational specific condition dictates more detailed analysis independent of the RPPI index. [4]

As mentioned previously, the use of pooled data induces uncertainty into the prediction. When pulling data for a component from N sources variance may be calculated as follow:

$$\sigma_{\hat{\lambda}}^2 = Var(\hat{\lambda}) = \frac{1}{\left(\sum_{i=1}^N n_i\right)^2} * \sum_{i=1}^N \left(n_i \hat{\lambda}_i^2\right)$$

where $\hat{\lambda}_i$ is the i^{th} empirical estimate of the failure rate, $\hat{\lambda}$ is the pooled estimate of the failure rate, and n_i is the number of failures in the i^{th} estimate of the failure rate. [4]

The concept of an iterative process reduces unnecessary commitment of resources to perform needless reliability prediction. The idea that a simple technique can be employed first and only those components needing further analysis identified leads to a more appropriate application of resources in reliability prediction. Unfortunately, the calculation of the RPPI can itself be cumbersome, requiring partial derivatives of the system reliability as a function of each component. This method also lacks a mechanism to incorporate the variance if provided by an individual source. The component

prediction variance is calculated based upon the given failure rates, with the uncertainty coming from the different rates for the sources, with no acknowledgment of the variance each of those sources brings.

Coit introduces a method to determine confidence intervals for complex systems when using estimated component reliability. The method, System Reliability Confidence Intervals (SRCI), is a three-step approach. First, the variances of the components are estimated, the system variance is calculated, and the system reliability CI is calculated based upon a lognormal distribution for the system reliability. [3]

SRCI applies only to systems of active redundancy, with a lognormal distribution for the system reliability, and component independence. Those assumptions limit the applicability to a specific set of systems, and therefore cannot be used for all cases.

A potential solution to the complexity of statistical calculation is the use of Monte Carlo simulation. Orman, Cassady, and Greenwood outline a method for using simulation to generate a model to evaluate the conceptual design of a proposed system. While this is not an entirely new concept, most previous approaches have been generated for a specific system. The approach presented, however, is a general simulation model. Without knowing the specific failure rates for the individual components, mission reliability, average time to failure and average mission cost can be estimated for the system. [13]

The model relies on the number of components in active and/or inactive redundancy, the known failure rate or failure rate probability distribution, the acquisition cost of the component, the length of the mission (required life cycle), and the cost of

mission failure. Over a set of replications, the expected reliability, the MTTF, and the cost of operation are estimated. The confidence interval can also be established.

Gedam and Beaudet provide a more detailed description of the use of Monte Carlo Simulation. In this approach, the block diagram is transformed into a table in an Excel[®] spreadsheet. After proving the randomness of the Excel random number generator, exponential, Wiebull, normal, uniform, and lognormal distributions were employed to simulate system reliability. An expression is provided to calculate the confidence intervals based upon the number of simulations. Further improvement can be made by instructing Excel to display Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs). [9]

The use of simulation provides a method to estimate system reliability and uncertainty without complex statistical calculations. However, the methods used to introduce the failure rates into the simulation are not faultless. Orman uses an optimistic, pessimistic, and most likely technique to derive an equation for the values of TTF to be pulled from. It may not be possible for a set of data sources to be combined into those three points smoothly. Gedam and Beaudet use provided mean and variance values for each component. As in the case with RPPI, those values may not always be possible to calculate.

Table 3 summarizes the characteristics of the organizational methods discussed. If some of the components of the methods were combined, a methodology could be developed that would avoid some of the weaknesses. By following such a methodology, the reliability engineer could perform the system prediction in a manner whereby the resources required would be less than by using any of the methods described.

Table 3: Summary of Organizational Methods

Method	Uncertainty Analysis	Reduces Resources	Identifies Techniques
DEF STAN 00-41/3	N	N	Y
MIL-STD-756B	N	N	Y
RPPI	N	Y	N
SRCI	Y	N	N
Simulation	Y	N	N

Chapter III Methodology

3.0 Prediction Methods

Borrowing the concept of iteration from the RPPI strategy [3], an iterative method is proposed. It will consist of three-phases, each requiring a significant increase in the committal of resources. The First Phase utilizes little expenditure of resources, and is more based upon educated estimates than numerical histories. The Second Phase uses the available historical data. The Third Phase requires life cycle testing under similar operating conditions. Figure 1 provides an overview of the methodology.

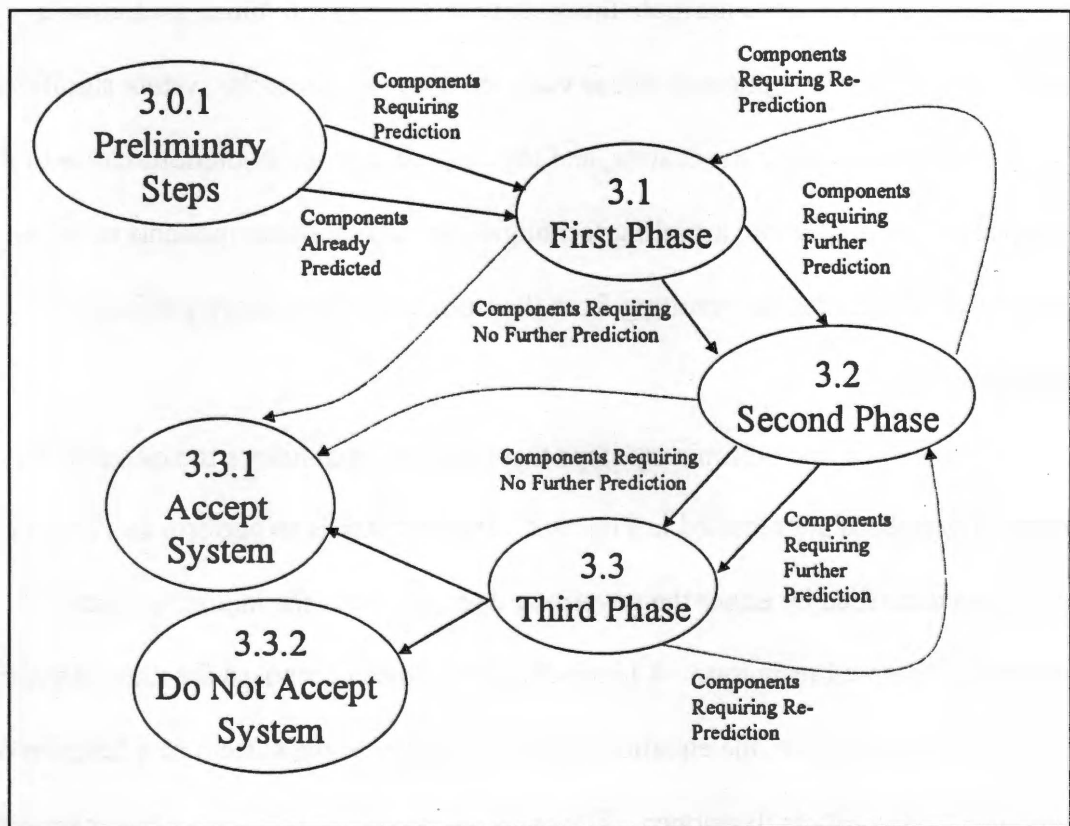


Figure 1. Overview of Methodology

During each phase, Monte Carlo simulation will be used to generate values for the MTTF. These values will be used to calculate the component and system reliability. The results of each iteration will be compared to a set lower reliability limit and the total number below the limit will be tallied. By dividing by the number of iterations performed, the probability of the system reliability falling below the given limit can be calculated. If that probability is too high (hence the prediction is unacceptable), more detailed predictions must be applied. If the system is deemed acceptable, the analysis may be stopped. This differs from the previously discussed techniques in that only the lower limit of reliability is a matter for concern. Before the next phase, the sensitivity of each component and sub-component will be calculated to assist in determining which component's predictions contribute the most to the system reliability prediction's uncertainty. Those components whose variance does not affect the system significantly can be accepted in their current state, and the values for those predictions carried into the next phase. Re-prediction, a cycling technique, permits those components to be re-analyzed if the uncertainty resulting from their prediction becomes significant in subsequent phases.

There are some preliminary steps that must be taken before the evaluation may begin. These steps are outlined in Figure 2. The first step is to perform an FMEA on the system, as described by either the governing documents for the industry, or any commonly accepted technique. A block diagram is then composed for the system, and from this block diagram, the equation for the reliability of the system as a function of the component reliability is developed. The engineer must then establish a lower acceptable reliability limit, R_L . Unless the lower limit is set well below the system's performance

capabilities, the imprecisions of reliability prediction will induce a probability that the system's reliability is actually below that lower limit. The engineer must therefore determine the acceptable probability for this event, Θ :

$$P_R \{R_s < R_L\} = \Theta$$

where R_s represents the calculated reliability of the system.

3.1 First Phase

The First Phase predictions should be made with either readily available data, such as in-house histories or manufacturer's reports or the PERT O-M-P technique. [11] Obviously, if information yielding a more precise distribution is present, the O-M-P technique should not be applied for that component and a distribution based on historical data used in its place. The steps required in the First Phase can be seen in Figure 3.

