DEGRADATION-BASED RELIABILITY ESTIMATE FOR

MARINE ELECTRIC MOTOR PUMP EQUIPMENT

A Thesis

Presented to

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In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in Industrial Engineering

by

Robert M. Conachey

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DEGRADATION-BASED RELIABILITY ESTIMATE FOR
MARINE ELECTRIC MOTOR PUMP EQUIPMENT

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ABSTRACT

Ship operators have collected condition monitoring data over 25 years, but the analysis of these vibration data for failure time prediction and maintenance management is sparse and critically needed within the marine industry.

This thesis explores the degradation-based failure time estimation for electric motor pump units by using vibration analysis data provided from ships. The work is unique because the data is taken under non-homogeneous environmental conditions, varying vibration measuring hardware and onboard units' characteristics, and small sample populations.

The degradation/vibration data are stochastically modeled functions with a predetermined limit which is considered failure when exceeded. Two methods are applied. In the first approach, the times to failure for individual paths are modeled by a probability distribution. In the second two-stage approach, the path model is estimated by combining the individual model parameter estimates. Accordingly, ship operators can assess the remaining life of electric motor-pump combinations and make informed decisions concerning equipment shutdown and repair.

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INTRODUCTION

1.1 Background of Marine Vessel Survey

The American Bureau of Shipping (ABS) is a marine classification society whose mission "is to serve the public interest as well as the needs of our clients by promoting the security of life and property and preserving the natural environment" [1]. The standards that ABS publishes are referred to as Rules and Guides. These standards are based on a primary standard referred to as the "Rules for Building and Classing Steel Vessels," [2] (the Rules) along with approximately one hundred additional Rules, Guides and Guidance Notes, [3] for vessels in specialized services such as oil tankers and bulk carriers. The Rules are subdivided into seven parts organized by subject areas such as hull structure (Part 3) or machinery (Part 4). Operational maintenance requirements for vessels in service are in Part 7 of the Rules entitled "Rules for Survey After Construction".

"The responsibility of the classification society is to verify that marine vessels and offshore structures comply with Rules that the society has established for design, construction and periodic survey.

The classification process includes:

- the development of standards, known as Rules
- technical plan review and design analysis
- surveys during construction
- source inspection of materials, equipment and machinery
- acceptance by the Classification Committee
- subsequent periodic surveys for maintenance of class
- survey of damage, repairs and modifications." [4]

Upon acceptance by the Classification Committee, the vessel is assigned a minimum of two classification symbols representing compliance with the hull structure and machinery requirements of the Rules denoted by **A1** and **AMS** respectively. Also, the vessel's design type (e.g., oil carrier, container carrier, mobile offshore drilling unit, etc.) along with other notations requested by the vessel's owner and as required by the country the vessel is registered in. Classed vessels are listed in an electronic format known as "ABS Eagle Record" which lists the vessel's main characteristics and classification.

Confirmation of the vessel condition is performed by ABS Surveyors who periodically perform surveys at least annually. Surveys are limited inspections of the condition of the vessel in accordance with the requirements listed in Part 7 of the Rules.

One year after a vessel enters service, the Rules require surveys of the hull structure and machinery in accordance with cite 7-1-2/1, page 17 [5]. Annual surveys are required to maintain classification for the vessel. After five years' service, the vessel is subject to a Special Survey in which the hull and certain machinery associated with propulsion and maneuverability are required to have a more in depth survey. For machinery, this involves Surveyor witnessed overhaul and testing of *all* the specified machinery and systems to confirm satisfactory operation. However, machinery scheduled for overhaul at the Special Survey may be operating satisfactorily or may have been repaired as a result of an earlier failure during this five year interval so the overhaul would not be necessary and wasteful of the vessel operator's resources. In response to ABS' clients, the Continuous Survey – Machinery (CMS) alternative was promulgated in 1958 [6]. This alternative requires approximately twenty percent of the machinery and systems subject to Special Survey to be overhauled annually and tested in the presence of the ABS Surveyor per the requirements of 7-2-1/7 (page 18) [5]. The machinery is selected by the vessel's owner and subject to the approval of ABS. This alternative approach is less intrusive to the vessel's schedule but, there is the possibility equipment is overhauled unnecessarily.

At the request of several ship operators in 1978, ABS developed the Preventative Maintenance Program (PMP) which permits the use of condition monitoring techniques to assess the condition of the machinery subject to the Special Survey per 7-A-14/5 [5] (page 461). Vessel operators enrolled in the PMP perform appropriate periodic condition monitoring techniques and when results indicate impending equipment failure, preventive maintenance action is performed to restore the condition of the equipment. The PMP permits the vessel's crew to perform the repairs without the presence of the Surveyor. When the Surveyor performs the Annual Confirmation Survey for the PMP, he or she notes that maintenance was performed on the equipment and credits the equipment towards CMS and thereby the Special Survey per 7-A-14/9.1 page 462 [5]. Equipment operation or testing in the presence of the Surveyor may be required at the Surveyor's discretion.

The PMP requirements permit consideration of several condition-monitoring techniques including vibration analysis which is the focus of this thesis. Vibration analysis techniques are applied to rotating equipment such as electric motor – pump combinations, steam turbines and other types of rotating equipment. The pertinent PMP requirements for the initial or "baseline" vibration analysis readings are listed in Table 1-1. These requirements have remained basically unchanged since the first publication of the PMP Guide in 1985. Since that time, there have been numerous advances in miniaturizing vibration measurement equipment and improving ease of analysis of vibration readings. Referring to cite 15.5.1(a) iv) in Table 1-1, the PMP Guide assumes vibration readings are collected periodically by vessel crew with a handheld probe. In cite 15.5.1(a) iii), the vibration analysis data is collected periodically: either quarterly or semi-annually. At the time of initial publication, continuous vibration monitoring was rarely performed onboard. The reference document in cite 15.5.1(a) vi) was last updated in 1987 [7]. The Society of Naval Architects and Marine Engineers (SNAME) has not indicated any plans to update the publication at present.

Table 1-1 Preventative Maintenance Program Initial Vibration Analysis Requirements

Cite from 7-A-14	Requirement
15.5.1(a) i)	A list and description of the machinery covered including:
a)	Method of data collection and analysis tools.
b)	Nominal rpm.
c)	Horsepower.
d)	Location and orientation of sensor attachments, which are to be permanently marked on machinery.
15.5.1(a) iii)	Schedule of data collection.
15.5.1(a) iv)	Type and model of data collection instrument, including sensor and attachment method and calibration schedule.
15.5.1(a) v)	Acceptance criteria of data.
15.5.1(a) vi)	*Baseline data.* Initial or baseline data are to be recorded in the presence of the Surveyor and/or a representative specialist of an ABS Recognized Condition Monitoring Company and are to be compared to the acceptable vibration levels shown in SNAME's T&R Bulletin 3-42 "Guidelines for the Use of Vibration Monitoring for Preventative Maintenance" or other equivalent national or international standards. The Owner is to be notified of all machinery that does not meet acceptance criteria (i.e., machinery with high vibration levels).

Steady state spectrum analysis readings are taken on equipment for the initial (baseline) reading in order to assess any resulting trends from subsequent readings. The ship operator then has a choice: to take overall vibration readings on a quarterly basis for the first three quarters followed by a spectrum vibration reading taken during the fourth quarter; or, spectrum vibration readings taken semi-annually. In both cases, the testing interval of 3 months or 6 months is applied to all equipment for all ships in all trades.

Cite 15.5.1(a) v) requires acceptance criteria be established during development of the condition monitoring plan. For overall vibration analysis two limits have been established: 0.30 in/sec and 0.45 in/sec. The lower limit warns the operator that the equipment is degrading and the upper limit warns the operator that failure is imminent and the equipment must be diagnosed and repaired. Li and Pham illustrate this concept in their Figure 2 by creating three zones: no action, preventive maintenance if the lower limit is exceeded, and corrective maintenance if the upper limit is exceeded [8]. Their model assumes preventive maintenance or corrective maintenance is performed immediately. This may not be practical according to the operational mode of the ship. Also, ships' machinery for this study is fully redundant and maintenance may be delayed for a short time (e.g., arrival at the next port).

1.2 Problem Statement

Although much condition monitoring data has been collected over the past 25 years by individual ship operators, the publication of these data is available only by subscription, and the analysis of these data is sparse. There is a critical need within the marine industry and ABS for:

- A determination of the failure time and accordingly, the remaining life of marine equipment once the condition monitoring technique identifies degradation occurring, and
- An inspection-based maintenance model applying the test interval as the decision variable. After a complete realization of the degradation results are observed, the initial assumptions are updated so as to improve future predictions.

With this information, ship operators can readily assess remaining life of electric motor-pump combinations and make informed decisions concerning equipment shutdown and repair. ABS can use the remaining life results and the inspection based maintenance model to improve the requirements in the PMP Guide. For example, determine if the testing intervals presently in the PMP Guide should remain the same or modified to a shorter interval. ABS can use the results to advise its customers so that they can apply them in their ship maintenance procedures and improve machinery and thus vessel reliability.

1.3 Literature Review

Many papers have been published on the subject of degradation with respect to various mechanical devices. There are two models for determining the degradation time and estimation of remaining life: a physics-based approach and a statistics-based approach per [9] (p. 1965). In the physics-based degradation models, the degradation phenomenon is described in a relationship such as the Arrhenius Law and corrosion initiation equation, or experimentally based results involving crack propagation or crack growth models. For the statistics based degradation models, the degradation phenomenon is described by a statistical model such as a regression analysis or Monte Carlo simulation [9]. Other probability models for degradation paths include linear degradation with normal-distributed, log-normal distributed, Weibull distributed or bivariate-normal distributed degradation rates. Non-linear degradation paths have also been modeled as exponential or logistic paths. Some researchers have proposed subdividing the modeling categories into determination of the time degradation exceeds some specified event or level [8] [9].

1.3.1 Literature Review on Physics-Based Modeling Approaches for Degradation

The following is a summary of some representative papers addressing the physics-based modeling approach. Nelson analyzed electrical equipment insulation aging-breakdown characteristics for several test temperatures to develop a lifetime distribution based on the performance-degradation relationship [10]. An Arrhenius degradation model was applied to temperature and exposure time. The Arrhenius relationship is well established as suitable for dielectric equipment. The distribution of the breakdown voltage was lognormal. The standard deviation of the log of the breakdown voltage is a constant that does not depend on temperature or exposure time.

Elsayed summarized nine additional papers published between 1984 and 1998 [9]. Topics researched include design of an accelerated degradation model to analyze the stability of biological standards, reliability estimation of an Integrated Logic Family using a degradation model, and predicting the lifetime of ball and roller bearings using a degradation model with a particular focus on lubricant cleanliness and both the size and the particle hardness of contaminants in the lubricant on bearing performance. Other topics include a generic model for a univariate degradation process, experimental design for system reliability improvement, development of a statistical lifetime model for cutting tools based on the tool-wear curve (tool-wear rate is directly proportional to degradation rate of the tool), application of the Arrhenius law to a thermally activated time-dependent model relating aging to catastrophic failure, application of a physics based relationship to model adhesive wear, and kinetic modeling for the degradation of light emitting diodes [9].

Elsayed states "The limitations of physics-based degradation models are:

(a) There is no universal physics-based or experimental-based relationship that describes the degradation phenomenon of all products, which makes it impossible to develop a general degradation model.

(b) It is time consuming to develop a physics-based (or experimental-based) relationship for new products.