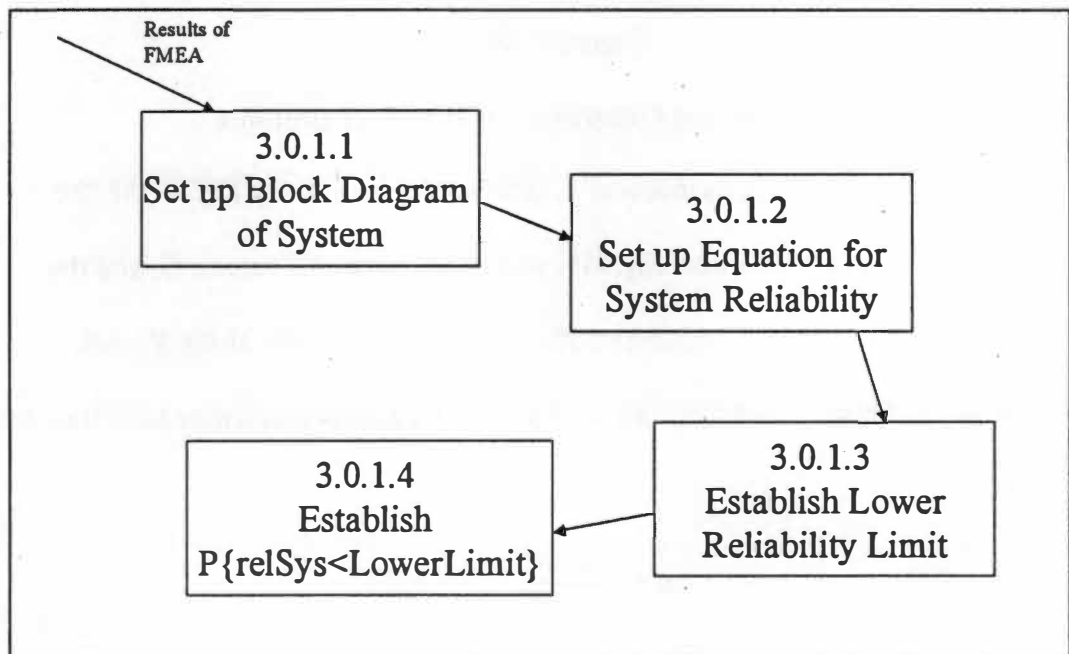


Figure 2. Preliminary Steps

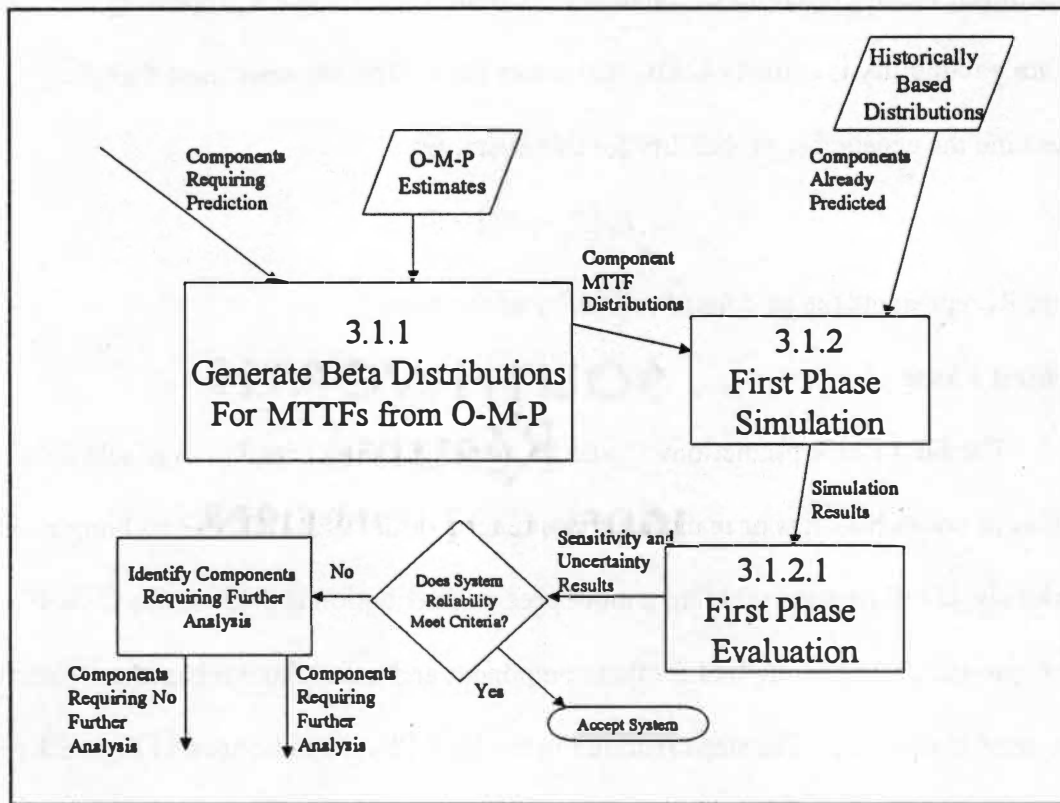


Figure 3. First Phase

3.1.1 O-M-P Estimation and Generation of Beta Distributions

The O-M-P technique involves estimating the most likely MTTF, M , the optimistic value of MTTF (whereby 95% would be below this value), O , and the pessimistic value of MTTF (whereby 95% would be above this value), P . After estimating the times, a beta function can be calculated. The mean time to failure would be [11]:

$$\mu = \frac{P + 4M + O}{6} = MTTF$$

The variance is [11]:

$$\sigma^2 = \frac{O - P}{3.2}$$

The alpha values are defined as

$$\alpha_1 = \frac{(\mu - P)(2M - P - O)}{(M - \mu)(O - P)} \text{ and } \alpha_2 = \frac{(O - \mu)}{(\mu - P)}$$

Sample calculations for these are available in Chapter 4. These values allow the beta distribution to be determined, and then related to back to the MTTF. This allows for easy transition into Monte Carlo simulation, as most software packages can generate beta values based upon the two alpha values. [14] Since the O-M-P estimation will be very broad, Figure 4 shows the circumstances when O-M-P is preferred.

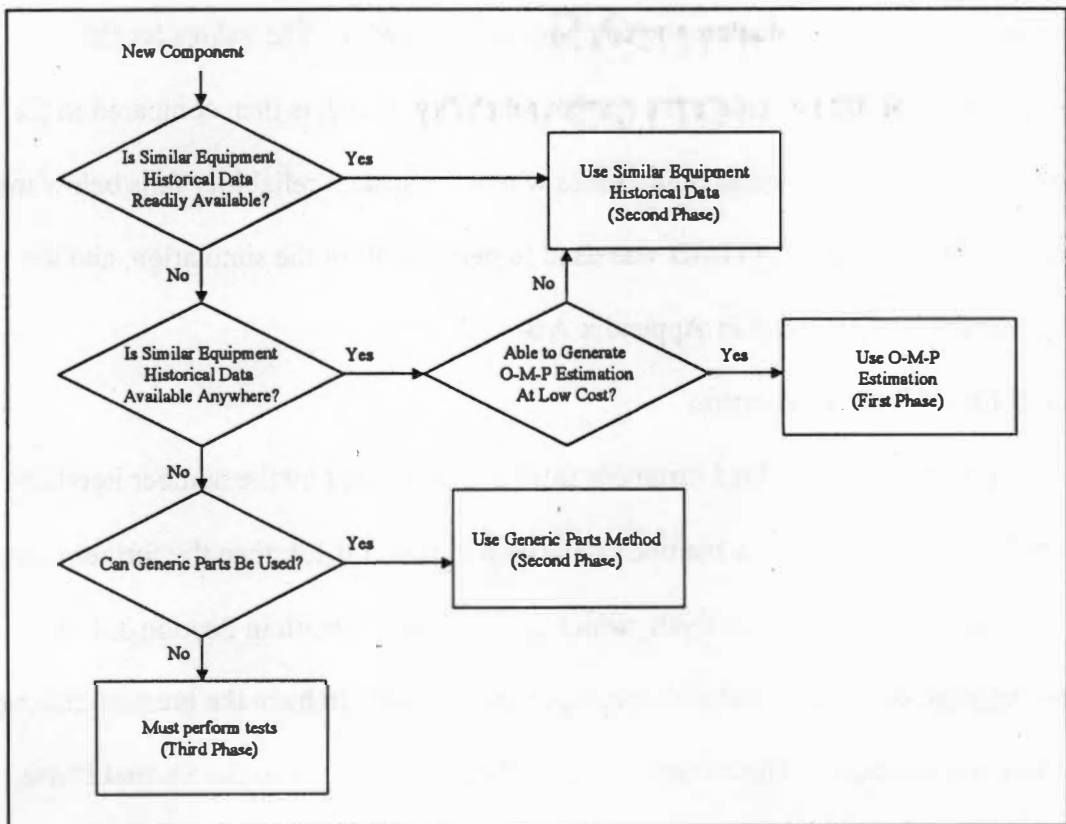


Figure 4. Decision Tree for Initial Data Source Selection

O-M-P estimation is only used when it is possible to develop credible estimates at a lower cost than would be incurred through the use of historical data as outlined in the Second Phase. Since there is no way to generate the O-M-P estimation without some previous experience with the component, a case where no historical data exists will force the immediate use of tests and trials.

3.1.2 First Phase Simulation

Monte Carlo simulation is used to generate values of the MTTF from the beta distribution. In each iteration of the simulation, the values for MTTF generated for every component are used to calculate the components' reliability. The values for the component are used to calculate the system reliability, which is then compared to the lower limit. The total number of instances where the system reliability falls below the lower limit are tallied. MATLAB was used to perform all of the simulation, and the sample codes may be found in Appendix A.3.

3.1.1.2 First Phase Evaluation

If the number of tallied instances from above divided by the number iterations results in a probability below the one established in step 3.0.1.4, then the further analysis will be needed. Sensitivity analysis, which is discussed in depth in Section 3.4, will allow the engineer to discover which component's prediction have the greatest effect on the system uncertainty. These components will require analysis in the Second Phase, while those components whose predictions have relatively minor effects on the system reliability prediction's uncertainty will be left as is. Predictions that are not expected to improve with further analysis will also be taken as is. If however, the probability that the

system reliability is above the set lower limit is greater than the value specified in step 3.0.1.4, the system is acceptable, and no further steps are necessary.

3.2 Second Phase

Any component whose initial predictions affected the system reliability in such a manner as to cause an unacceptable probability of being below an acceptable level must be considered for further study. As noted in the military documents, historical data from similar equipment is preferred, however, since the variability will be calculated, the use of the Generic Parts Method is acceptable if needed. Components requiring the application of the Generic Parts Method will be more likely to require further analysis, as the variance will be higher. The Second Phase borrows the recommended prediction techniques from DEF STAN 00-41/3 and MIL-HDBK-756B.

Since data from pooled sources can come in a few different forms, diligent care must be applied in the application of this data. Recalling that many sources of pooled data reflect different operating conditions, the environmental factors supplied by the generic parts count method or the particular source must be applied to each individual data source before the pooled reliability is estimated. Because of the variety of levels of information provided, there is no simple manner by which to combine data from different sources and still provide an accurate reflection of the variance of all sources. Therefore, the values for MTTF will be provided from all of the sources. In each iteration of the simulation, a source will be selected using a source identifier, and then the value of the MTTF will be selected from that source using Monte Carlo. Figure 5 shows graphically the steps involved in Second Phase.

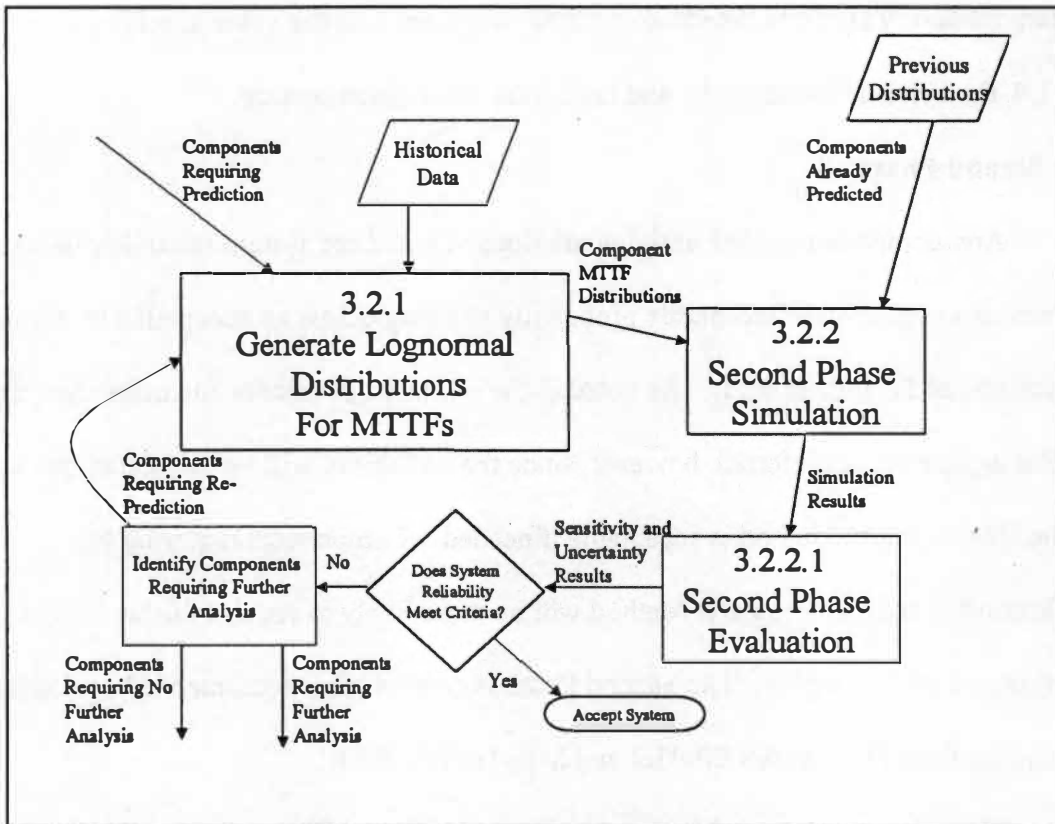


Figure 5. Second Phase

3.2.1 Generation of Lognormal Distributions

Data sources will provide either: the failure rate, the failure rate and the variance, or the failure rate and the 90% confidence intervals. Since most sources give no indication as to the distribution of the estimates, the studies of Moss are relied upon to estimate the distribution. Moss notes that for a majority of process industry equipment (including rotating equipment), the distribution of the estimated MTTF is lognormal. [12] Since the lognormal distribution requires only a mean and a standard deviation, those cases where the variance and the mean are given, no further manipulation of the data is required to set up the simulation. For cases where numerical limits are supplied in

lieu of the variance, the worst case variance may be calculated using Chebychev's inequality,

$$P\{|x - \mu| \geq k\sigma\} \leq \frac{1}{k^2}$$

where $\frac{1}{k^2}$ is the confidence interval. For the common 90% confidence interval, k is 1.05409. Information from sources whose only information is number of failures and mean will be treated as described in RPPI. Recalling that a weighted average is used to calculate the mean, the equation for the variance is [3]:

$$\sigma_{\hat{\lambda}}^2 = Var(\hat{\lambda}) = \frac{1}{\left(\sum_{i=1}^N n_i\right)^2} * \sum_{i=1}^N \left(n_i \hat{\lambda}_i^2\right)$$

The data for this component may now be fit as a lognormal distribution for the simulation. The provided distribution will be used for the simulation.

3.2.2 Second Phase Simulation

As stated, the random selection of the source will be based upon a weighted method. The weight of each source on the can be determined as $n_i / \sum_{i=1}^N n_i$, where n_i represents the number of failures comprising source i , and N represents the number of sources used. The weights are then set up on a cumulative scale such that the probability of selecting a source will be a function of the range of its weight. When a random number is generated from a uniform [0,1] distribution, the number will fall within a range, and the source for that iteration will be identified. A sample of this is shown in Section 4.2.1. Because the simulation in the Second Phase is more complex, a graphical

representation is given in Figure 6. As shown, the simulation must generate two variables for each component. The first, the source identifier, will be a uniform distribution between 0 and 1. This will be compared to the sequence of the source weights and a source will be chosen. The second variable will be generated from a distribution matching the distribution of that source, and used to generate the MTTF. Once the component MTTF has been determined, the simulation proceeds as it did in the First Phase. Note that the predictions that were left as is in Phase 1 are handled identically as the Phase 1 simulation (step 3.1.2).

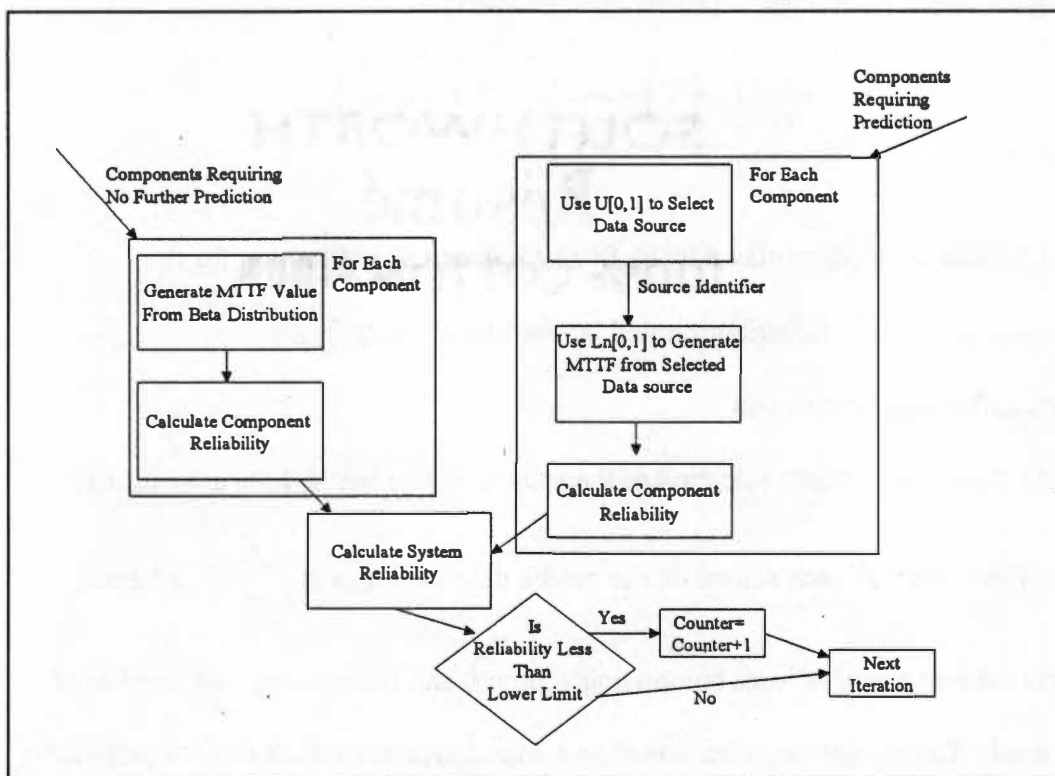


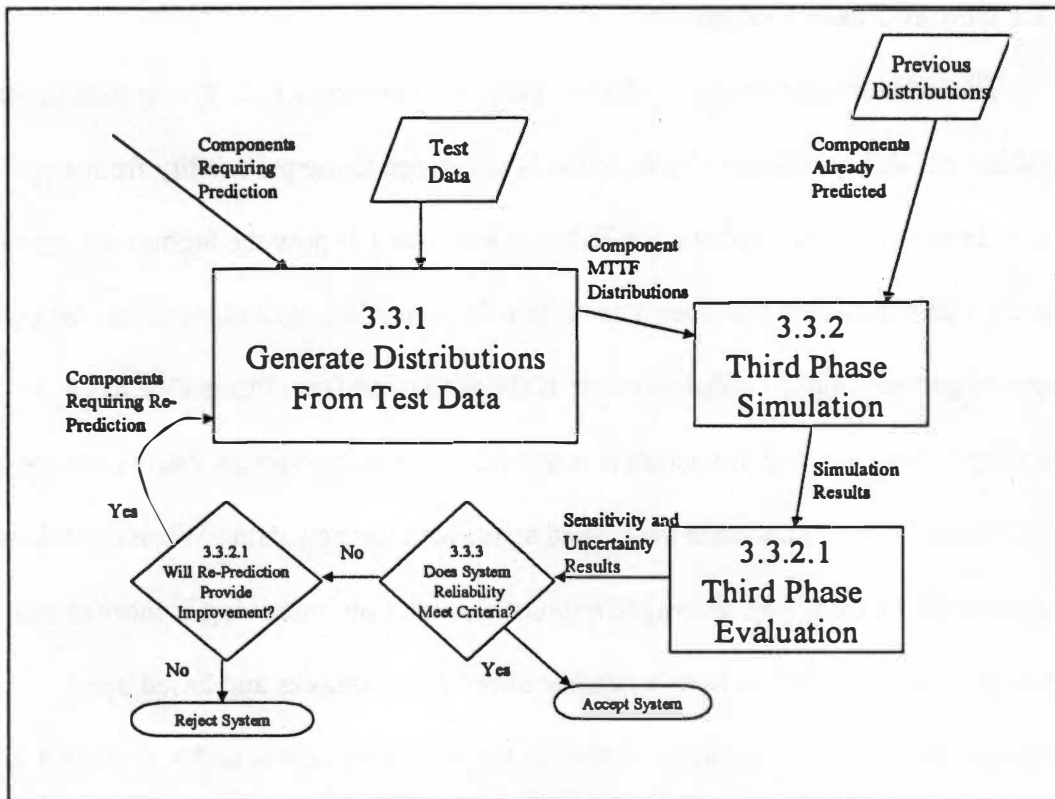
Figure 6. Second Phase Simulation

3.2.2.1 Second Phase Evaluation

The evaluation is similar to the one performed in step 3.1.2. The probability that the system reliability is below the set value is compared to the probability from step 3.0.1.4. In the event that a prediction left as is in Phase 1 is now the highest source of variance, that component becomes a candidate for re-prediction, and historical data will be used to generate a MTTF distribution. If the prediction from Phase One has a possibility to improve, the prediction is now performed using Second Phase techniques, and the Phase Two simulation is performed again with the new data. When considering a component for Phase Three, the expectation of a prediction improving is more crucial. If the historical data was taken from a number of reputable sources and based upon conditions similar to the operating conditions the current system is under, there is a lower probability that the prediction will improve through tests and trials. If this is the case, regardless of the variance induced into the system reliability prediction by that component's prediction, that prediction should be taken as is. Replication of tests already performed is costly, and if it does not improve the prediction, it is not a worthwhile cost to incur. If the historical data is based upon dissimilar operating conditions or based upon a small number of failures, there is a much better chance for improvement in the Third Phase.

3.3 Third Phase

The Third Phase utilizes testing under similar to operating conditions. As shown in Figure 7, the procedure is otherwise similar to the other two phases. The data resulting from similar condition testing must be fit to a function for use in simulation.



While it may be tempting to use a weighted approach as in the Second Phase, doing so assumes that the upper and lower limits represent the extreme limits of the mean time to failure, a highly unlikely scenario in any limited test. Steps 3.3.2 and 3.3.2.1 are similar to the corresponding steps in Phases 1 and 2. Step 3.3.3 is the significant difference.

3.3.3 Acceptance or Rejection of System

If the system does not meet the requirements laid out in steps 3.0.1.3 and 3.0.1.4, the system will be rejected in its current configuration. The system's reliability performance may be improved by either adding components in redundancy, or by replacing certain components with more reliable ones. The sensitivity and variance

analysis will have identified the “bad actors,” those components who have the most detrimental effect on the system reliability.

3.4 Sensitivity Calculations

From Coit, the sensitivity of a subcomponent is the partial derivative of the system with respect to the subcomponent. (COIT) For a single component (R_x):

$$\frac{\partial R_s}{\partial R_x} = \frac{\partial R_s}{\partial R_x} (R_1 * R_2 * R_3 * \dots * R_x) = \frac{\partial R_s}{\partial R_x} R_x = 1$$

For a sub-component in a *k-out-of-n* parallel configuration (R_{xy}), the component sensitivity must first be calculated, and then the effect of each sub-component will be calculated. Care must be taken when identical components are installed in parallel. Any variation will be multiplied due to the reoccurrence of that component or sub-component in the system.

In order to calculate the actual values for the sensitivity, the means and variances must be established. The O-M-P method allows for easy calculation of these. The Second and Third Phase Methods require a more complex calculation. Since the sources are often based upon varying numbers of failure, the mean can be calculated using the weighted average as follows:

$$\mu = \frac{\sum_{i=1}^N n_i MTTF}{\sum_i^N n_i}$$

The variance will be estimated by simulation. The variance of each component's estimation will be calculated as follows:

$$\sigma^2 = \frac{\sum_{j=1}^J (\mu - MTTF_j)}{J-1}$$

where j is the current iteration, J is the number of iterations, and $MTTF_j$ is the MTTF for the current iteration. Sample calculations for these procedures are provided in Chapter 4.

By multiplying each component's sensitivity and variance, the effect of variance on the overall system reliability can be identified. Those components whose variance has little effect on the system reliability would be good candidates to ignore in the next phase.

Also of interest would be the maximum and minimum values of system reliability that a fluctuation in any sub-component could produce. By substituting 1 (maximum reliability) and 0 (minimum reliability) for the sub-component reliability and recalculating the system reliability for each subcomponent, the maximum and minimum system reliability can be calculated. Those components or subcomponents whose reliability could drop all the way to zero or increase to one and not have a significant effect on the system reliability would be good candidates to ignore for future prediction techniques. This may be ignored for systems whose components may be modeled in series, as the results are evident without additional calculations.