(c) Physics-based (or experimental-based) degradation models may not be suitable for the development of closed form reliability functions. This is due to the fact that some of the parameters are random variables; the degree of difficulty of deriving a reliability function depends on the distribution of these random variables. Except for simple cases, the reliability function cannot be easily derived." [9]

1.3.2 Literature Review on Statistics-Based Modeling Approaches for Degradation

Some representative papers address the probabilistic (statistical) approach for modeling degradation. Mroczkowski, and Maynard applied a statistical approach in determining the reliability of electrical connectors [11]. An adequate statistical analysis of the test data can be accomplished based on consideration of the following issues: active degradation mechanisms must be identified and categorized by their importance; appropriate environmental tests must be determined for these degradation mechanisms; the statistical approach to estimating reliability from the test data must be agreed upon; and an acceptance criterion appropriate for the application of interest must be established. An estimate of the reliability of the connectors is made by applying an asymptotic extreme-value distribution. Comparison with a Military Handbook (MIL-HDBK-217) which is used to predict failure rates in electronic equipment shows the publication is obsolete.

Lu and Meeker analyzed crack growth as a degradation model [12]. Failure was considered to have occurred when the crack length exceeded a predetermined limit. This paper developed statistical methods for using degradation measures to estimate a time-to-failure distribution for several degradation models. A non-linear mixed-effects model was used to develop methods based on Monte Carlo simulation to obtain point estimates and confidence intervals for reliability assessment.

Huang and Askin presented a generalized stress-strength interference (SSI) reliability model for considering stochastic loading and strength aging degradation [13]. It is applied to any non-homogenous Poisson loading process, and any kind of strength aging degradation model. A numerical recurrence formula based on the Gauss-Legendre quadrature formula is used to solve the SSI reliability equation. Three example problems are solved applying numerical analysis for both homogenous and non-homogenous Poisson loading processes.

Wang presented a case study of predicting residual life of items monitored based upon the condition information obtained in the form of a distribution [14]. When the prediction was available, a model for condition-based maintenance decision making could be established. A six-rolling element bearing setup under accelerated life testing was monitored on an irregular basis to simulate indirect monitoring, since the true condition of the item monitored was unknown but correlated with the measured vibration signals. The modeling assumptions were: items were monitored irregularly at discrete time points; there was no maintenance on the bearings; residual delay time was a random variable, which might be described by a probability distribution and may be conditional on available condition information. The condition information obtained at time $t_,$ for example at the current time, was also a random variable which may be described by a distribution function whose mean was assumed to be a function of the current residual delay time. Wang applied the Weibull, Gamma, Normal and Lognormal distributions and determined the Weibull distribution provided the best approximation.

Gebraeel proposed a stochastic degradation modeling framework for computing and continuously updating residual life distributions of partially degraded components which could be modeled as exponential functional forms [15]. Roller bearing elements were subjected to an accelerated life test by way of removing half of the rolling elements and overloading the bearing assembly to promote failure. The proposed methodology combined population-specific degradation characteristics with component-specific condition monitoring data acquired from sensors in order to compute and update remaining life distributions. Two sensory updating methodologies were proposed: the first utilizing sensory signal values to update distributions while the second analyzed the entire history of sensory information. The author noted the first methodology may be beneficial in applications that involve discrete sensory acquisition as opposed to continuous monitoring.

Gebraeel et al. sought to model the functional form of the degradation process by using vibration (velocity) readings taken for bearings in an accelerated wear test [16]. A Bayesian updating approach was applied by combining (i) the distribution of the parameters across the population of devices; (ii) real time sensor information collected from the device through condition monitoring. The objective was to make reasonable predictions about the residual life distribution of the device. The velocity meter readings were analyzed by two different exponential degradation signal models. The first model assumed the signal exhibits independent random fluctuations about an exponential signal trajectory. The second model assumed the error fluctuations follow a Brownian motion process. The models were used with their updated parameters to develop residual life distributions for a partially degraded device.

Das and Acharya proposed two alternative policies for preventive replacement of a component which showed signs of occurrence of a fault; but continued to operate for some random time with degraded performance, before failure [17]. The time between fault occurrence and component failure was referred to as delay time. The two policies were referred to as age replacement during delay time policy (ARDTP) for which replacement of the faulty component occurs at failure or at a fixed time after detection; and opportunistic age replacement policy (OARDTP) which extends ARDTP to opportunistic age replacement during a planned shutdown of the facility. The model created accounts for maintenance costs to replace the component, along with degradation costs during the delay time and costs associated with shutdown.

Glinski et al. applied theory of diffusion processes elements to develop methods for predicting the reliability and the moments of the time to first failure of systems with non-constant failure rates and exhibit degradation failure [18]. Systems characterized by k independent parameters were considered each of which exhibits degradation failure. The time behavior of each of the system parameters is assumed to be characterized by a Brownian process (a particular diffusion or Markov process). The method permitted predictions of reliability and the moments of the time to first failure to be made from data taken early in life tests. The application of the theory was developed. An example reliability prediction for electrical resistors was presented.

Park discussed modeling of wear and deriving the optimal wear-limit for preventive replacement [19]. The author noted that wear connotes any type of degradation accumulating through use and observed continuously in time. The assumptions for this model were that: the failure rate is dependent on the wear rate, wear accumulates continuously in time, and the item is replaced instantaneously. The gamma distribution was used to model the wear.

Son and Savage discussed a method for the design stage for assessing performance reliability of systems with competing time-variants applicable to components with uncertain degradation rates [20]. System performance measures or selected responses are related to their critical levels by time dependent limit-state functions. System failure was defined as the non-conformance of any response. This permitted unions of the multiple failure regions to be formed. Degradation path models were chosen versus degradation distribution models. With this approach, there were numerous degradation paths and the authors applied the Monte Carlo approach. This proposed method resulted in a more realistic manner to predict performance reliability than either worst case, or simple average-based approaches.

Phelps et al. proposed a prognostic approach by using probabilities of binary random signals to track a system's health [21]. Sensor alarm thresholds were deliberately set low (unlike typical practice to set alarm thresholds higher to avoid annoying false alarms). For tracking purposes, measurement averaging through use of Kalman filters using kinematic models and the interacting multiple model (IMM) were used. Two separate algorithms estimate the time to failure: a deterministic algorithm accurate in the near term and a probabilistic algorithm that is more accurate and gives confidence intervals.

Elwany and Gebraeel developed a sensor-driven decision model for components replacement and spare parts inventory by integrating a degradation modeling framework for estimating remaining life distributions using condition-based sensor data with existing replacement and inventory decision models [22]. An exponential sensor-driven degradation model was employed which was updated periodically for the specific bearing. Dynamic updating of replacement and inventory decisions could then be made based on the physical condition of the equipment.

Gebraeel et al. presented a degradation modeling framework utilizing failure time data which were easier to obtain and readily available from historical maintenance/repair records [23]. Using the same failure data for roller bearing elements mentioned previously the failure time values were initially fitted to a Bernstein distribution whose parameters were then used to estimate the prior distributions of the stochastic parameters of the initial degradation model. The initial degradation model assumptions were updated when the complete realization of a degradation signal was observed. The updated model could then be applied for future predictions. This paper validated this approach by testing a rolling element thrust bearing. Further, the proposed approach was suitable for linear or exponential models where the failure time data fit a Bernstein distribution.

1.3.3 Literature Review on Determining Condition Monitoring Inspection Intervals

The following section addresses some representative papers discussing the approach for determining condition monitoring inspection intervals. Christer and Wang presented a model for assessing condition monitoring results in a production plant and determining frequency of monitoring [24]. The condition monitoring test example was wear state of a bearing. A binary signal was recorded which indicated if the bearing wear was satisfactory (1) or exceeded a predetermined critical level (0). A linear wear model for the bearing was developed and applied to determine the optimum inspection interval. The approach suggested by the authors is flexible by permitting an appropriate probability distribution for the component being assessed.

Wang reported on model development to determine the optimal critical level and condition-monitoring interval in terms of a criterion such as cost, down time or any other issue of interest [25]. The model's basis was the random coefficient growth model where the coefficients of the regression growth model are assumed to be in accordance with known distribution functions. An example using a Weibull distribution was used to demonstrate the ideas.

Barbera, Schneider, and Kelle discussed a condition-based maintenance model with exponential failures, and fixed inspection intervals [26]. A condition of the equipment, such as vibration, was monitored at equidistant time intervals. When the variable indicating the condition exceeded a predetermined threshold an instantaneous maintenance action was performed and the monitored condition took on its initial value. The equipment can fail only once within an inspection interval. The model assumed time to failure follows a non-homogeneous Poisson process. The failure probability was exponential and the failure rate was dependent on the equipment's condition. The paper also sought to minimize maintenance costs associated with maintenance actions and failures. They studied the optimal solution via dynamic programming and compare it to an approximate steady state solution based on renewal theory.

1.3.4 Literature Review on Additional Degradation Related Research

The following section addresses some representative papers discussing various other aspects of degradation and reliability. Coit and Jin developed maximum likelihood estimators for the gamma distribution when there was missing time-to-failure data [27]. This approach was useful with regard to maintenance field data collected by operators/maintenance personnel. The approach permitted field data to be systematically analyzed. The authors noted practitioners have made simplifying assumptions when analyzing data which may not represent the actual distribution, so that the data can be used. The authors warned a distribution should not be chosen unless there is a physical, theoretical or empirical rationale. The gamma distribution was chosen because it is capable of modeling a variety of different probability density functions.

Li and Pham developed a generalized condition-based maintenance model subject to multiple competing failure processes including at least two degradation processes, and random shocks [8]. Upon inspection, one needed to decide whether to perform a maintenance action, such as preventive or corrective, or to do nothing. The optimum maintenance policy was calculated by applying the Nelder – Mead downhill simplex method to calculate the optimum policy that minimized the average long-run maintenance cost rate.

Wu, Gebraeel, and Lawley used the same failure data for roller bearing elements mentioned in [16] [15] and [23] to develop an integrated neural-network based decision support model for predictive maintenance of rotating equipment [28]. The model was comprised of three components: a vibration based degradation database, an artificial neural network model developed to estimate life percentile and failure times, and a cost matrix and probabilistic replacement model that optimized expected cost per unit time. The authors stated this approach can be applied to various equipment types across various industries.

Ghasemi, Yacout, and Ouali proposed methods to estimate the parameters of condition monitored equipment whose failure rate follows Cox's time-dependent Proportional Hazards Model (PHM) [29]. Because of measurement errors, misinterpretations, or limited accuracy of the measurement instruments, the observation process was not perfect, and accordingly does not directly reveal the exact degradation state. A stochastic relation between the indicator's values to the unobservable degradation state was provided by an observation probability matrix. The paper considered imperfect observations and assumed the degradation state follows a Hidden Markov Chain. "The observed indicator for the equipment's degradation state had a stochastic relationship with the degradation state of the equipment via a stochastic matrix, and did not reveal the real degradation state of the equipment." The authors assumed the failure rate of the equipment followed Cox's PHM and an approach to estimate the parameters of the PHM, the Markov process transition matrix, and the probability matrix of observations/states applying the Maximum Likelihood Estimation method was introduced. The authors concluded the parameters of the PHM showed a higher level of sensitivity to censored data. The higher the level of censored data, the higher the estimated parameter was from the real value. However, the parameters of the Markov process, and the stochastic matrix of observations/states were not very sensitive to the percentage of data censoring.