Chapter IV Sample Analysis

4.0 Introduction

A hypothetical sample system for consideration is presented in Figure 8. The system consists of 7 components. Component 1 is a single component. Component 2 is a system of 4 identical sub-components in standby redundant configuration, 2 of which must function for the component to function. Component 3 is a system of 2 non-identical sub-components in active redundancy, one of which is required to function for the component to function. The lower limit for reliability is determined to be 91.5% for 1000 hours of

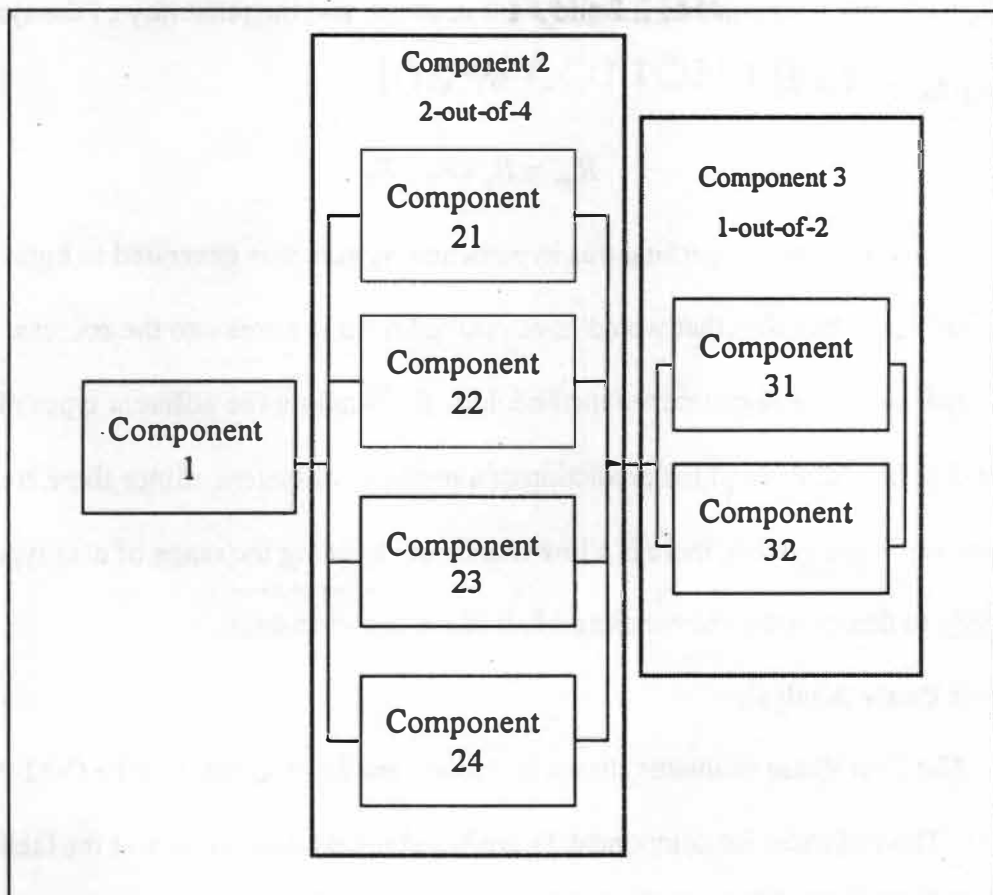


Figure 8. Sample System

operation. The probability of the system reliability being above this value must be 91.5% or above.

The reliability of component 2 is given from Kales where, for a 2-out-of-4 system, the system MTTF is equal to thirteen twelfths of the failure rate of the identical components. ($R_2=13R_{21}/12=13R_{22}/12=13/R_{23}/12$) [10]. Using the same reference for component 3, the MTTF is:

$$MTTF_3 = \frac{\lambda_{31}^2 + \lambda_{32}^2 + \lambda_{31}\lambda_{32}}{\lambda_{31}^2\lambda_{32} + \lambda_{31}\lambda_{32}^2}$$

where λ_x represents the failure rate of component x. The reliability of component three is then $R_3 = e^{\frac{-t}{MTTF_3}}$. Components 1, 2 and 3 are in series, and the reliability of the system can then be defined as

$$R_{sys} = R_1 \times R_2 \times R_3$$

The information regarding this hypothetical system was generated to both realistically simulate data that would have resulted from inquiries into the sources mentioned, and to demonstrate the methodology for handling the different types of data expected to be encountered the prediction of a mechanical system. Since there are so few components in the system, there is a low chance of obtaining the range of data types necessary to demonstrate the handling of all of the common ones.

4.1 First Phase Analysis

The First Phase estimates shown in Table 4 are developed using the O-M-P method. The estimates for component 31 are based upon a long history at the facility, and are taken as very accurate. Components 1,2, and 32 are new to this operating

	Table 4: Data Generated for The First Pass			
	Optimistic	Most Likely	Pessimistic	Mean
MTTF ₁	34000	24000	18000	24666.67
MTTF ₂	36000	19000	12000	20666.67
MTTF ₃₁	32000	21000	14000	21666.67
MTTF ₃₂	34500	27000	17500	26666.67

environment, but 31 and 32 have been in operation in other somewhat similar conditions before.

The mean for component one is calculated as:

$$\mu_1 = \frac{O + 4M + P}{6} = \frac{34000 + 4 * 24000 + 18000}{6} = \frac{148000}{6} = 24666.6667$$

Using the failure rates as the inverse of the MTTFs for components 31 and 32, the failure rates are:

$$\lambda_{31} = \frac{1}{MTTF_{31}} = \frac{1}{21666.67} \quad \lambda_{32} = \frac{1}{MTTF_{32}} = \frac{1}{26666.67}$$

Substituting the values for λ_{31} and λ_{32} into the equation for the MTTF of component 3:

$$MTTF_3 = \frac{\lambda_{31}^2 + \lambda_{32}^2 + \lambda_{31}\lambda_{32}}{\lambda_{31}^2\lambda_{32} + \lambda_{31}\lambda_{32}^2} = \frac{\left(\frac{1}{21666.67}\right)^2 + \left(\frac{1}{26666.67}\right)^2 + \left(\frac{1}{21666.67}\right)\left(\frac{1}{26666.67}\right)}{\left(\frac{1}{21666.67}\right)^2\left(\frac{1}{26666.67}\right) + \left(\frac{1}{21666.67}\right)\left(\frac{1}{26666.67}\right)^2}$$

$$MTTF_3 = 36379.2$$

The system reliability using the means is

$$R_{means} = e^{\frac{-1000}{24667}} * e^{\frac{-1000}{20667}} * e^{\frac{-1000}{36379.2}} = 0.8901$$

4.1.1 Simulation

The system reliability was calculated using 100,000 iterations of Monte Carlo simulation. The system reliability for each iteration was compared against the established lower limit, and the percentage of those values falling below the lower limit was noted. In order to perform the simulation, the alpha variables for the beta function must be calculated, as demonstrated by these calculations for component 1:

$$\alpha_1 = \frac{(\mu_1 - P)(2M - P - O)}{(M - \mu_1)(O - P)} = \frac{(24667 - 18000)(2 * 24000 - 18000 - 34000)}{(24000 - 24667)(34000 - 18000)} = 2.5$$

$$\alpha_2 = \frac{(O - \mu_1)}{(\mu_1 - P)} \alpha_1 = \frac{(34000 - 24667)}{(24667 - 18000)} * 1.333 = 3.5$$

The variance is

$$V = \left(\frac{O - P}{3.2} \right)^2 = \left(\frac{34000 - 18000}{3.2} \right)^2 = 25,000,000$$

The simulation was performed in MATLAB using the code found in Appendix A.3.

After 100,000 iterations, there was a 39.51% chance that the system reliability would be below the established lower limit of .915.

4.1.2 Sensitivity Analysis

As shown in Chapter 3, the partial derivative of each component is 1. This signifies that whatever percent change occurs in any component, the system reliability will change identically. The partial derivative for subcomponents 31 and 32 are not so simply calculated. Therefore, the indirect analysis method was used. The value of the first component's mean MTTF was changed by 25%, and the reliability recalculated. The percentage change was multiplied by the prediction's variance to give the weighted

variance. The value for the mean MTTF was reset, and the same procedure was repeated for all four predictions. The prediction causing the most variance in the system was component 2 (weighted variance =547000), followed by component 1 (203530). Components 31 (84990) and 32 (101900) contributed less to the system variance. These values give an indication as to the respective contribution of their prediction's variance into the uncertainty of the system reliability prediction. Using these, the predictions for components 31 and 32 will be left as is.

4.2 Second Phase Analysis

Data for components 1 and 2 were generated to represent possible values from the source mentioned in Chapter 2, and are shown in Table 5. Recalling that the MTTF is the inverse of the failure rate, the failure rates can be converted into MTTFs easily. In order to preserve uniformity of the analysis, the failure rates have already been converted into MTTFs. The data for component 2 is typical of what would be found in IEEE 500 and CCPS. Data for component 1 is typical of results from ENI and RADC. Variance in the form A% +/- YYY.Y indicates that with A% confidence, the MTTF will be within the given mean plus or minus the YYY.Y. Recalling that the MTTF is the inverse of the

Table 5: Historical Data Values for Second Pass Method

Source	Components				
	1			2	
	MTTF(hrs)	Failures	Variance	MTTF(hrs)	Failure Variance
1	26178	15	90% +/- 1029	35000	35 N/A
2	27000	25	95% +/- 2565	26500	50 N/A
3	31000	150	1200	29560	17 N/A
4	32000	198	1500	29800	18 N/A
5				31500	150 N/A
6				26000	60 N/A
7				26700	40 N/A

failure rate, the failure rates can be converted into MTTFs easily. Variances given as confidence intervals will be transformed into worst-case variances using Chebychev's equation. Source 1 for component 1 would be calculated as follows:

$$P\{|x - \mu| \geq k\sigma\} = 0.9 \leq \frac{1}{k^2} \Rightarrow k \leq 1.05$$

$$1.05\sigma = 1029 \Rightarrow \sigma = \frac{1029}{1.05} = 980$$

The mean for component 1 would be calculated as

$$\begin{aligned} \mu_1 &= \frac{\sum_{i=1}^N n_i * MTTF_i}{\sum_{i=1}^N n_i} = \frac{15 * 26178 + 25 * 27000 + 150 * 31000 + 298 * 22000}{15 + 25 + 150 + 298} \\ &= \frac{15253670}{488} = 31257.05 \end{aligned}$$

4.2.1 Simulation

From table 5, source 1 for component 1 is responsible for 15 of the 488 failures, or 0.0307. For all instances where the source identifier for component 1 is below .0307, the MTTF used will be $26178 \pm 980 * X$, where X is a lognormally distributed random variable with a mean of 0 and a variance of 1. The second source would be chosen when

the source identifier falls between 0.0307 and $\frac{25}{488} + 0.0307 = 0.0819$. When source 1

for component 1 is selected, the value for the MTTF will be taken as

$$MTTF = 26178 + (e^x - e^{0.5}) * 980$$

for x uniformly distributed over the range $[0,1]$, and $e^{0.5}$ represents the mean of the lognormal distribution given by x . [8]

Each iteration chooses a source identifier and a subsequent MTTF for each component. This MTTF is used to generate a value for component reliability. The MTTF is also compared to the mean to establish a variance for each component's MTTF. The component's reliabilities are used to calculate the system reliability. The system reliability is then compared to the lower limit. At the end of the simulation, the total number of incidents where the system reliability was below 0.915 is tabulated and divided by the total number of iterations. The same is done for the variances. Since the predictions for components 31 and 32 were left as is from the First Phase, the values for the MTTF for components 31 and 32 were again taken from the Beta distribution.

After 100,000 iterations, the probability that the system reliability was below the lower limit was 23.79%. This value is below the minimum set for the prediction; therefore, the Third Phase method must be employed for at least one of the components. The calculation of the system reliability using the means of the MTTFs yields a reliability of .9109.

4.2.2 Sensitivity Analysis

Performing the sensitivity analysis as done in step 4.1.2, the predictions for components 32 (101900) and 1 (90650) have the most effect on the system reliability prediction uncertainty, while components 31 (84990) and 2 (85260) have the least. Since the prediction from component 32 was pulled in from step 4.1, some improvement might be expected using Second Phase analysis, so it will be re-predicted. The historical data for the component 32 is found in Table 6. Repeating the same procedure as earlier, but substituting in the new values for component 32 yields $\Theta=0.9135$, which is below the set limit. The majority of the variance comes from component 1 (92362), while components

Table 6: Historical Data Values for
Component 32

Source	MTTF(hrs)	Failures	Variance
1	29500	100	3400
2	20500	50	9000

2 (863180) and 31 (84988) are also significant. Component 32 (25607) contributes the least variance. Since the data for component 2 was compiled from 7 sources, there is a lower chance that the tests required in the Third Phase would provide much improvement. Therefore, only component 1 will be analyzed in the Third Phase.

4.3 Third Phase Analysis

10 components of type 1 were tested for 4 failures each, with the resulting data in Table 7. The mean and variance are calculated as 32271.58 and 2564.66^2 , respectively. The data produces a curve in the shape a lognormal distribution.

4.3.1 Simulation

The simulation methods for the components not re-analyzed in the Third Phase remain the same. For component 1, the test data resulted in a lognormally distributed curve with a mean and a variance. This distribution was used to generate data points for

Table 7: Results of Testing for Component 1

Pump No.	1	2	3	4	5	6	7	8	9	10
TTF (hrs)	30500	29810	31227	31526	30003	34462	34453	30971	31607	31313
TTF (hrs)	30771	32626	30359	42838	30835	31207	33885	31118	30890	30179
TTF (hrs)	31540	29921	32591	37133	37133	33064	34783	29831	29881	32182
TTF (hrs)	30532	32517	32917	34977	32454	34461	29977	30997	32583	30809

component 1. The data from the Second Phase was used for components 2 and 32, and the original O-M-P estimate was used for component 31.

After 100,000 iterations, the probability that the system reliability is above the set lower limit is 91.78%. The reliability based upon the mean values of the MTTFs was .9118.

4.4 Results

The system reliability was found to be above .915 with more than 91.5% confidence. Component 1 required O-M-P estimation, the use of historical data, and testing. Components 2 and 32 required O-M-P estimation and the use of historical data. The O-M-P estimate for component 32 was left as is throughout the entire analysis. Four types of components were predicted using 6 different prediction trials. The only resource-consuming test performed was justified by the uncertainty resulting in the use of the data sources.

Chapter V

Conclusions and Recommendations

5.0 Comparison to Other Methods

Referring to the sample analysis, the methodology presented herein will now be compared to the methods described in Chapter 2. Table 8 summarizes the points made in the comparison.

5.0.1 Comparison to Military Standards

DEF STAN 00-41/3 would have recommended that similar equipment methods were used whenever possible. For any components not subject to the similar equipment method, tests and trials would have been used. Only if this was impossible would the generic parts count method be used. If the estimation from the generic parts count method were in fact precise enough to meet the system reliability goals, then resources required for tests and trials would have been expended unnecessarily. Since DEF STAN 00-41/3 does not provide a method to evaluate the uncertainty of the prediction, this would not have been known.

MIL-HDBK-756B would have required the use of certain data sources, or if those data sources were not sufficient, the use of the generic parts count method. For

Table 8: Summary of All Organizational Methods

Method	Uncertainty Analysis	Reduces Resources	Identifies Techniques
DEF STAN 00-41/3	N	N	Y
MIL-STD-756B	N	N	Y
RPPI	N	Y	N
SRCI	Y	N	N
Simulation	Y	N	N
Methodology Developed	Y	Y	Y

reliability without any indication as to the uncertainty associated with that prediction.

both methods, the resulting predictions would have given a value for the system

5.0.2 Comparison to RPPI and SRCI

RPPI would help divide the components into two groups, the first of which would be subject to the majority of the analysis. The calculation of the RPPI is only based upon the number of failures and the MTTFs of the data sources, and do not take into account the variances in each of the sources. The RPPI would not recommend prediction methods to use, although it would be obvious that the more resource consuming prediction methods would be used for the components in group one. Additionally, there are the four exceptions described in chapter 2 that bypass the values of the RPPI to be placed automatically in group one. If the engineer were not averse to the computational complexity of the RPPI, the resulting information would be merely a separation of the components into two groups for analysis.

The use of SRCI would be impossible for this model because of the presence of standby, rather than active redundancy. If, in fact, the system analyzed were in an active redundancy configuration, then the resulting confidence limits could have been obtained through statistical analysis. Although this approach is a useful evaluation tool in certain cases, the simple system given in Chapter 4 could not have been analyzed using this method.

Both of these methods require more strenuous calculation on the part of the user, and neither takes into account the quality of the data used. The methodology developed here requires less strenuous calculation, takes into account the quality of the data used, and provides an iterative method which identifies methods to procure the data.

5.0.3 Comparison to Simulation Methods

Both simulation methods required that the component reliability be given by a single time to failure function. The model from Orman et al. uses the minimum, maximum, and most likely approach with a triangular distribution. [12] Given that for mechanical components, the anticipated time to failure function is given by a Weibull distribution, the probability of error is high. The resulting anticipated system reliability and confidence intervals convey the same information as provided by the methodology developed here. The model proposed by Gedam allows for the use of multiple distributions (including the exponential, Weibull, and lognormal), and provides the system reliability and confidence intervals as well. [9]

Both of these models were designed as evaluation tools. They provide no information regarding the source of the data entered, and no recommendation for dealing with unsatisfactory results. As discussed earlier, the derivation of time to failure distribution from the MTTF and its confidence intervals is difficult, if not impossible for multiple sources of information.

5.1 Conclusions

A methodology has been presented by which an engineer can more efficiently estimate the reliability of the system by identifying the components whose predictions require the largest expenditure of resources. As seen in the analysis, the statistical manipulation required to use this methodology is minimal. A knowledge of Monte Carlo simulation is required, but the simulation itself is relatively simple. The greatest computational challenge facing the user is the curve fitting in the Third Phase. Most statistical analysis software, some simulation packages and many spreadsheets perform

this task quickly and often guide their users to identify the correct curve to fit based upon the given data.

5.2 Limitations

The methodology developed will only apply to those components where some degree of historical data is available. For a completely revolutionary component, or in a situation where there is no access to data, the methodology has no basis to begin. Additionally, when the distribution of the data is unknown, the only alternative given is the approximation of a beta distribution using the O-M-P method. There is no manner by which to account for modes of failure, and for repairable systems, there is no consideration given to the significance of availability.

The simulation used in the methodology is only effective if the system reliability can be modeled as a function of the components' MTTF. In an interdependent system, where failures cause changes in the reliability characteristics of other components, this is not always the case.

5.3 Recommendations for Further Development

As mentioned, the methodology was developed without regard to multiple modes of failure for components. The incorporation of modes of failure would have many benefits. Recalling when certain sub-components failed may be easier than estimating the failure rate for the entire component. Additionally, maintenance plans typically are geared to affect one or two modes of failure, rather than every mode of failure for the component. Estimating the effects would be more difficult without the ability to break up the different modes of failure. Since some of the sources cited provide data for the percentage of failures represented by each mode, those estimates can be included in the

simulation. The estimates for the modes of failure can be developed using the iterative methodology presented in Chapter 3.

The estimates of mean time to repair (MTTR) are based upon the particular mode of failure as well. While the only prediction made was MTTF, for repairable systems, the availability is a more significant measure. Availability is a function of MTTF and MTTR. MTTR requires another estimation, one fraught with all of the difficulties of MTTF prediction, but also one more dependant on the mode of failure. MTTR estimations are given in some of the cited sources of pooled data, and can be developed using the iterative methodology presented in Chapter 3.

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Appendices

WITHDRAWN
Results
10/10/2017

Appendix A.1

Reliability Background

Moss and Strutt provide an adequate introduction to the basic concepts of reliability.

Using λ to represent the equipment failure rate, the reliability, or probability that the equipment will perform its intended function, over time period t is

$$R(t) = e^{-\lambda t}$$

From this, the probability of failure F in time t is defined as

$$F(t) = 1 - R(t) = 1 - e^{-\lambda t}$$

Bloch and Gietner relate the manner in which these equations can be applied to systems of equipment. Failure rate, λ , is introduced as the expected number of failures per time period. The mean time between failures, MTBF, is then the reciprocal of the failure rate. The reliability, $R(t)$, as a function of time then becomes:

$$R(t) = e^{-\lambda t} = e^{\frac{-t}{MTBF}}$$

When multiple parts exist in a system, they can be in two configurations, parallel or series. For n parts in series, the reliability of the system, R_s , is defined as

$$R_s = R_1 \times R_2 \times \dots \times R_n = e^{-(\lambda_1 + \lambda_2 + \dots + \lambda_n)}$$

For parts in parallel, several scenarios exist. A failure of one component may cause a failure in the system. A failure in all components may be required to cause failure of a system. Bloch and Geitner only deal with these two cases. A third case is possible. A failure of a portion of the components may cause a failure in the system. This last case is described as a k -out-of- n system. The first two cases can be viewed as special cases of the k -out-of- n system. Applying the binary distribution, the reliability of a k -out-of- n system can be represented as:

$$R_s = \sum_{x=k}^n \binom{n}{x} R^x (1-R)^{n-x}$$

For the case when a single part failing causes the system to fail, this translates to:

$$R_s = R_1 \times R_2 \times \dots \times R_n$$

For the case when every part must fail before the system fails [1]:

$$R_s = 1 - [(1 - R_1)(1 - R_2) \dots (1 - R_n)]$$

The afore-mentioned model for a *k-out-of-n* system applies only to non-interdependent components with active redundancy. Active redundancy exists when each parallel component in the system is actively running at all times. Non-interdependent systems only exist where the failure of one component does not affect the reliability of the other components. This scenario is not as frequently seen in the realm of rotating equipment. The more common scenario is standby redundancy, where a component remains idle until it is needed to cover a failure of another component in the system. The most efficient mathematical models for this type of configuration are developed as Markov chains, and have been catalogued for a number of possible configurations. [10] Appendix A.2 provides a short discussion of the use of the Markov chain method in reliability prediction and some sample values for commonly encountered configurations.

Appendix A.2

Summaries of Data Sources Provided by the Institute of Mechanical Engineers [5]

<i>Data Source:</i>	1 CCPS
<i>Full Name:</i>	<i>Guidelines for Process Equipment Reliability with data tables prepared by the Equipment Reliability Subcommittee of the Centre for Chemical Process Safety and Science Applications International Corporation</i>
<i>Published by:</i>	American Institute of Chemical Engineers
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1990
<i>Type of components:</i>	A wide range of chemical process equipment
<i>No. of component types:</i>	76 process equipment type
<i>Type of information:</i>	Failure rates based on both calendar and operating time. Failures of demand are also included where appropriate.
<i>Source of data:</i>	Data sources include plant specific data and general data. Plant specific data reflects plant process, environment, and maintenance practices. Generic data was collated from a variety of sources. All major published sources of available generic equipment reliability and failure rate data were used, including reliability studies, published research works, reliability data banks, government reports containing information gathered from chemical process, nuclear, off-shore oil, and fossil fuel industries around the world.
<i>Type of data:</i>	The data are characterized as equipment failures per 10^6 operating hours for time-related failure rates and failures per 10^3 demands for demand related failure rates. Rates are given for common chemical process equipment. Equipment used for transport of chemicals are not covered. The cause of equipment failures, the means to improve reliability and the 'most' reliable equipment are not addressed.

<i>Data Source:</i>	3 DEF STAN 00-41 pt 3
<i>Full Name:</i>	<i>MoD Practices and Procedures for Reliability and Maintainability, Part 3: Reliability Prediction, Report No. 00-41 (Part 3)/Issue 1 (Issue 2 does not contain this data.)</i>
<i>Published by:</i>	Ministry of Defence
<i>Type of Source:</i>	Standard
<i>Date of publication:</i>	December 1983
<i>Type of components:</i>	Equipment covered in Table 5 (mechanical components) include a variety of static and rotating devices, instruments and connectors. A range of valve types are covered. Equipment covered in Table 6 is limited to accelerometers, actuators, aerals, circuit breakers, counters, gyroscopes, timers, transducers, solenoids and a few miscellaneous items.
<i>No. of component types:</i>	95 mechanical components and 28 electro-mechanical components
<i>Type of information:</i>	Table 5 of this reference contains mechanical components failure rates and Table 6 provides electro-mechanical failure rates. Table 8 contains reliabilities of one-shot items, which may be of some interest to the mechanical engineer.
<i>Source of data:</i>	Reference sources for individual failure rates are not provided.
<i>Type of data:</i>	For each component, a basic failure rate per million hours is not provided, this being considered representative of a 'ground fixed' operating regime. Environmental factors are then listed for 'ground mobile', 'ship protected', 'ship exposed', 'air protected', and 'air exposed' operating regimes. The user is intended to select the factor most closely reflecting his component environment and multiply it by the base failure rate. It is important to note that not all environmental factors are provided for all components.