Swanson proposed an algorithm referred to as Prognostic Health Management (PrHM) [30]. This technology used objective measurements of condition and failure hazard to adaptively optimize a combination of availability, reliability, and total cost of ownership of a particular asset. Prognostics for the signature feature were determined by transitional failure experiments. These experiments were used to determine the failure alert threshold and advance warning the operator can expect by continually monitoring the assets' condition. PrHM is a four step process consisting of: an RCM analysis; fault detection through sensors; detection algorithms; and prognostics.

Elsayed, Liao and Wang proposed an accelerated life testing (ALT) model which was more general and robust with respect to unknown underlying failure processes than models then in existence [31]. The Extended Linear Hazard Regression (ELHR) model accounted for the proportional hazards effect, the time-varying coefficients effect and the time-scale changing effect. The paper presented the results of simulations and analyses of real laboratory data to demonstrate ELHR model provided accurate reliability estimates.

Zio and Podofillini proposed a risk-informed approach to system design and management in which the importance measures were incorporated in the development of a multi-objective optimization problem to direct the design towards a solution which was optimal for economics and safety and "balanced" in the sense that all components had similar importance values without bottlenecks or "high-performing" components [32]. Test and maintenance activities were calibrated according to components' importance ranking. A demonstration was done for a multi-state system design optimization for a high pressure injection system of a pressurized water reactor.

Doksum and Hoyland considered step-stress accelerated testing by which each unit in an experiment was subjected to a particular pattern of specified stresses for a specified time interval until the unit failed [33]. In some cases testing stopped before all units had failed so there was censored data to consider. For this analysis the time to failure was modeled as accumulated decay governed by a continuous Gaussian process whose distribution depends on the stress assigned to the unit at each time point. Failure was considered to have occurred when the accumulated decay exceeded a fixed critical boundary. Time to failure followed a time-transformed inverse Gaussian distribution. Maximum likelihood methods were used to estimate the model parameters.

Gopalakrishnan, Ahire, and Miller proposed generation of an adaptive Preventive Maintenance (PM) schedule to maximize the net savings from PM subject to workforce availability constraints [34]. There were two components: task prioritization based on a multi-logit regression model for each type of PM task; and task rescheduling based on a binary integer programming model with constraints on workforce availability.

Goode, Moore and Roylance developed a model on the basis that the failure pattern could be divided into two distinct phases: stable and unstable phases, which could be distinguished from one another by using statistical process control methods [35]. Depending on the manner in which the machinery's failure progressed, the first method relied entirely on a reliability model. For this paper, a Weibull distribution hazard rate was applied. The second method applied a combination of reliability (a Weibull distribution in the form of a cumulative density function) and condition monitoring methods (with intervals adjusted so as to be before a predetermined probability of functional failure) to focus the time to a failure 'window'.

Lin and Makis considered helicopter gearbox data in proposing recursive filters for a failure-prone system operating continuously and subject to condition monitoring at discrete times [36]. It was assumed that the state of the system evolved as a continuous-time Markov process with a finite state space. The observation process was stochastically related to an unobservable state process, except in the failure state. The failure information and information obtained through condition monitoring were combined and the change of measure approach was applied and a general recursive filter was obtained. A procedure based on the estimated maximum algorithm, was developed which was suitable for offline parameter estimation. The estimation of the probability of failure at some time in the future and calculations of the expected residual life using information up to the present time were presented with sensible results.

1.3.5 Failure Limit Policies

Several papers addressing failure limit policies were reviewed. Preventive maintenance is performed when the equipment or system reaches a predetermined limit which can be based on reliability, age or for the purposes of this study, vibration.

Love and Guo applied several Weibull processes to model the lifespan of a Postal Canada vehicle fleet [37]. A semi-Markov model was applied to the repair limit analysis and was used to aid in the decision to repair or replace a vehicle at the time of failure. The authors concluded the decision structure applied was also applicable to other types of covariate information resulting from a condition monitoring program.

Jia and Christer applied the gamma distribution to model a non-decreasing degradation process to determine the expected life until a predetermined threshold was attained [38]. A cost model was developed and optimized to minimize the life cycle inspection costs by determining the initial inspection interval and subsequent inspection intervals. An example wear phenomena that follows a gamma distribution along with some assumed costs was demonstrated.

Zheng and Nasser proposed initiating maintenance or replacement of a unit based on the hazard rate attaining a predetermined limit [39]. If the unit failed earlier, maintenance would be performed and the unit would resume operation but, the hazard rate would remain the same. When the unit reached the hazard rate limit, it would be replaced upon subsequent failure.

1.3.6 Summary

There are a large number of papers addressing various topics associated with degradation of machinery. The physics-based modeling approach is suitable only for equipment in a particular application. There is no universal physics based relationship that can be applied to the degradation phenomenon for equipment. Another criticism of this approach is the time consuming process to develop the physics-based relationship, especially for new products. Tseng et al. and Lu and Meeker's degradation modeling framework utilizing degradation measurements over time is the focus of this study [40] and [12]. They obtained satisfactory results from application of their approaches. This thesis uses real degradation data from vibration analysis measurements performed onboard several vessels to determine if a degradation modeling framework can be applied.

1.4 Research Objective and Significance

The results of this study can be applied by ABS to update the Preventative Maintenance Guide with regard to vibration analysis monitoring intervals. The methodology can be incorporated in computerized machinery maintenance software used by ship operators to assess the remaining life of their affected equipment. Therefore, the ship's personnel can make an informed decision with regard to residual life which should lead to improved equipment reliability and availability thereby leading to safer shipping.

1.5 Scope and Data Availability

The scope of the equipment examined was limited to electric motor driven pumps for the salt water, fresh water, lubricating oil, hydraulic oil, steam generating and fuel oil service systems. These pump types were chosen because they are duplicated on all ships and can be compared to one another. Data was provided by a condition monitoring specialist who would provide data taken over several years for several ships of varying ship types (e.g., tankers, roll-on, roll-off (RO-RO), container carriers). A tanker operating company provided vibration data for one of their tanker classes. This proved quite useful for the analysis as there are five ships in this class. Ships of the same *class* have identical hull dimensions and machinery.

Chapter 2
METHODOLOGY

2.1 Overview

The condition based monitoring records have been provided from two sources: a condition-monitoring specialist company and a tanker operator. The data from the vibration specialist company consisted of overall vibration readings and spectrum analyses taken with a velocity-meter approximately every six months over a period of several years for specific machinery. The data from the tanker operator were taken monthly over varying periods for each of the five tankers from approximately 12 to 36 months.

The analyses were limited to one of the electric motor-pump equipment for the supporting auxiliary systems related to the propulsion and steering systems. This machinery is duplicated. In the event of failure of one pump, for example, sensors on the failed pump will detect the failure and send a signal to automatically start the standby pump, thereby maintaining auxiliary system functionality and thereby propulsion or steering. Typical marine operations practice is to operate the machinery (duty role) for one week continuously with the duplicated machinery equipment on standby. In the following week, the equipment roles are reversed with the "standby" pump switching to the duty role. In many instances, the equipment received from the condition monitoring company operated satisfactorily during the time measurements were taken and accordingly, degradation could not be evaluated.

For this study, the vibration readings for various pumps in hydraulic, salt water, fresh water, lubricating oil, steam generation and fuel oil service systems were analyzed. All of these pumps are powered by electric motors coupled to the pump. The majority of the motor pump installations are horizontal; but for some installations the motor-pump installation is vertical. The pump types are dependent on the fluid and will be of the positive displacement, centrifugal or screw types. The shafts of this equipment are supported by roller bearings and thrust bearings.

The approaches to determine the remaining life of the equipment are based on application of degradation-based reliability models described by Tseng et al. and Lu and Meeker [40] and [12].

2.2 Ship data

The vibration specialist company provided condition based monitoring records and analyses for nine ships. These ships are of four categories: two Roll-on, Roll-off (RORO), two tankers, two chemical carriers, and three container carriers. Fortunately, for the comparison purposes of this thesis each ship type is composed of sister vessels. The actual ships are not identified at the request of the specialist firm so an alternate identifier is provided. The anonymity is requested because the machinery condition may be used by competitors for their economic advantage.

The tanker operating company provided data for one class consisting of five ships.

Principal characteristics for all ships evaluated are listed in Appendix 1, Table A-1. These ships are of substantial size and propulsion power. Vessel lengths range from approximately 178 to 248 m, beams range from 27 to 42 m and depths (keel to strength deck (main deck) range from 16 to 22 m. Vessel displacements between ship types vary considerably: from 15,000 to 105,000 tonnes. Installed main propulsion power ranges from 5,000 to 21,000 kW.

There are two sources of vibration signals: internally generated signals and externally generated signals. The internally generated signals may produce useful information concerning the machine's condition. "Most usable vibratory signals from rotating machinery are generated at frequencies related to the speed of rotation of the machine. The fundamental rotational frequency is often the signal of greatest interest. Its magnitude is indicative of the degree of unbalance present. Changes in the amplitude of the fundamental frequency signal are indicative of deterioration in the unit's mechanical condition. Rotational frequency signals also may be generated by machine looseness, misalignment, casing distortion (caused by connecting pipes or braces), pump starvation/cavitation, or open iron in a motor rotor" [7].

Accordingly, direct comparisons of equipment type vibration monitoring characteristics from one ship type to another are not anticipated to be possible for the following reasons:

- the installed propulsion power ratings are different and the prime movers for these ships are medium speed diesels, low speed diesels or steam turbines,
- ship motions in the at sea condition will vary considerably as a result of different vessel dimensions and displacements,
- machinery maintenance practices vary among ships, even of the same company, and machinery failure rates will be different [41],
- the trading patterns for each ship type varies and accordingly the environmental conditions will affect readings, and
- the equipment under analysis has been manufactured by a variety of electric motor and pump manufacturers so the differing individual components will affect readings.

The installed power onboard will affect vibration signals. Higher propulsion powers necessitate higher powered auxiliary equipment whose vibrations will be transmitted through the machinery space supporting structure to other nearby equipment. The propeller operates in a non-homogenous wake which will induce strong vibratory excitation at the propeller blade-rate frequency. This frequency is equal to the shaft rotational frequency times the number of propeller blades. Low frequency background vibratory excitations may be produced by the propeller and shafting system attributable to mass or propeller pitch unbalance [7].

Ship motions are dependent on hull shape, displacement and sea conditions, which are a function of sea state (wave height), and weather (wind speed and relative heading to ship direction) and time of year. The hull structure's response will affect measurement results. Ship displacement (laden or ballast condition) has an effect on vibration levels with the ballast condition amplitudes typically higher than those for laden condition.

The trading patterns of the ships will have an effect on vibration levels. Some of these vessels operate on trans-Pacific routes while others operate on United States east coast routes.

Since the equipment in each ship type is identical in all respects, there are at least two or sometimes three identical pieces of equipment on each ship. With two sister vessels, there is a total of two to six pieces of equipment for comparison of degradation characteristics.