<i>Data Source:</i>	5 Dexter and Perkins DP-1633
<i>Full Name:</i>	<i>Component Failure Rate Data with Potential Applicability to a Nuclear Fuel Reprocessing Plant.</i> Report No. DP-1633 by A.H. Dexter and W.C. Perkins
<i>Published by:</i>	El Du Pont de Nemours and Company
<i>Type of Source:</i>	Report
<i>Date of publication:</i>	July 1982
<i>Type of components:</i>	A wide variety of static, rotating and reciprocating devices, both electrical and mechanical in nature and having passive, process or safety function. Instrumentation used in nuclear installations receives good coverage.
<i>Type of information:</i>	This document contains an extensive collection of component failure rate data compiled from published literature and a number of computer databases. There are 136 subject categories containing over 1200 individual data points, with special emphasis on components having application in the nuclear fuel reprocessing industry.
<i>Source of data:</i>	Literature source of the data comprised reliability and safety analysis journals published during the period 1970-1980, plus a number of non-journal source. Computer databases searched were the ORNL Energy Data Base and Nuclear Science Abstracts Data Base, and the DIA-LOG Compendex, Inspec, Ismec and Scisearch databases.
<i>Type of data:</i>	Data is presented as an alphabetical list giving failure rates per hour with upper and lower bound points where these are available. A reference number is provided for each component failure rate enabling the user to identify the source via a standard list of references at the end of the document. A few data points are presented in terms of failure rate per demand or per cycle. In a very few cases an indication of the operating environment of the components can be deduced, for example, 'heavy duty', or 'light duty'.

<i>Data Source:</i>	6 EIREDA
<i>Full Name:</i>	<i>European Industry Reliability Data Handbook Vol. 1 – Electrical Power Plants</i>
<i>Published by:</i>	EUROPSTS, 38 rue Sedaine, 75011 Paris, France
<i>Type of Source:</i>	Data collected at 50 French nuclear power plants between 1978 and 1988
<i>Date of publication:</i>	October 1991
<i>Type of components:</i>	Mechanical components (pumps, valves, tanks, heat exchangers, filters, compressors, auxiliary turbines, etc), electrical components (batteries, circuit breakers, transformers, motors and generators, power distribution etc) and instrumentation and control equipment.
<i>No. of component types:</i>	92
<i>Type of information:</i>	A double page spread is devoted to each component type. The first page details engineering characteristics (type, r/min, power, pressure, temperature, medium environment etc) and operational characteristics (operating mode, running hours and/or demands per year, maintenance policy and test frequency). It also has a coloured photograph of the component. The second page contains a table of failure rates (with error factors) for one or more failure modes (critical failure modes only) and mean repair times. Background information in each Table includes the number of components/plants and number of plant/years, and a separate table lists comparable failure rates drawn from other published sources where available (mainly WASH1400, IEEE 599, RKS 85-25 and American nuclear power station data.) Introductory sections define the scope of the data book and discuss the choice of components, boundaries and statistical methods used, and an appendix indicates how the data could be applied to other industries.
<i>Type of data:</i>	Mainly pooled data from similar designs of power stations. Only critical failures have been selected, i.e. complete loss of function of the component. Voluntary shut-down of a component to avoid severe degradation is not necessarily considered to be a critical failure. Expert judgment has been used to components with sparse data.

<i>Data Source:</i>	7 ENI
<i>Full Name:</i>	<i>ENI Reliability Data Bank – Component Reliability Handbook</i> , by G. Galvanin, V. Colombari, and C. Bello
<i>Published by:</i>	Ente Nazionale Idrocarburi (ENI)
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	October 1982
<i>Type of components:</i>	Valves, pumps, motors, generators, turbines, transformers, switch-gear, relays, controllers, switches, thermocouples, transmitters, detectors, annunciators, cables, compressors, bursting disks, etc.
<i>No. of component types:</i>	30
<i>Type of information:</i>	Handbook summarizing the contents of the ENI Data Bank and giving component and equipment failure rates in convenient form.
<i>Source of data:</i>	Statistical processing of even reports from various sites within ENI Group during the periods 1978-1982. Since ENI is the national industry responsible for hydrocarbon development within Italy, it is likely that much of the data originates from offshore installations and petrochemical process facilities. The total sample size was about 6000 items.
<i>Type of data:</i>	All failure rates are expressed as failures per year; there are no failure on demand rates. Sample sizes, numbers of events, and operational experience in years are provided. Failure modes are expressed as occurrence rates for events categorized as major failures (loss of function), minor failures (reduced performance) or leakage. Mean times to restore to service are provided, expressed in hours.

<i>Data Source:</i>	8 Greene and Bourne
<i>Full Name:</i>	A.E. Green and A.J. Bourne <i>Reliability Technology</i>
<i>Published by:</i>	Wiley-Interscience
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1972
<i>Type of components:</i>	The tables cover mainly electronic components with some mechanical components
<i>Type of information:</i>	The book outlines the theory and application of reliability technology to the evaluation and validation of the reliability of industrial systems. A range of reliability data is presented in tabular form in appendix A.
<i>Source of data:</i>	The data has no referenced source.
<i>Type of data:</i>	Table A.7 lists average failure rates ($f/10^6$) for electronic and mechanical components. Table A.8 provides stress level factors for use in parts count analyses for the overall environment, rating and temperature.

<i>Data Source:</i>	9 IAEA-TECDOC
<i>Full Name:</i>	International Atomic Energy Agency
<i>Published by:</i>	International Atomic Energy Agency
<i>Type of Source:</i>	Database
<i>Date of publication:</i>	1989
<i>Type of components:</i>	Mechanical components, electrical components, instrumentation and control, (I&C) equipment and emergency power sources.
<i>No. of component types:</i>	430
<i>Type of information:</i>	Failure rates and probabilities for modes of failure and environments
<i>Source of data:</i>	The IAEA Data Base Version 1.0 consists of about 1000 records compiled from 21 different data sources and include all data from nuclear power plant components usually modeled in PSAs (probabilistic safety assessment).
<i>Type of data:</i>	The IAEA Data Base contains about 1000 records. More than 430 different components are addressed, having an average 2.2 failure modes.
<i>Note:</i>	The database will run on IBM compatible personal computers.

Data Source:	10 IEEE 500
Full Name:	<i>IEEE Guide to the collection and presentation of electrical, electronic, sensing component and mechanical equipment Reliability data for Nuclear Power Generating Stations. Std 500-1984</i>
Published by:	The Institution of Electrical and Electronic Engineers
Type of Source:	Book
Date of publication:	1983
Type of components:	A wide range of mechanical and electro-mechanical components plus instrumentation and some light electrical components. Components are divided according to function into seventeen chapters, each with a hierarchical structure. There is no alphabetical index of components.
No. of component types:	Approximately 1200
Type of information:	Data is presented in the form of a hardback standard comprising 1424 pages. Each component is presented on a standards format Which locates it in its hierarchy and gives, where available, failures per 10^6 hours, failures per 10^6 cycles and out of service time (or repair and restoration time). If several sources are combined on one data sheet, the highest and lowest values are also given. Rates are given for different failure modes where possible and a reference to the source of data is given. Composite component data sheets are created by combining data from lower down the hierarchical structure, where meaningful.
Source of data:	Data relates mainly to American nuclear power station experience but some American general industrial and military sources. A structured expert judgment method had been used to fill gaps in the collected data.
Type of data:	Some specific, some pooled. Size and application information is given for some components. Little environmental information is given but tables of environmental factor multipliers are given for electrical components.

<i>Data Source:</i>	11 LEES
<i>Full Name:</i>	<i>Loss Prevention in the Process Industries</i> , F.P. Lees
<i>Published by:</i>	Buttersworth, London
<i>Type of Source:</i>	Book (2 Volumes)
<i>Date of publication:</i>	1980
<i>Type of components:</i>	The appendices in Volume 2 contain a wide range of data on process plant components, mechanical and electrical items, and a failure and event database used in the 1978 HSE Canvey study. Volume 1 contains a human error database and reference is made to common cause failures.
<i>Type of information:</i>	The books give detailed models and methodologies for extensive application of loss prevention and risk analysis. A wide range of reliability data is given including an extensive reference list.
<i>Source of data:</i>	The main sources of reliability data are UKAEA, USAEC and Green and Bourne (q.v.), however, many other sources are used including the author's own work which is listed in the references. Lees <i>et al.</i> , then Lees published a series of journal articles in the early 1970s on the reliability and failure modes of instruments in the chemical plant environment. These were followed by a more extensive article which also included maintenance man-hours and a paper adding nuclear data was presented at the IchemE. Symposium 47.
<i>Type of data:</i>	Data is presented in a series of tables according to generic type with the source reference. Failure rates, in some cases broken down into failure modes, event rates, human error probabilities and outage data are given.

<i>Data Source:</i>	12 MIL-HDBK-217F
<i>Full Name:</i>	Military Handbook – <i>Reliability Prediction of Electronic Equipment</i> – Issue F
<i>Published by:</i>	US Department of Defense
<i>Type of Source:</i>	Report
<i>Date of publication:</i>	December 1991
<i>Type of components:</i>	The reference pertains principally to electronic/electrical small devices, e.g., semiconductors, wave tubes, resistors, capacitors, inductors, relays, switches, connectors, meters, lamps, filters, fuses. However, it also contains data for some electromechanical rotating devices, e.g., motors.
<i>No. of component types:</i>	19 but many sub-classes
<i>Type of information:</i>	The handbook contains two methods of reliability prediction – Parts Stress Analysis and Parts Count Analysis. The former method is of interest from a data source point of view (see type of data section below). The latter is used mainly in the conceptual design phase
<i>Source of data:</i>	The source of data is unspecified, although the report states ‘the failure rates and their associated adjustment factors presented herein are based upon evaluation and analysis of the best available data at the time of issue’.
<i>Type of data:</i>	Each device is assigned a base failure rate, expressed in failures per million hours, which is then multiplied by a series of environmental factors chosen according to the manufacturing method, quality level and duty, to give a corrected rate for the selected application. There are no failure on demand rates.
<i>Note:</i>	Although this document is now in the public domain, it was initially produced for military use. Many software packages are available to carry out prediction to MIL HDBK 217.

<i>Data Source:</i>	13 NPRD-91
<i>Available from:</i>	Reliability Analysis Center, PO Box 4700, Rome, New York, 13441-8200
<i>Type of Source:</i>	Report and database
<i>Date of publication:</i>	1991
<i>Type of components:</i>	General engineering components approximately 50 per cent are mechanical including hydraulic and pneumatic components. The remainder are divided between electro-mechanical, instrumentation and light electrical components.
<i>No. of component types:</i>	1400
<i>Type of information:</i>	The data has been collected by the Reliability Analysis Center as an unclassified report. Data for each component type is separated, where possible into different operating environments. For each entry, the number of data sets is given, with the number of failures and operating hours. From these are derived point failure rate estimates together with 80 per cent upper level and 20 per cent lower level values if failures occurred and 60 per cent upper levels if no failures occurred. Corresponding MTBFs are printed in a separate table. Another section of the report tables failures mode distributions for the component types. Some of the information is presented graphically. The data is also available on a PC-accessible floppy disk.
<i>Source of data:</i>	The course of the reliability data is not specified in detail, but is predominantly from American military sources with substantial input from commercial/industrial sources. Sources are labeled M(military) of C(commercial)
<i>Type of data:</i>	Data is generic and pooled where appropriate. No information is given about size or application although the environment is stated.

<i>Data Source:</i>	14 OREDA 84
<i>Full Name:</i>	<i>Offshore Reliability Data Handbook (1st Edition)</i>
<i>Published by:</i>	PennWell Publishing Company on behalf of the OREDA participating companies
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1984
<i>Type of components:</i>	Covers only equipment used in the offshore oil and gas industry and includes safety systems, e.g., firefighting and ESD systems, process equipment, e.g., pumps, compressors, valves, power generation, drilling, and lifting equipment.
<i>No. of component types:</i>	Around 170 different offshore components are covered
<i>Type of information:</i>	It has the advantage that environmental factors normally associated with the relatively severe operating conditions do not need to be considered.
<i>Source of data:</i>	The data was collected from a group of eight participating companies operating installations in the North Sea and the Adriatic Sea during the period 1983-1984.
<i>Type of data:</i>	Data is presented in tabular form grouped by taxonomy, giving the total population of items and the number of different data sources (samples) for each component type. Calendar and operational times are provided and also the numbers of demands for non-rotating mechanisms such as valves. Failure modes are categorized as critical (total loss of function), degraded (partial loss of function), incipient (function not immediately lost but likely future impairment of performance), or unknown. The numbers of recorded failures under each category are given. Failure rates are expressed in failures per million hours; lower and upper bounds as well as mean rates are listed where available. In some cases repair data is provided in terms of active repair time and repair man-hours. System boundary diagrams are listed for each component.

<i>Data Source:</i>	15 OREDA 92
<i>Full Name:</i>	<i>Offshore Reliability Data Handbook (2nd edition)</i>
<i>Published by:</i>	The Oreda participants and distributed by DnV Technica.
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1992
<i>Type of components:</i>	Covers equipment used in the offshore oil and gas industry and includes; process systems, safety systems, electrical equipment, utility systems, crane systems and drilling equipment.
<i>Type of information:</i>	For each item covered, the quantitative generic information consists of: Failure modes, failures rates for each failure mode, repair, e.g., active repair time given in man hours, supportive information. Qualitative information is also included covering; item descriptions, offshore applications, environmental and operational conditions, failure causes and additional descriptions of failure modes, data sources and item boundary specifications.
<i>Source of data:</i>	The data was collected from a group of ten participating companies operating installations in the North Sea between 1983 and 1992.
<i>Type of data:</i>	Data is presented in tabular form grouped by taxonomy, giving the total population of items and the number of different data sources (samples) for each component type. Format is similar to OREDA 84.

<i>Data Source:</i>	16 RKS/SKI 85-25
<i>Full Name:</i>	<i>Reliability data book for components in Swedish nuclear power plants.</i>
<i>Published by:</i>	RKS-Nuclear Safety Board of the Swedish Utilities, SKI-Swedish Nuclear Power Inspectorate.
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1987
<i>Type of components:</i>	Pumps, valves, instruments, and electrical power equipment such as circuit breakers, transformers, standby generators.
<i>No. of component types:</i>	54
<i>Type of information:</i>	Data is reported in English in the form of a paperback book and comprises 145 pages. One table is given to each component type. It contains a table of failure rates for one or more failure modes and average repair times for each of eight nuclear reactors. Background information in each table includes the number of components, demands, and failures in the sample. Most tables include a schematic diagram of the component and its related services and control equipment to define the component boundaries. Introductory chapters define the scope of the data book and discuss the choice of components, boundaries, and statistical methods.
<i>Source of data:</i>	Data collected at four Swedish nuclear power stations up to 31 December 1982.
<i>Type of data:</i>	Some data is specific and some is pooled. Where data is specific, size information is given. No environmental information is given since all components are located in power stations. Applications are not usually stated on the tables, but a table is given all of the power station systems from which data was drawn.

<i>Data Source:</i>	17 Rothbart
<i>Full Name:</i>	H.A. Rothbart, <i>Mechanical Design and Systems Handbook</i> .
<i>Published by:</i>	McGraw-Hill
<i>Type of Source:</i>	Book
<i>Date of publication:</i>	1964
<i>Type of components:</i>	Mainly general engineering, but includes approximately 20 per cent electronic and light electrical
<i>No. of component types:</i>	214
<i>Type of information:</i>	Information is tabulated in 10 pages in the book. A table of mean failure rates plus upper and lower extreme values. An additional table of generic life-expectancy distributions is given for a similar number of items from a different source. Mean life expectancy is a measure of life (in hours or cycles) at which the wear out phase begins. Tables of severity factors are given for each table to take account for different operating conditions.
<i>Source of data:</i>	Data sources were not stated. However, they will probably originate from American industry and may include some aerospace data.
<i>Type of data:</i>	Data is generic. There is some subdivision into different types but not into sizes or applications.

Data Source:	18 Smith
Full Name:	D.J. Smith, <i>Reliability and Maintainability in Perspective</i> (3 rd Edition)
Published by:	MacMillan, London
Type of Source:	Book
Date of publication:	1988
Type of components:	The data tables include electronic components, sensors and mechanical components.
Type of information:	This book describes the reliability techniques to achieve reliability and maintainability targets. It also covers the measurement and prediction of reliability together with various management topics. The third edition also includes a chapter, chapter 22, which lists some of the common reliability data sources and provides a useful list of failure rates for engineering and microelectronic components together with data on human error rates and fatality rates for various activities.
Source of data:	Unkown
Type of data:	Table 1 General Failure Rates Table 2 Microelectronic failure rates Table 3 Fatality rates Table 4 Human error rate Table 5 Percentage failure modes The majority of the failure rates in Table 1 are quoted as ranges rather than point estimates of failure rate.

<i>Data Source:</i>	20 Wash 1400
<i>Full Name:</i>	<i>Reactor Safety Study. An Assessment of Accident Risks in US Commercial Nuclear Power Plants.</i>
<i>Type of Source:</i>	Multi-volume report. Reliability data mainly confined to Appendix III – Failure Data. Available on microfiche.
<i>Date of publication:</i>	1974
<i>Type of components:</i>	General mechanical and electrical, e.g., pumps, valves, pipes and fittings, diesels, battery power supplies, instrumentation, clutches, motors, relays, switches and circuit breakers, fuses and wires, transformers, solid state devices.
<i>No. of component types:</i>	30
<i>Type of information:</i>	Tables of mean failure rate/ 10^6 hours or failures per demand for principal failure modes, with upper and lower bounds and comparison of nuclear and industrial data. Limited common mode failure data.
<i>Source of data:</i>	Data collected in 17 American nuclear power plants during 1972 is compared with data from 29 published sources from, e.g., American industry, NASA, and Air Force data.
<i>Type of data:</i>	Generic. Only valves and switched are separated into different types.
<i>Note:</i>	The data and associated material assembled in the report incorporate ranges of error bands. These have sufficient accuracy, detail, and resolution to satisfy the original requirements of the study. However, the data may not be sufficiently detailed, general, or accurate enough for use in other quantitative reliability models or in applications involving greater specificity.

<i>Data Source:</i>	21 RMC Harris
<i>Full Name:</i>	<i>Hazards and Reliability Information System</i>
<i>Published by:</i>	RM Consultants Ltd, Abingdon, England, OX14 1DY, 0235 555755
<i>Type of Source:</i>	Database, data sheets
<i>Date of publication:</i>	1992
<i>Type of components:</i>	Mechanical, electrical, rotating machinery, instrumentation, process, safety, offshore oil and gas, nuclear, petrochemical.
<i>No. of component types:</i>	600+ component types, 1700+ reliability data entries.
<i>Type of information:</i>	Data sheet presented on screen, basic failure statistics plus additional information on operating environment. Also maintainability and hazardous incident databases available.
<i>Source of data:</i>	Data from public domain sources and field failure studies.
<i>Type of data:</i>	Mean failure rate, operating experience, total number of failures, percentage failure modes.

<i>Data Source:</i>	22 SRD Data Centre
<i>Full Name:</i>	SRD Data Centre consists of a Technical Information Data Library and a Computerised Databank
<i>Published by:</i>	Access via Data Products Manager or SRD Association Manager
<i>Type of Source:</i>	Technical Data Library: books, reports, conference papers, etc. Computerised Databank: field collected event data.
<i>Date of publication:</i>	Ongoing data availability
<i>Type of components:</i>	Over 300 component classifications across general industry, i.e., process, petrochemical, transport, defence, electricity supply, water, manufacturing, computing, etc.
<i>No. of component types:</i>	Over 200 component classifications from <u>A</u> ctuators to <u>W</u> indscreen wipers
<i>Type of information:</i>	Technical Information Library: public domain literature and reports. Databank: field collected event data processed into component populations.
<i>Source of data:</i>	Field collected event data obtained as a result of collaborative data collection campaigns with customer organisations.
<i>Type of data:</i>	Component Reliability Data: operational and calendar failure rates, failure modes and causes, environmental factors, operating regime, maintenance and testing regime, even history information, availability, etc.

Appendix A.3

MATLAB Code Used in Analysis

% MATLAB Code for the First Phase

```
mttf=[34000 24000 18000 0 0 0 0 0
      36000 19000 12000 0 0 0 0 0
      32000 21000 14000 0 0 0 0 0
      34500 27000 17500 0 0 0 0 0];

i=1;
while i < 5
    mttf(i,4)=(1/6)*(mttf(i,1)+4*mttf(i,2)+mttf(i,3));
    mttf(i,5)=(mttf(i,4)-mttf(i,3))*(2*mttf(i,2)-mttf(i,1)-
    mttf(i,3))/((mttf(i,2)-mttf(i,4))*(mttf(i,1)-mttf(i,3)));
    mttf(i,6)=mttf(i,5)*(mttf(i,1)-mttf(i,4))/(mttf(i,4)-mttf(i,3));
    mttf(i,7)=beta(mttf(i,5),mttf(i,6));
    mttf(i,8)=((mttf(i,1)-mttf(i,3))/3.2)^2;
    i=i+1;
end

fid=fopen('BETAONE');

mult=[1 13/12 1 1];

countOneLow=0;
j=1;
while j<1001
    i=1;
    while i < 5
        BETAONE;
        MTTF(i,2)=mttf(i,3)+(mttf(i,1)-mttf(i,3))*X;
        MTTF(i,3)=exp(-1000/(mult(i)*MTTF(i,2)));
        i=i+1;
    end
    lam1=1/MTTF(3,2);
    lam2=1/MTTF(4,2);
    MTTF(3,3)=exp(-
        1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
    Rsys(j)=MTTF(1,3)*MTTF(2,3)*MTTF(3,3);
    if Rsys(j)<0.915
        countOneLow=countOneLow+1;
    end
    j=j+1;
end
lam1=1/mttf(3,4);
lam2=1/mttf(4,4);
Rthree=exp(-
1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
RmeanOne=exp(-1000/mttf(1,4))*exp(-1000/mttf(2,4))*Rthree;
probOneLow=countOneLow/(j-1);
fprintf('\nProbability too low %1.4f\n',probOneLow)
fprintf('\n Variances %7.2f %7.2f %7.2f %7.2f
\n',mttf(1,8)/max(mttf(:,8)),mttf(2,8)/max(mttf(:,8)),mttf(3,8)/ma
x(mttf(:,8)),mttf(4,8)/max(mttf(:,8)))
varblurb=mttf(:,8);
```

% MATLAB Code for the Second Phase, First Attempt

```
mttf2=[35 35000 0
        50 26500 0
        17 29560 0
        18 29800 0
        150 31500 0
        60 26000 0
        40 26700 0];
```

```
mttf1=[15 26178 980
        25 27000 2500
        150 31000 1200
        298 32000 1500 ];
```

```
sum2=sum(mttf2(:,1));
i=1;
mean2=0;
while i < 8
    mean2=mttf2(i,1)*mttf2(i,2)+mean2;
    i=i+1;
end
mean2=mean2/sum2;
```

```
summer=0;
var2l=0;
i=1;
while i < 8
    summer=mttf2(i,1)+summer;
    mttf2(i,1)=summer;
    var2l=mttf2(i,1)*(mttf2(i,2))^2;
    i=i+1;
end
var2form=(var2l/(sum2^2))^0.5;
```

```
sum2=sum(mttf1(:,1));
i=1;
mean1=0;
while i < 5
    mean1=mttf1(i,1)*mttf1(i,2)+mean1;
    i=i+1;
end
mean1=mean1/sum2;
mttf1(:,1)=mttf1(:,1)/sum2;

summer=0;
```

```

i=1;
while i < 5
    summer=mttf1(i,1)+summer;
    mttf1(i,1)=summer;
    i=i+1;
end

countTwoLow=0;
j=1;

var2=0;
var1=0;
var3=0;
while j < 1001

    i=3;
    BETAONE;
    MTTF(3,2)=mttf(i,3)+(mttf(i,1)-mttf(i,3))*X;
    MTTF(3,3)=exp(-1000/MTTF(i,2));

    i=4;
    BETAONE;
    MTTF(4,2)=mttf(i,3)+(mttf(i,1)-mttf(i,3))*X;

    MTTF(2,2)=mean2+(exp(randn)-exp(0+1^2/2))*var2form;
    MTTF(2,3)=exp(-1000/(13*MTTF(2,2)/12));
    var2=var2+(MTTF(2,2)-mean2)^2;
    fprintf('%7.2f\n',MTTF(2,2))

    i=4;
    source(2)=4;
    while i < 5
        x21=rand;
        if x21<mttf1(i,1)
            source(2)=i;
            MTTF(1,2)=mttf1(source(2),2)+(exp(randn)-
                exp(0+1^2/2))*mttf1(source(2),3);
            MTTF(1,3)=exp(-1000/MTTF(1,2));
        end
        var1=var1+(MTTF(1,2)-mean1)^2;
        i=i+1;
    end

    lam1=1/MTTF(3,2);
    lam2=1/MTTF(4,2);
    MTTF(3,3)=exp(-
        1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
    RsysTwo(j)=MTTF(1,3)*MTTF(2,3)*MTTF(3,3);
    if RsysTwo(j)<0.915
        countTwoLow=countTwoLow+1;
    end
end