Machinery vibration readings are taken with a velocity meter and an accelerometer in way of the bearing housings on the electric motor and pump. Nominal equipment rotating speeds are either 1200, 1800 or 3600 rpm. Uni-axial or bi-axial readings and at least one tri-axial reading are taken for each bearing in the horizontal, vertical and axial directions. A diagram of the reading locations is shown in Figure 2-1. The vibration specialist took vibration readings approximately every six months. This alternative interval as per the request of the ship's operator is in accordance with cite 7-A-14/15.11 of the PMP Guide pertaining to the semi-annual alternative [5]. It is noted that there are three broad-band alarm levels for each equipment: an "early warning limit", an "alert limit value" and a "fault limit value" [42]. The early warning limit alerts the ship operator that the equipment has begun to degrade. However this should not be interpreted to mean this is the point at which degradation can be detected. The alert limit value indicates to the ship operator that degradation has progressed to the point that more frequent condition monitoring is necessary to measure the increasing vibration readings. It is typical in marine practice to assign this limit to be 0.30 in/sec for horizontally mounted equipment and 0.45 in/sec for vertically mounted equipment. This corresponds to "rough" running per general machinery vibration severity charts developed by T.C. Rathbone and presented in SNAME T&R 3-42 [7]. If ISO 2372 is applied, this limit corresponds to Severity

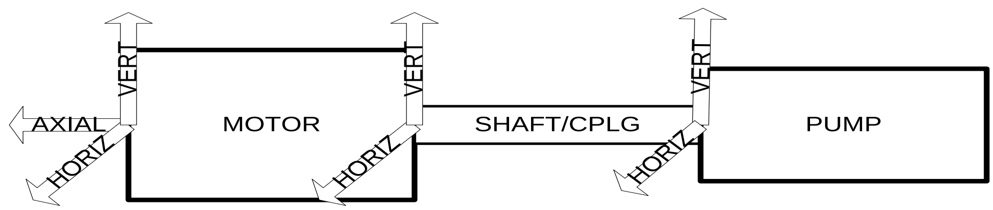
Range D for Class II equipment [7]. ISO 2372 was superseded by ISO 10816-1 in 1995 and the severity chart located in Annex B, Table B.1. This is reproduced in Figure 2-2. When these readings meet or exceed the fault limit value, the equipment is to be repaired. An example report format for filtered vibration readings at 60 Hz for three pump units onboard is shown in Table 2-1. The ship's designation name for the equipment and equipment number for the data are listed along with the testing dates. Although only the results for one testing point are shown, these pumps were tested at four measuring points (e.g., two bearings supporting the pump, one bearing supporting the motor and one axial reading for the shaft).

The vibration data received for this research was subjected to a spectrum vibration analysis for all data. The degradation analysis has been performed for relevant frequencies.

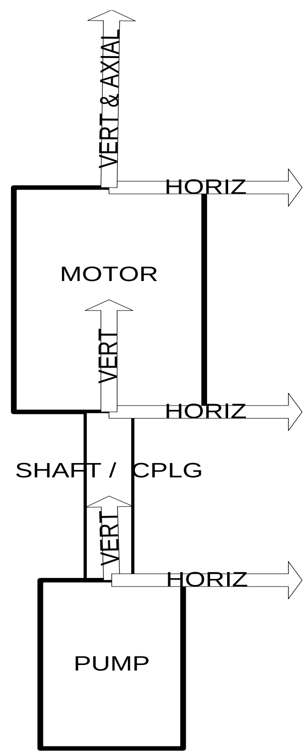
Table 2-2 is a representative equipment list for Chemical Carriers 1 and 2. The other ships can be expected to have similar equipment installed onboard.

2.3 Internally Generated Signals Interpretation

Vibration analysis testing is performed on the electric motor driven pumps to ascertain if any of the faults listed in Table 2-3 are in the process of occurring. This table was adapted from Figure 1.3.2.1 of SNAME T&R Bulletin 3-42 [7]. The frequency, order number and direction of the vibration are also listed. Tables similar to this are frequently used by vibration specialists as an aid to diagnose the underlying causes of high vibration measurements. These causes, if left unrepaired, will eventually lead to failure of the affected component and loss of equipment function. The individual causes can be modeled by applying an appropriate degradation model.



Horizontally Mounted



Vertically Mounted

Figure 2-1 Example Vibration Measurement Location Diagram [7]

<table>
<tr><th colspan="2">R.m.s vibration velocity</th><th>Class I</th><th>Class II</th><th>Class III</th><th>Class IV</th></tr>
<tr><td>0.28</td><td>0.011</td><td rowspan="3">A</td><td rowspan="4">A</td><td rowspan="5">A</td><td rowspan="6">A</td></tr>
<tr><td>0.45</td><td>0.018</td></tr>
<tr><td>0.71</td><td>0.028</td></tr>
<tr><td>1.12</td><td>0.044</td><td rowspan="2">B</td></tr>
<tr><td>1.8</td><td>0.071</td><td rowspan="2">B</td></tr>
<tr><td>2.8</td><td>0.110</td><td rowspan="2">C</td><td rowspan="2">B</td></tr>
<tr><td>4.5</td><td>0.177</td><td rowspan="2">C</td><td rowspan="2">B</td></tr>
<tr><td>7.1</td><td>0.280</td><td rowspan="5">D</td><td rowspan="2">C</td></tr>
<tr><td>11.2</td><td>0.441</td><td rowspan="4">D</td><td rowspan="2">C</td></tr>
<tr><td>18</td><td>0.709</td><td rowspan="3">D</td></tr>
<tr><td>28</td><td>1.10</td><td rowspan="2">D</td></tr>
<tr><td>45</td><td>1.77</td></tr>
</table>

Notes:

Zone A: The vibration of newly commissioned machines would normally fall within this zone.

Zone B: Machines with vibration within this zone are normally considered acceptable for unrestricted long-term operation.

Zone C: Machines with vibration within this zone are normally considered unsatisfactory for long-term continuous operation. Generally, the machines may be operated for a limited period in this condition until a suitable opportunity arises for remedial action.

Zone D: Vibration values within this zone are normally considered to be of sufficient severity to cause damage to the machine.

Class I: Large machines with rated power above 300 kW, speeds of 120 to 15,000 rpm

Class II: Medium size machines with rated power above 15 kW to and including 300 kW, speeds above 600 rpm

Class III: Pumps with multivane impeller and with separate driver with rated power above 15 kW.

Class IV: Pumps with multivane impeller and with integrated driver with rated power above 15 kW.

Figure 2-2 Example Vibration Severity Chart [7] [43] [44]

Table 2-1 Spectrum Velocity Data for 3 Auxiliary Boiler Feed Pumps Trending at 59.5 Hz

Aux Boiler Feed Pump No. 1/ Motor No. 1/ Motor DE 2H			Aux Boiler Feed Pump No. 2/ Motor No. 2/ Motor DE 2H			Aux Boiler Feed Pump No. 3/ Motor No. 3/ Motor DE 2H		
Date	Elapsed Time (days)	Value (in/sec rms)	Date	Elapsed Time (days)	Value (in/sec rms)	Date	Elapsed Time (days)	Value (in/sec rms)
10/21/2009	0.0	0.13	10/27/2009	0.0	0.07	10/22/2009	0.0	0.02
10/28/2009	7.0	0.15	10/27/2009	0.0	0.05	12/8/2009	47.0	0.03
11/9/2009	19.0	0.11	12/8/2009	42.0	0.04	12/30/2009	69.0	0.03
12/1/2009	41.0	0.20	1/18/2010	83.0	0.04	12/30/2009	69.0	0.03
12/3/2009	43.0	0.28	1/25/2010	90.0	0.05	2/6/2010	107.0	0.04
12/3/2009	43.0	0.28*	1/27/2010	92.0	0.05	3/27/2010	156.0	0.04
12/7/2009	0.0	0.02	2/22/2010	118.0	0.04	4/11/2010	171.0	0.04
12/7/2009	0.0	0.18	3/6/2010	130.0	0.04	5/5/2010	195.0	0.02
12/8/2009	1.0	0.14	4/11/2010	166.0	0.04	6/15/2010	236.0	0.03
1/1/2010	25.0	0.13	5/5/2010	190.0	0.02	7/28/2010	279.0	0.01
2/22/2010	77.0	0.11	6/12/2010	228.0	0.10	8/3/2010	285.0	0.04
3/6/2010	89.0	0.18	7/16/2010	262.0	0.03	8/6/2010	288.0	0.08

Note: * Failure occurred and unit repaired.

Table 2-2 Equipment List for Chemical Carriers 1 and 2

Identification No.	Equipment Name[1]		Identification No.	Equipment Name[1]
1	STBD STEERING GEAR PUMP - AFT		11	FWD M/E PISTON COOLING PUMP
2	PORT STEERING GEAR PUMP - FWD		12	AFT M/E PISTON COOLING PUMP
3	M/E LUBE OIL PUMP INBD		13	INBD FUEL VALVE COOLING PUMP
4	M/E LUBE OIL PUMP OTBD		14	OTBD FUEL VALVE COOLING PUMP
5	M/E CROSS-HEAD LO PUMP INBD		15	INBD M/E SW SERVICE PUMP
6	M/E CROSS HEAD LO PUMP OTBD		16	OTBD M/E SW SERVICE PUMP
7	FWD FUEL OIL BOOSTER PUMP		17	HARBOR SW SERVICE PUMP
8	AFT FUEL OIL BOOSTER PUMP		18	INBD M/E FW COOLING PUMP
9	INBD M/E JACKET WATER PUMP		19	OTBD M/E FW COOLING PUMP
10	OTBD M/E JACKET WATER PUMP		20	HARBOR FW COOLING PUMP

Notes: 1 FW – fresh water; FWD – forward; INBD – inboard; LO – lubricating oil; M/E – main engine; OTBD – outboard; STBD - starboard; SW – salt water

The additional complicating factor with regard to analysis and interpretation of the vibration frequencies is that the vibration frequencies can correspond to multiple faults. Typically, each potential fault has to be investigated and a determination made to identify the particular fault. Referring to Tables 2-3 and 2-4, it is possible there may be as many as ten potential faults to investigate for each measurement point on an electric-motor pump unit.

Table 2-3 Electric Motor Pump Fault-Frequency Chart [7]

Fault Type	Frequency/Order	Direction
Unbalance	1 x rpm	Radial
Misalignment Bent Shaft	Usually 1 x rpm 2 x rpm or 3 and 4	Radial and Axial
Ball/Roller Bearing Noise	See Table 2-5	Radial and Axial
Loose Journal Bearing	1/3 or 1/2 x rpm	Mostly radial
Loose Mounts or Joints	2 x rpm and 0.5, 1.5, 2.5 x rpm	
Unbalanced Couples	1 x rpm and/or harmonics	Mostly radial

Referring to the Fault Types in Table 2-4, degradation models were assumed for each fault. These assumptions are based on cite 7/5 and Section 7, Table 5 of ABS Guidance Notes on Reliability-Centered Maintenance [45]. The Fault Type, corresponding failure characteristic and potential degradation model are listed in Table 2-5. The appropriateness of a particular degradation model is subject to the particular characteristics of the component.

2.4 Degradation-based Approaches for Estimating Failure Time

The goal of this part of the study is to determine an appropriate degradation model for predicting failure time. The stochastic degradation models to be assessed are those functions listed in Section 2.4.1. The most appropriate degradation function is selected. A unique issue for this study is the limited number of equipment available for analysis, two to as many as six units. For the majority of the equipment, there is only one failure in the equipment population for the time period analyzed. Accordingly, Rousseuw and Verboven recommended special statistical techniques to use, if appropriate, to estimate function parameters [46]. Finally, the residual life model is developed by deriving the failure time based on the degradation model, where the failure time is defined as the time the degradation path reaches a predetermined failure threshold or the "alert limit value" in this study.