```

```

    j=j+1;
end
lam1=1/mttf(3,4);
lam2=1/mttf(4,4);
Rthree=exp(-
    1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
RmeanTwo=exp(-1000/mean1)*exp(-1000/mean2)*Rthree
var2=var2/(j-2);
var1=var1/(j-2);
var31=mttf(3,8);
var32=mttf(4,8);
vars=max([var1 var2 var1 var32]);
fprintf('\n Vars %7.3f %7.3f %7.3f %7.3f \n',var1,var2,var31,var32)
fprintf('Vars %7.3f %7.3f %7.3f %7.3f
\n',var1/vars,var2/vars,var31/vars,var32/vars)
probTwoLow=countTwoLow/(j-1)

```

% MATLAB Code for the Second Phase, Second Attempt

```
mttf2=[35 35000 0
        50 26500 0
        17 29560 0
        18 29800 0
        150 31500 0
        60 26000 0
        40 26700 0];
```

```
mttf1=[15 26178 980
        25 27000 2500
        150 31000 1200
        298 32000 1500 ];
```

```
mttf32=[100 29500 3400
        50 30500 9000];
```

```
sum2=sum(mttf2(:,1));
i=1;
mean2=0;
while i < 8
    mean2=mttf2(i,1)*mttf2(i,2)+mean2;
    i=i+1;
end
mean2=mean2/sum2;
```

```
summer=0;
var21=0;
i=1;
while i < 8
    summer=mttf2(i,1)+summer;
    mttf2(i,1)=summer;
    var21=mttf2(i,1)*(mttf2(i,2))^2;
    i=i+1;
end
var2form=(var21/(sum2^2))^0.5;
```

```
sum2=sum(mttf1(:,1));
i=1;
mean1=0;
while i < 5
    mean1=mttf1(i,1)*mttf1(i,2)+mean1;
    i=i+1;
end
mean1=mean1/sum2;
mttf1(:,1)=mttf1(:,1)/sum2;
```

```
summer=0;
i=1;
while i < 5
```

```

    summer=mttf1(i,1)+summer;
    mttf1(i,1)=summer;
    i=i+1;
end

sum2=sum(mttf32(:,1));
i=1;
mean32=0;
while i < 3
    mean32=mttf32(i,1)*mttf32(i,2)+mean32;
    i=i+1;
end
mean32=mean32/sum2;
mttf32(:,1)=mttf32(:,1)/sum2;

summer=0;
i=1;
while i < 3
    summer=mttf32(i,1)+summer;
    mttf32(i,1)=summer;
    i=i+1;
end

countTwoLow=0;
j=1;

var2=0;
var1=0;
var32=0;
while j < 1001

    i=4;
    BETAONE;
    MTTF(4,2)=mttf(i,3)+(mttf(i,1)-mttf(i,3))*X;
    MTTF(4,3)=exp(-1000/MTTF(i,2));

    MTTF(2,2)=mean2+(exp(randn)-exp(0+1^2/2))*var2form;
    MTTF(2,3)=exp(-1000/(13*MTTF(2,2)/12));
    var2=var2+(MTTF(2,2)-mean2)^2;
    %fprintf('%7.2f\n',MTTF(2,2))

    i=4;
    source(2)=4;
    while i < 5
        x21=rand;
        if x21<mttf1(i,1)
            source(2)=i;
            MTTF(1,2)=mttf1(source(2),2)+(exp(randn)-
                exp(0+1^2/2))*mttf1(source(2),3);
            MTTF(1,3)=exp(-1000/MTTF(1,2));
        end
        var1=var1+(MTTF(1,2)-mean1)^2;
        i=i+1;
    end
end

```

```

end

i=1;
source(3)=2;
while i < 3
    x32=rand;
    if x32<mttf32(i)
        source(3)=i;
        MTTF(3,2)=mttf32(source(3),2)+(exp(randn)-
            exp(0+1^2/2))*mttf32(source(3),3);
        MTTF(3,3)=exp(-1000/MTTF(3,2));
    end
    var32=var32+(MTTF(3,2)-mean32)^2;
    i=i+1;
end

lam1=1/MTTF(3,2);
lam2=1/MTTF(4,2);
MTTF(3,3)=exp(-
    1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
RsysTwo(j)=MTTF(1,3)*MTTF(2,3)*MTTF(3,3);
if RsysTwo(j)<0.915
    countTwoLow=countTwoLow+1;
end
j=j+1;
end

lam1=1/mttf(3,4);
lam2=1/mttf(4,4);
Rthree=exp(-
    1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
RmeanTwo=exp(-1000/mean1)*exp(-1000/mean2)*Rthree
var2=var2/(j-2);
var1=var1/(j-2);
var31=mttf(3,8);
var32=var32/(j-2);
vars=max([var1 var2 var31 var32]);
fprintf('\n Vars %7.3f %7.3f %7.3f %7.3f \n',var1,var2,var31,var32)
fprintf('Vars %7.3f %7.3f %7.3f %7.3f \n',var1/vars,var2/vars,var31/vars,var32/vars)
probTwoLow=countTwoLow/(j-1)

varblurb=[var1 var2 var31 var32];

```

% MATLAB Code for the Third Phase

```
mttf2=[35 35000 0
        50 26500 0
        17 29560 0
        18 29800 0
        150 31500 0
        60 26000 0
        40 26700 0];
```

```
mttf1=[15 26178 980
        25 27000 2500
        150 31000 1200
        298 32000 1500 ];
```

```
mttf32=[100 29500 700
        50 30500 900];
```

```
sum2=sum(mttf2(:,1));
i=1;
mean2=0;
while i < 8
    mean2=mttf2(i,1)*mttf2(i,2)+mean2;
    i=i+1;
end
mean2=mean2/sum2;
```

```
summer=0;
var21=0;
i=1;
while i < 8
    summer=mttf2(i,1)+summer;
    mttf2(i,1)=summer;
    var21=mttf2(i,1)*(mttf2(i,2))^2;
    i=i+1;
end
var2form=(var21/(sum2^2))^0.5;
```

```
sum2=sum(mttf32(:,1));
i=1;
mean32=0;
while i < 3
    mean32=mttf32(i,1)*mttf32(i,2)+mean32;
    i=i+1;
end
mean32=mean32/sum2;
mttf32(:,1)=mttf32(:,1)/sum2;
```

```

summer=0;
i=1;
while i < 3
    summer=mttf32(i,1)+summer;
    mttf32(i,1)=summer;
    i=i+1;
end

countTwoLow=0;
j=1;

var2=0;
var1=0;
var32=0;
while j < 1001

    i=4;
    BETAONE;
    MTTF(4,2)=mttf(i,3)+(mttf(i,1)-mttf(i,3))*X;
    MTTF(4,3)=exp(-1000/MTTF(i,2));

    MTTF(1,2)=32271.76+(exp(randn)-exp(0+1^2/2))*2564.66;
    MTTF(1,3)=exp(-1000/(13*MTTF(2,2)/12));
    var2=var2+(MTTF(2,2)-32272)^2;

    MTTF(1,2)=mean2+(exp(randn)-exp(0+1^2/2))*var2form;
    MTTF(1,3)=exp(-1000/(13*MTTF(2,2)/12));
    var2=var2+(MTTF(2,2)-mean2)^2;
    %fprintf('%7.2f\n',MTTF(2,2))

    i=4;
    source(2)=4;
    while i < 5
        x21=rand;
        if x21<mttf1(i,1)
            source(2)=i;
            MTTF(1,2)=mttf1(source(2),2)+(exp(randn)-
                exp(0+1^2/2))*mttf1(source(2),3);
            MTTF(1,3)=exp(-1000/MTTF(1,2));
        end
        var1=var1+(MTTF(1,2)-mean1)^2;
        i=i+1;
    end

    i=1;
    source(3)=2;
    while i < 3
        x32=rand;
        if x32<mttf32(i)
            source(3)=i;
            MTTF(3,2)=mttf32(source(3),2)+(exp(randn)-
                exp(0+1^2/2))*mttf32(source(3),3);
            MTTF(3,3)=exp(-1000/MTTF(3,2));
        end
    end
end

```

```

        var32=var32+(MTTF(3,2)-mean32)^2;
        i=i+1;
    end

    lam1=1/MTTF(3,2);
    lam2=1/MTTF(4,2);
    MTTF(3,3)=exp(-
        1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
    RsysTwo(j)=MTTF(1,3)*MTTF(2,3)*MTTF(3,3);
    if RsysTwo(j)<0.915
        countThreeLow=countThreeLow+1;
    end
    fprintf('%7.3f %7.3f %7.3f
%1.4f\n',MTTF(1,3),MTTF(2,3),MTTF(3,3),RsysTwo(j))
    j=j+1;
end
lam1=1/mttf(3,4);
lam2=1/mttf(4,4);
Rthree=exp(-
    1000/((lam1^2+lam2^2+lam1*lam2)/(lam1^2*lam2+lam1*lam2^2)));
RmeanThree=exp(-1000/32272)*exp(-1000/mean2)*Rthree
var2=var2/(j-2);
var1=var1/(j-2);
var31=mttf(3,8);
var32=var32/(j-2);
vars=max([var1 var2 var31 var32]);
fprintf('\n Vars %7.3f %7.3f %7.3f %7.3f \n',var1,var2,var31,var32)
fprintf('Vars %7.3f %7.3f %7.3f %7.3f
\n',var1/vars,var2/vars,var31/vars,var32/vars)
probThreeLow=countThreeLow/(j-1)

varblurb=[var1 var2 var31 var32];

```

```
% MATLAB Code for generation of Beta distribution
% Developed using algorithm provided by Fishman [9]
```

```
d1=min(mttf(i,5),mttf(i,6));
d2=max(mttf(i,5),mttf(i,6));
d3=d1+d2;
d4=((d3-2)/(2*d1*d2-d3))^0.5;
d5=d1+1/d4;
```

```
accept=0;
while accept <1
    U1=rand;
    U2=rand;
    V=d4*log((U1/(1-U1)));
    W=exp(V);
    Z1=U1*U1*U2;
    R=d5*V-log(4);
    S=d1+R-W;
    T=log(Z1);
    if S+1+log(5)>=5*Z1
        accept=1;
    elseif S>=T
        accept=1;
    end
end
if d1>mttf(i,5)
    X=W/(d2+W);
else
    X=d2/(d2+W);
end
```

Vita

Thomas Blake Brinly was born in Louisville, Kentucky on August 21, 1977 to Robert and Ann Brinly. He attended high school at The Indian Springs School in Birmingham, Alabama and Clear Lake High in Houston, Texas, graduating from Clear Lake in 1995. He attended the University of Tennessee, Knoxville as an undergraduate until graduating with a B.S. in Mechanical Engineering in the spring 2000. He continued at the university as a graduate student, receiving a M.S. in Industrial Engineering in spring 2002. As an undergraduate, he had the honor of playing on the lacrosse team, which won two conference titles. His practical experience as a student ranged from interns with Eastman Chemical and FMSC Group to a co-op at TRW-Koyo.