Table 2-4 Ball/Roller Bearing Frequency/Order Formulae [7]

Bearing Catalog Values	
Pitch Diameter D	Speed in RPM N
Ball Diameter d	Bore Diameter B
Number of Balls n	Bearing O.D. O
Contact Angle β	
Geometry Computations	
Effective Ball Diameter	$A = d \cos \beta$
Diameter of Inner Race	$D_i = D - A$
Diameter of Outer Race	$D_o = D + A$
Shaft Rotational Frequency	$f_r = N/60$
Frequency Computations	Fundamental Frequency, Multiply Results by Integers to Obtain Harmonic Frequencies
For a rotating inner race	$f_t = t_i = f_r\ D_i / 2D$
For a rotating outer race	$f_t = f_{to} = f_r\ D_o / 2D$
If both races are rotating	$f_t = \mid f_{ti} + f_{to} \mid$ (sign depends on relative direction of f_{ti} and f_{to}
Relative frequency between cage and rotating raceway	$f_{tr} = f_r - f_t$ where $f_t = f_{ti}$ or f_{to}
Ball-spin frequency	$f_s = f_r\ D_i\ D_o / 2\ D\ d$ or by $f_s = f_{ti}\ D_o / d$
Ball defect frequency	$f_{bd} = 2\ f_s$
Defect on stationary raceway	$f_{sd} = n\ f_t$ where $f_t = f_{ti}$ or f_{to}
Defect on rotating raceway	$f_{rd} = n\ f_{tr}$ where $f_{tr} = f_{ti}$ or f_{to}

Table 2-5 Electric Motor Pump Fault-Type and Degradation Model

Fault Type	Failure Characteristic	Potential Degradation Model
Unbalance	Wear-in failure Random Wear-out failure	Exponential Linear
Misalignment Bent Shaft	Wear-in failure Random	Exponential Logarithmic Gompertz Lloyd-Lipow
Ball/Roller Bearing Noise	Random	Exponential Logarithmic Gompertz Lloyd-Lipow
Loose Journal Bearing	Random	Exponential Logarithmic Gompertz Lloyd-Lipow
Loose Mounts or Joints	Random	Exponential Logarithmic Gompertz Lloyd-Lipow
Unbalanced Couples	Wear-in failure Random	Exponential Logarithmic Gompertz Lloyd-Lipow

The applied approach is to mathematically model the functional form of the degradation signals assuming the signal evolves according to a continuous-time stochastic process (also referred to as a random coefficient regression model or a random coefficient growth model).

This modeling approach has been applied on numerous occasions per Wang, Lu and Meeker, Tseng et al., Gebraeel et al., and Son and Savage, etc., [25], [12], [40], [15], [16], [23], [20]. The degradation signal $S(t_{ij})$ is defined as the level of the signal of the i^{th} component at time t_j where$i$ = 1, 2, ..., and j = 1, 2, ..., and $S(t_{ij}) = \eta(t_j, \varphi, \beta_i) + \varepsilon(t_{ij})$, where $\eta(\cdot)$ describes the mean path followed by the degradation signals. The parameter φ is deterministic, fixed-effect and constant across all units of a given population of components. The parameter β_i, is a stochastic coefficient that characterizes the particular degradation rate of the i^{th} component among the individual units of the given population. The parameter β, is assumed to follow a distribution denoted as, $\pi(\beta)$, across the components' population. The term, $\varepsilon(t_{ij})$, is applied to model signal noise and transients and is assumed to be independent and identically distributed (i.i.d.) with $N(0, \sigma^2)$, across the population of devices. The parameters β and $\varepsilon(t_{ij})$, are independent of each other.

The variable representing the failure time is denoted as T. The distribution of T is determined by evaluating the failure times for the equipment items upon reaching the predetermined failure threshold, D. For this thesis, D, is the "alert limit value". The failure time is expressed as

$$F_T(t) = P\{T \leq t\} = F_T(t; \varphi, \beta, D, \eta). \quad (1)$$

Alternatively, the distribution of T can be determined by evaluating the time the degradation signal reaches the predetermined failure threshold, D, for a non-decreasing degradation process,

$$F_{\mathrm{T}}(t) = P\{T \leq t\} = P\{\eta(t; \varphi, \beta) + \varepsilon(t) \geq D\}. \quad (2)$$

2.4.1 Estimating Failure Time based on Individual Degradation Paths

In the approach illustrated by Tseng et al. the degradation signal is defined as a stochastic model [40]. For this analysis, several stochastic degradation models are analyzed namely: linear, exponential, power, logarithmic, Gompertz and Lloyd-Lipow functions as follows. A degradation path for each equipment item is calculated applying a regression method.

Linear degradation model:

$$S(t_{ij}) = \varphi_i + \beta_i t_j + \varepsilon(t_{ij}). \tag{3}$$

Exponential degradation model:

$$S(t_{ij}) = \varphi_i e^{(\beta_i t_i + \frac{\sigma^2}{2})} + \varepsilon(t_{ij}), \tag{4}$$

where σ is a constant.

Power degradation model:

$$S(t_{ij}) = \varphi_i \mathrm{t}_{\mathrm{i}}^{\beta_i} + \varepsilon(t_{ij}). \tag{5}$$

Logarithmic model:

$$S(t_{ij}) = \varphi_i + \beta_i \ln t_j + \varepsilon(t_{ij}). \tag{6}$$

Gompertz model:

$$S(t_{ij}) = \varphi_i \beta_i^{\mathrm{c_i^{t_j}}} + \varepsilon(t_{ij}), \tag{7]}$$

where c_i is a constant.

Lloyd-Lipow model:

$$S(t_{ij}) = \varphi_i + \frac{\beta_i}{t_j} + \varepsilon(t_{ij}). \tag{8}$$

From the degradation path for each equipment item, the predicted lifetime $\widehat{t_\iota}$ is determined, that is the time at which the alert limit value is reached.

The predicted lifetimes for all components are analyzed to determine if they can be fitted by a distribution. The following distributions are considered: exponential, normal, log-normal, generalized-Gamma, Logistic, LogLogistic and Weibull. Bartlett's test is applied to the various distributions to determine the most appropriate one. Other tests such as Levene's test or Welch's test will be considered if Bartlett's is inconclusive.

2.4.2 Two-Stage Approach for Estimating Failure Time

Another approach to estimating the time to failure based on degradation models is illustrated in Lu and Meeker [12]. The degradation path models to be considered are identical to those listed in Section 2.4.1. The stochastic parameter θ_i follows a multivariate distribution function $G_{\theta i}(\cdot)$ dependent on several unknown parameters that must be estimated during the data analysis. Accordingly, the degradation path for linear degradation is written identically to Equation 3.

Lu and Meeker use the symbol θ for the stochastic parameter β used in Section 2.4.1. (*For the remainder of this section Θ will be used to avoid transcription errors.*) The stochastic parameter θ follows a multivariate normal distribution (MVN) with a mean vector μ_θ and variance-covariance matrix Σ_θ. Then it is assumed $\theta_i = (\theta_{1i}, \theta_{2i}, \ldots, \theta_{ni})' \sim \mathrm{MVN}(\mu_\theta, \Sigma_\theta)$ (i = 1, 2, ..., n). The distribution of the time to failure in Equation 1 is rewritten as:

$$F_T(t) = P\{T \leq t\} = F_T(t; \varphi, \mu_\theta, \Sigma_\theta, D, \eta). \tag{9}$$

Lu and Meeker then proceed with the following two-stage method:

Stage 1: Obtain the estimates of the degradation model parameters for each unit's sample path. That is, for each unit's degradation path, the parameters $\widehat{\varphi_\iota}$ and $\widehat{\theta_\iota}$ are calculated using the least squares estimates. The Stage 1 estimated parameters are transformed so that the random-effects parameters are modeled as a multivariate normal distribution.

Stage 2: the estimated transformed parameters are combined to produce estimates of φ, μ_ϑ, and Σ_ϑ. That is, the parameters are estimated as follows:

$$\hat{\varphi} = \frac{1}{n} \sum_{i=1}^{n} \widehat{\varphi_\iota} \tag{10}$$

$$\widehat{\mu_\theta} = \frac{1}{n} \sum_{i=1}^{n} \widehat{\theta_\iota} \tag{11}$$

The asymptotic variance-covariance matrix Σ_θ can be estimated from the differences of the matrix expression $M_a - M_b$ which may not always be non-negative definite. Lu and Meeker suggest applying a procedure by Amemiya shown in Table 2-6 that always results in a non-negative definite [47].

Table 2-6 Procedure of Amemiya

$\hat{\Sigma}_\theta = M_a - M_b$	If $M_a - M_b$ is non-negative definite
$\hat{\Sigma}_\theta = 0$	If $M_a - M_b$ is negative definite
$\hat{\Sigma}_\theta = \Gamma_+ (\Lambda_+ - I)\Gamma_+'$	otherwise

We analyzed the vibration data by determining the Stage 1 estimates for the model parameters $\widehat{\varphi_\iota}$ and $\widehat{\theta_\iota}$ along with the corresponding standard errors designated as $s_{\widehat{\theta\iota}}$, an estimate of the measurement error standard error deviation $\hat{\sigma}_{\varepsilon i}$ and the first order autocorrelation r_1 for the residuals. Next the two-stage estimates for the basic model parameters μ_θ and Σ_θ are obtained. For this study a random number generator is applied to the basic model parameters instead of the bootstrap method used by Lu and Meeker to develop a failure time distribution. The results of this method are then compared with that of Tseng's in Section 2.4.1.

2.4.3 Preventive Maintenance based on Failure Limit Policies

Based on the results of reliability models from Section 2.4.1 and 2.4.2, the preventive maintenance policy is optimized using the failure limit methods reviewed in Section 1.3.5. The inspection interval in the preventive maintenance policy is determined when the reliability of equipment or systems reaches a predetermined limit.

Chapter 3
ANALYSIS OF THE PROBLEM

3.1 Verification of Two-stage Method

We re-evaluated and re-confirmed Lu and Meeker's two-stage method by applying their data. The exception to the method was in lieu of using the parametric bootstrap simulation procedure; normally distributed random numbers were generated using SAS software based on a random number generator developed by Matsumoto and Nishimura, the Mersenne-Twister [48].

Details of the data used are listed in Appendix 2, Table B-1. The fatigue crack growth data were developed from Bogdanoff and Kozin, Figure 4.5.2 on page 242 [49]. A least squares regression analysis was performed on the 21 paths to estimate the path parameters Θ_1 and Θ_2, along with the standard errors $s_{\Theta 1}$ and $s_{\Theta 2,}$ an estimate of the measurement error standard deviation σ_ε, and the variances and covariances of the path parameters. The comparison of the results published by Lu and Meeker, and our recalculation of the model parameters using Lu and Meeker's approach are in Table 3-1. The calculation results for the path parameters are considered satisfactory. These checks of Lu and Meeker's calculations helped confirm the calculation approach used in this thesis for the degradation data is correct. Accordingly, the calculated two-stage estimates of the basic model parameters are:

$$\hat{\mu}_\theta = \begin{pmatrix} 3.714 \\ 1.620 \end{pmatrix} \qquad \hat{\Sigma}_\theta = \begin{pmatrix} 0.50861 & -0.04612 \\ -0.04612 & 0.06844 \end{pmatrix} \tag{12}$$

Table 3-1 Comparison of Calculated and Published Stage 1 Estimates for Fatigue-Crack Growth Data

	Calculated	Lu and Meeker
Mean ($\widehat{\boldsymbol{\Theta}}$)		
$\widehat{\Theta}_1$	3.714	3.732
$\widehat{\Theta}_2$	1.620	1.571
Mean Std Error ($s_{\widehat{\Theta}}$)		
$s_{\widehat{\Theta}_1}$	0.036	0.034
$s_{\widehat{\Theta}_2}$	0.098	0.100
Avg Std Error ($\hat{\sigma}_\varepsilon$)	0.003	0.006
Covariance		
$\widehat{\Theta}_1$	-0.04612	-0.09373/-0.09554
$\widehat{\Theta}_2$	-0.04612	-0.09373/-0.09554
Variance		
$\widehat{\Theta}_1$	0.50861	0.54652/0.54560
$\widehat{\Theta}_2$	0.06844	0.07808/0.06654
Standard error		
$\widehat{\Theta}_1$	0.71317	0.73927
$\widehat{\Theta}_2$	0.26161	0.27944

The results from the randomly generated numbers are listed in Table 3-2. As part of the analysis, three groups of random numbers were generated for quantities of 500, 1250 and 2500 to determine the effect on the variables' mean, variance, covariance, and minimum and maximum values. The Lu and Meeker data statistics were recalculated to verify the calculation method used in this thesis is correct. There was agreement for most statistics to the second or third significant figure. The largest discrepancy was for calculation of the covariance. The published covariance was twice the recalculated value. The recalculated value was in agreement with those covariances calculated with random numbers. The mean, variance and covariance for both variables were in close agreement to the recalculated Lu and Meeker data.

3.2 Software Used for the Analysis

Several software applications were used to evaluate the vibration data, including Omnitrend™, Excel, Weibull++™, and SAS. Omnitrend™ software was provided by Ludeca and used to extract the vibration data in the form of frequency spectrum analyses from the five ships' databases provided by the ship owner. The software can create frequency spectrum figures or "waterfall diagrams" which show multiple spectrum analyses over time. An example "waterfall diagram" is shown in Figure 3.1. These diagrams are useful in identifying trends. The numerical data extracted from Omnitrend™ was sorted by equipment, measurement location, vibratory frequency and measurement date. The quantity of data records was significant varying from 10,000 to 15,000 per measurement point for ships recently implementing vibration measurement to 80,000 to 90,000 records per measurement point for ships with 30 months of data. Vibration readings were taken monthly by the vessels' personnel. A representative output exported to an Excel spreadsheet is shown in Table 3-3 after the data has been sorted by frequency. The data for several representative frequencies related to nominal operating speed and several bearing frequencies unique to the equipment were extracted in the format shown in Table 3-4.

Excel software was used for sorting and organizing the vibration data so as to be processed by Weibull++ and SAS. For use by Weibull++, an identification code is necessary for each data point. The identification code format used is shown in Table 3-5.

Table 3-2 Comparison for 500, 1250 and 2500 random numbers for Theta1 and Theta2

Variable or statistic	Lu and Meeker Results as	Lu and Meeker Results as	500 Simulations	1250 Simulations	2500 Simulations
$\widehat{\Theta}_1$	3.732	3.714	3.711	3.725	3.729
$\widehat{\Theta}_2$	1.571	1.620	1.631	1.626	1.621
Variance Theta1	0.546	0.509	0.540	0.541	0.523
Variance Theta2	0.067	0.068	0.068	0.068	0.069
Covariance	-0.096	-0.046	-0.036	-0.046	-0.044
Mean of residuals					
Theta1			-4.000E-10	-9.920E-09	8.400E-10
Theta2			4.600E-09	-6.684E-09	5.200E-10
Mean of cycles to failure					
Mean (millions of	0.108	0.107	0.125	0.124	0.124
Std deviation	0.024	0.024	0.028	0.030	0.028
Maximum value	0.170	0.172	0.345	0.644	0.644
Minimum value	0.089	0.088	0.075	0.065	0.065
Std dev max value	NA	NA	7.802	17.188	18.258
Std dev min value	NA	NA	1.771	1.977	2.090

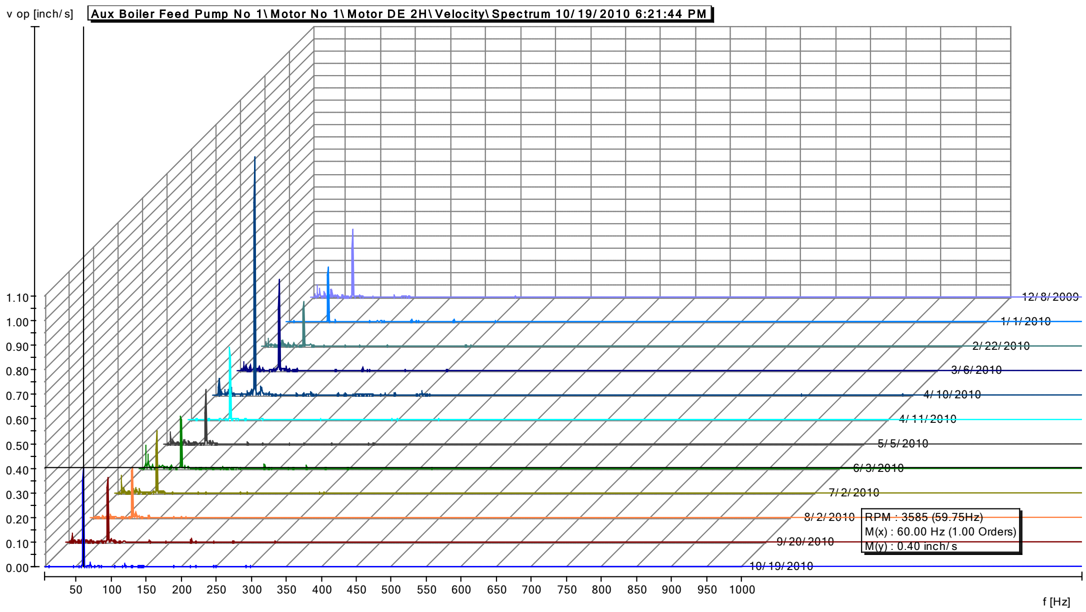


Figure 3-1 Auxiliary Boiler Feed Pump No. 1 Vibration Measurement Map (Waterfall Diagram)

Table 3-3 Spectrum Analysis Data Output from Omnitrend™

Path of Location Tanker 101\Boiler System\Boiler Feed Pump #1\Motor #1\Motor NDE 1H\Velocity				
Number of Meas. Values : 89600				
Meas. Task : Machine				
Meas. Type : Spectrum				
Unit: inch/s (rms)				
	Date	Time	f (Hz)	Value
	10/28/2009	2:52:17 AM	59.5	0.1
	11/9/2009	4:04:31 AM	59.5	0.11
	12/1/2009	4:28:16 PM	59.5	0.14
	12/3/2009	9:23:53 PM	59.5	0.21
	12/3/2009	11:03:00 PM	59.5	0.19

Table 3-4 Spectrum Analysis Data Prepared for Analysis

f (Hz)	Date	Time Elapsed	Value	Data ID and Alpha Code
59.5	10/28/2009	7.0	0.10	30702040918_101_NDE1H_1_59.5_
	11/9/2009	19.0	0.11	30702040918_101_NDE1H_1_59.5_

Path ID	Unit ID
A	30702040918_101_NDE1H_1_59.5_A
A	30702040918_101_NDE1H_1_59.5_A

Table 3-5 Data Identification Code Format

ASTM Marine Machinery Code	Ship ID	Measurement Point	Machine ID	Frequency	Path No.
30702040918_	105_	DE2H_	1_	59.5_	A

The extracted measurement data were evaluated using Weibull++™ (version 8) software to determine appropriate closed form degradation path models (see 2.4.1) using the sum of the square error (SSE) to rank the data fit. This software was also applied to develop the degradation figures and distribution functions. The degradation paths are extrapolated to determine the time at which the vibration limit would be exceeded. These "survival times" are then used to determine an appropriate survival distribution from among 11 distribution models. Additionally, SAS (version 8.3) software was used to evaluate some of the statistical characteristics of the vibration data and generate random numbers for the two-stage method.

3.3 Initial Evaluation

In the initial thesis proposal, vibration data for three auxiliary boiler-feed water-pumps from Tanker 102 were selected for analysis. One of these pumps had experienced a failure earlier in 2010; but the other two pumps had operated satisfactorily. Vibration data was limited because the crews had only recently been provided with the training and equipment to take vibration measurements onboard. There are four sister ships to Tanker 102 which potentially offered a larger population for the statistical analyses. The ship owner had advised that the reliability of identical equipment on sister ships could vary considerably based on the maintenance management practices of the chief engineer onboard [41].

Storage, retrieval and limited analysis of the collected vibration data is accomplished through the use of Omnitrend™ software. The vibration data is transmitted to the ship management office and a vibration consulting firm which reviews, analyses and issues reports advising necessary maintenance actions on equipment with high vibration levels. The report lists the equipment analyzed and alerts the ship management staff ashore and the ship's crew of equipment in the early stages of degradation or on the verge of failure. Based on the vibration characteristics, the report lists possible failure modes for the crew to investigate.

The ship owner expanded training and implementation of condition monitoring techniques on additional ships in their fleet. Subsequently, comprehensive vibration data from the four sister ships of Tanker 102 along with an additional year of vibration data for Tanker 102 became available and were submitted during mid-2011.

It was at this time the semi-annual vibration data provided by another vibration specialist firm was determined to be unsuitable for further analysis because the 6-month interval between measurements is too long.

3.4 Estimating Failure Time based on Individual Degradation Paths

The Omnitrend™ software organizes ship's machinery systems in a hierarchy. Equipment operating at an acceptable vibration level, approaching or exceeding a pre-determined vibration limits are visually identified in the hierarchy by a green, yellow or red symbol, respectively. The yellow and red symbols alert the operator to monitor the equipment's condition more closely or to perform maintenance to avoid imminent failure. The equipment lists of all five ships were reviewed and the boiler water feed pumps were selected because of the "larger" population of 15 motor-pumps to evaluate, past reported failures and potential future degradation problems.

The spectrum analyses for all motor-pumps were reviewed to focus on areas of obvious degradation. As Motor-Pump #1 on Ship 102 had experienced mechanical problems, the spectrum analysis revealed a clear degradation issue at 59.5 Hz which is equal to the equipment's operating speed of 3570 rpm. Accordingly, the vibration amplitudes at 59.5 Hz were extracted to an Excel spreadsheet for all 4 measuring points, for each of the three pumps on each of the 5 ships using Omnitrend™ software's export utility. This represented 60 equivalent measurement points.

Also provided are the measurement dates, intervals and indications when the alarm limits are exceeded. When the equipment is repaired, a vibration measurement is taken to verify the cause of the high amplitude has been repaired and to serve as a new baseline for subsequent measurements. For the purposes of this thesis it is assumed the system is repairable and reverts to its initial state. Repairs were identified by vibration readings taken within one day of each other along with a decrease in the vibration level. This is illustrated in Figure 3-2 on a calendar basis. However, when repairs are made, the elapsed time is reset to 0 days. This is illustrated in Figure 3.3. When a repair is made a new degradation Path ID is created (e.g., A is the initial path, followed by B, C, …)

The repair dates for the equipment were identified and Weibull++ was used to determine the appropriate function for the degradation paths. All of the degradation paths were determined to be a linear function as the best fit. These are listed in Appendix 3 by ship number in Tables C-1 through C-5. It was noted in many cases the slope of the linear function was negative. These degradation paths were not used further in this analysis as the results would not be meaningful. It is believed these negative slope paths are the result of various environmental factors such as wind, varying wave heights and their relative direction to the ship; vessel loading condition: ballast or laden; and effects of other machinery operating nearby. In other words, the vibration data measurements taken from time to time are not under homogenous environmental conditions which lead to inconsistent measurements.

After the linear functions with negative slopes were discarded from the vibration data, an analysis of the data fit for the linear paths and an analysis of the residuals was conducted using the ARIMA Procedure in the SAS software. The results are shown in Tables C6 through C12 which are organized by measurement points NDE1H or 1V, DE2H or 2V, DE3H or 3V and NDE4H or 4V. Figures 3-4 and 3-5 indicate Residual Correlation Diagnostics for the degradation path Yest and Residual Normality Diagnostics. It is assumed the error term ε_{ij} for the path model described in Section 2.4 is $N(0, \sigma^2)$ and the results for this analysis of the residuals show the assumption is reasonable. Lu and Meeker advise degradation on a specimen over time is a time series which can exhibit autocorrelation. The ARIMA Procedure checked for trending and correlation which is illustrated in Figure 3-76. Based on an acceptable check of the residuals, the determination of the failure time estimates could proceed.

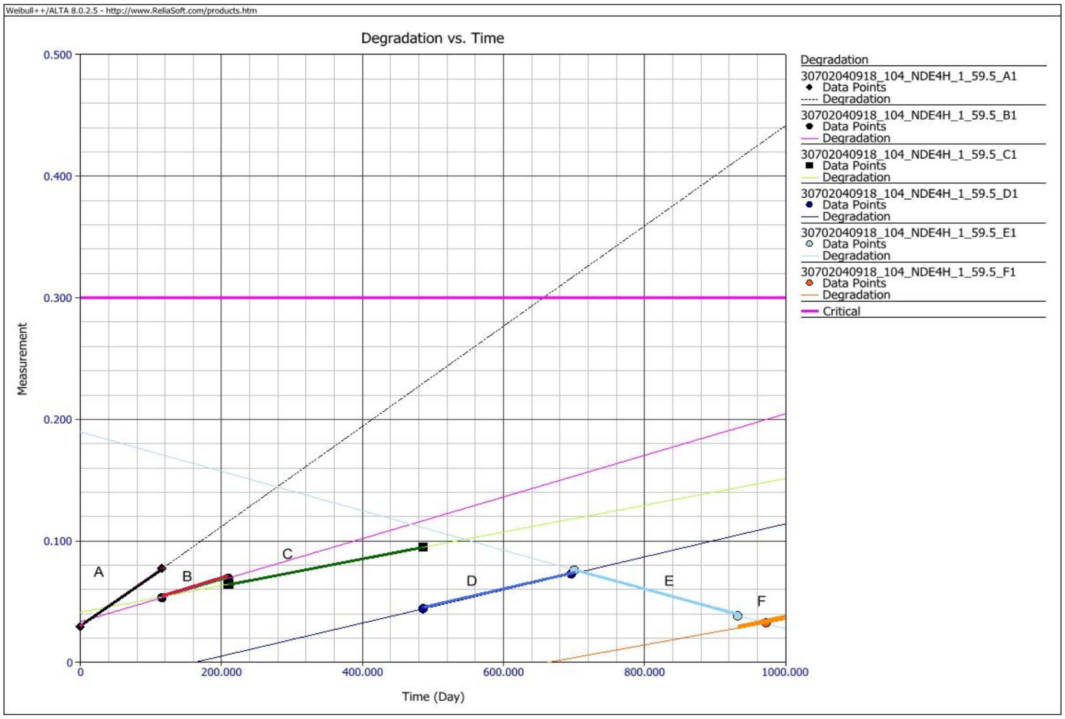


Figure 3-2 Reparability and Degradation Path – Calendar Time

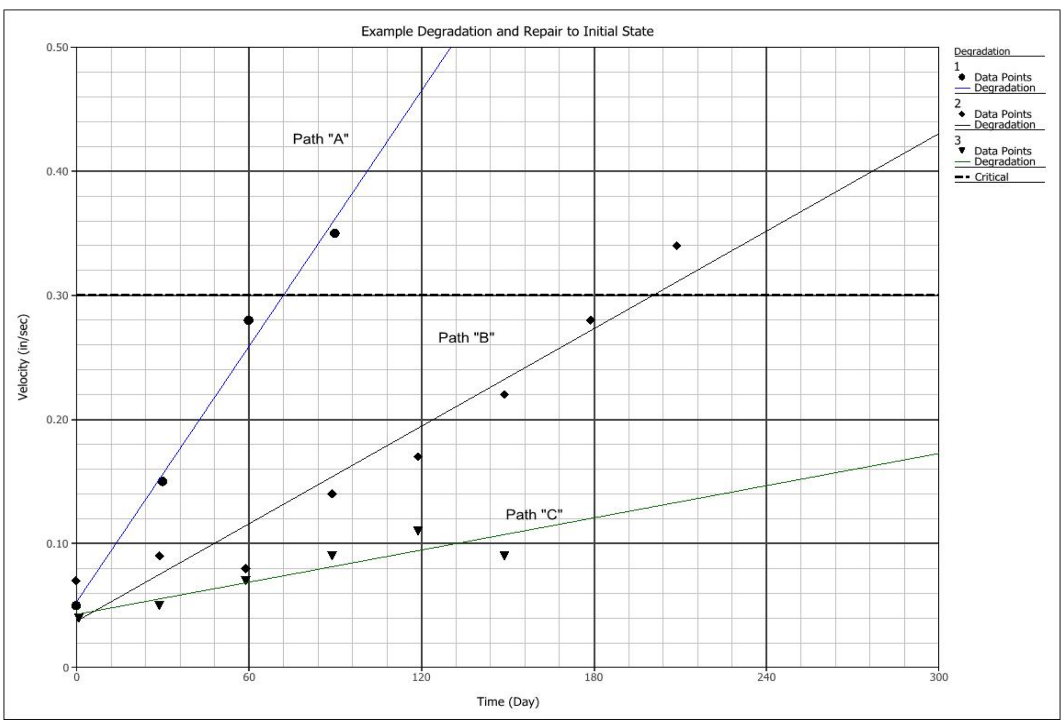


Figure 3-3 Reparability and Degradation Path –Time Reset to 0

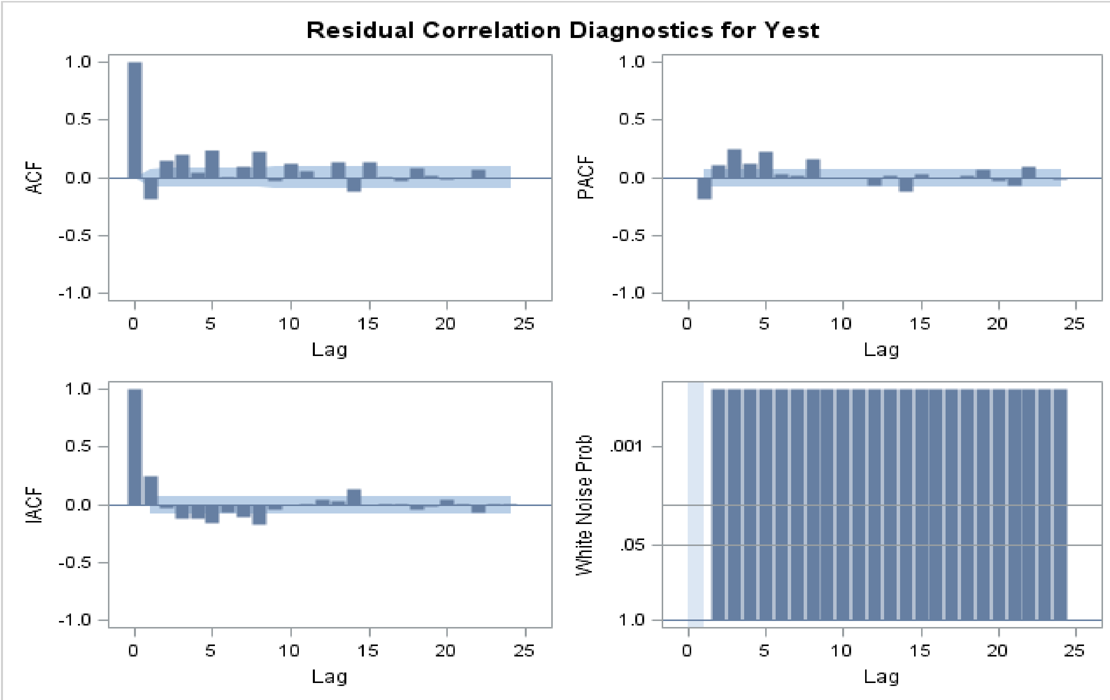


Figure 3-4 Residual Correlation Diagnostics for Degradation Parameters

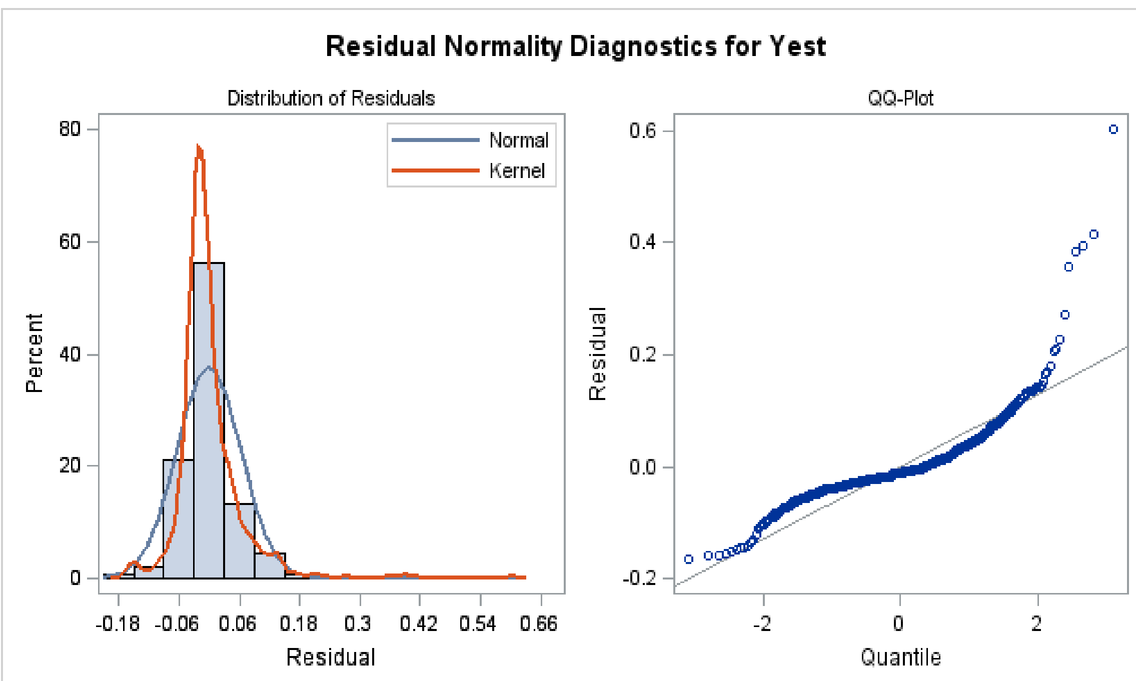


Figure 3-5 Residual Normality Diagnostics for Degradation Parameters

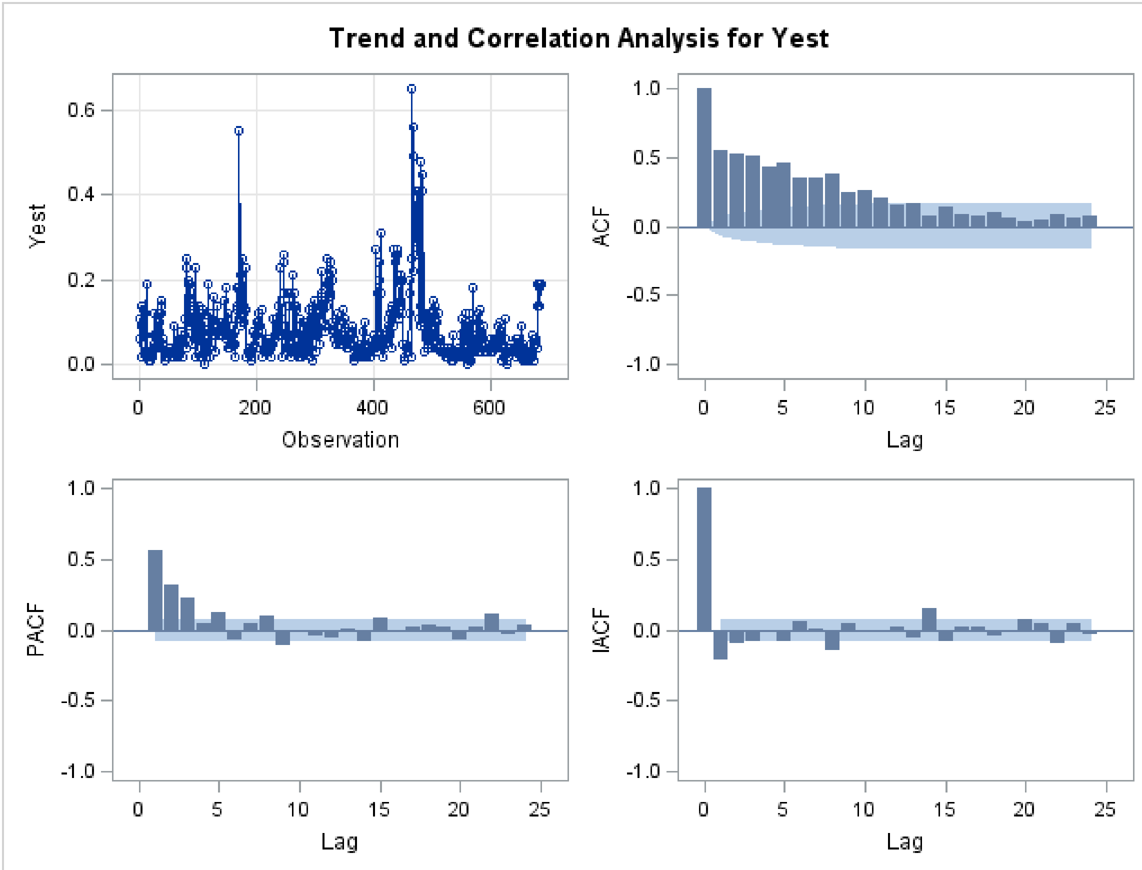


Figure 3-6 Residuals Trend and Correlation Analysis for Degradation

The vibration data was evaluated in two manners. The first was to determine if the vibration data could be evaluated as a parametric model at the vibration measurement locations. The second approach was to determine if the vibration data could be combined with the data from several measurement locations on the same ship. This second approach was to rule out any correlations occurring unbeknownst to me.

When the degradation paths were analyzed in Weibull++, with few exceptions the three-parameter Generalized Gamma Distribution was indicated as the best fit. Approximately 100 degradation paths were considered and/or evaluated as part of this study. The summary of the parameters for the three-parameter Generalized Gamma Distribution are listed in Table 3-5.

Combined plots for the probability density functions (PDF) for all four measurement locations along with corresponding cumulative density functions (CDF) are shown in Figures 3-7 and 3-8. It is noted that for measurement points NDE1H or 1V and NDE4H or 4V that the density functions are zero until 200 days and 600 days respectively because the premature failure data was discarded.

Table 3-5 Parameter Summary for 3 P Generalized Gamma Distribution

Hertz	59.5			
Measurement Point	NDE1H or V	DE2H or V	NDE3H or V	NDE4H or V
Distribution:	G-Gamma-3P			
Analysis:	Maximum Likelihood Estimate			
CB Method:	Fisher Matrix			
Ranking:	MEDIAN			
Mu (Day)	6.510	5.990	7.419	6.476
Sigma	1.162	1.533	2.325	0.043
Lambda	-1.914	-2.470	-0.014	-50.000
LK Value	-78.350	-78.186	-68.857	-61.377
Fail \ Susp	9 \ 8	9 \ 10	8 \ 7	7 \ 10
Covariance Information				
Var-Mu	0.679	1.128	0.512	0.000
CV Mean-Std	0.270	0.542	0.183	0.001
CV Mean-Lambda	1.287	1.843	0.001	0.765
Var-Sigma	0.177	0.381	0.411	0.012
CV Std-Lambda	0.484	0.851	0.000	13.939
Var-Lambda	2.920	1.427	0.001	16294.740

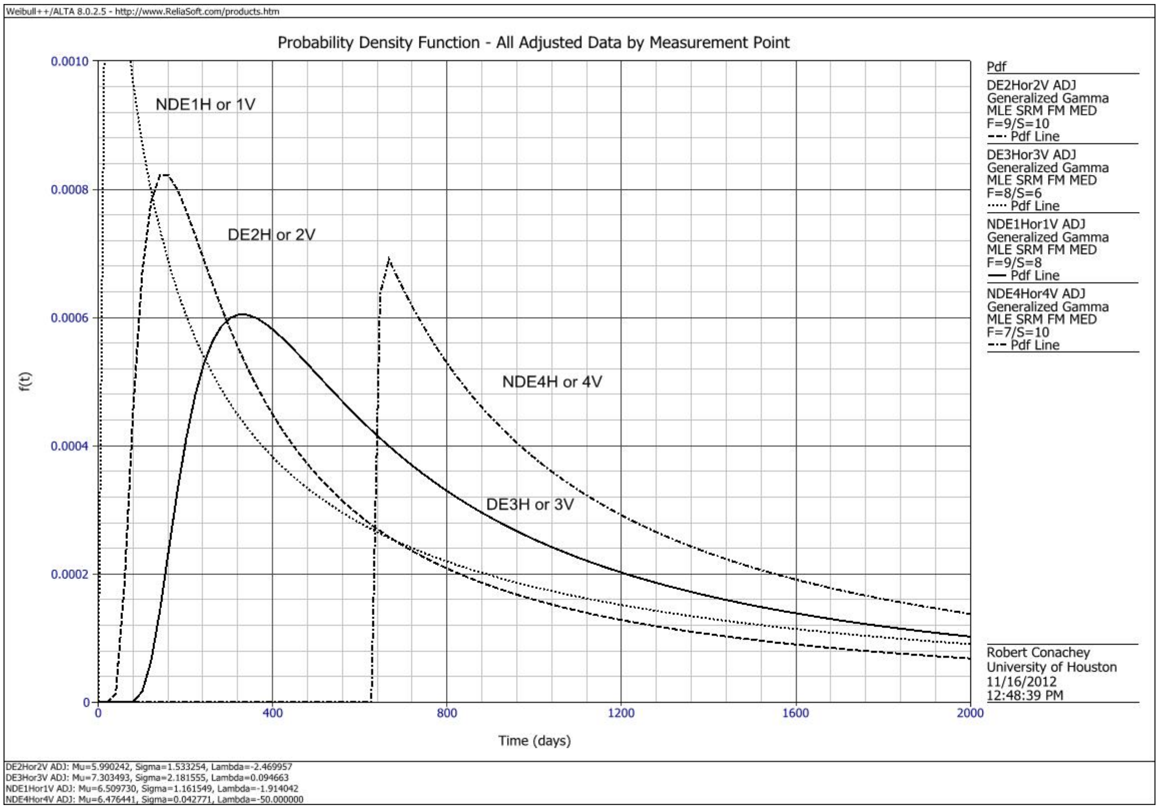


Figure 3-7 PDF Adjusted Data by Measurement Point

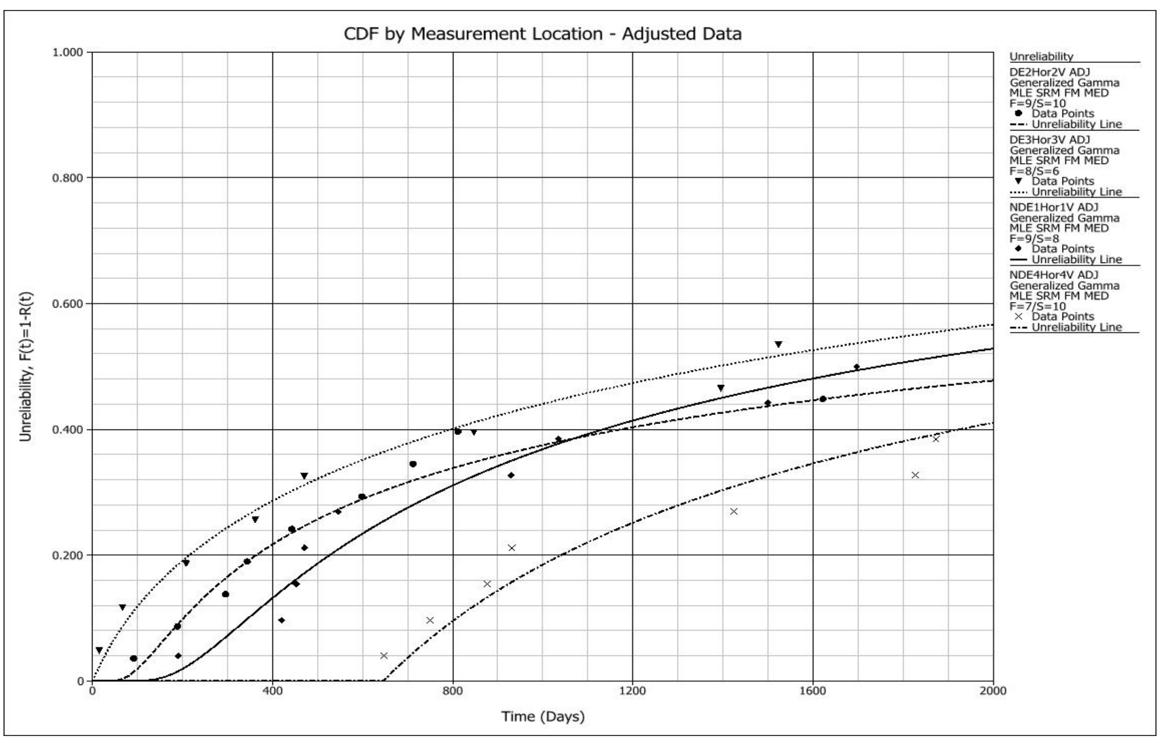


Figure 3-8 CDF Adjusted Data by Measurement Point

In addition to the comparative plots, Figures 3-9 through 3-12 list CDF for individual measurement points with two sided 90% confidence bounds (Type I). The upper confidence level in Figure 3-9 is not unique for measurement points NDE1H or 1V compared with that calculated for the other measurement points because of the discarded early failure data and relatively few data points evaluated. With additional data points we would expect the resulting upper boundary to closely resemble those in Figures 3-10 through 3-12.

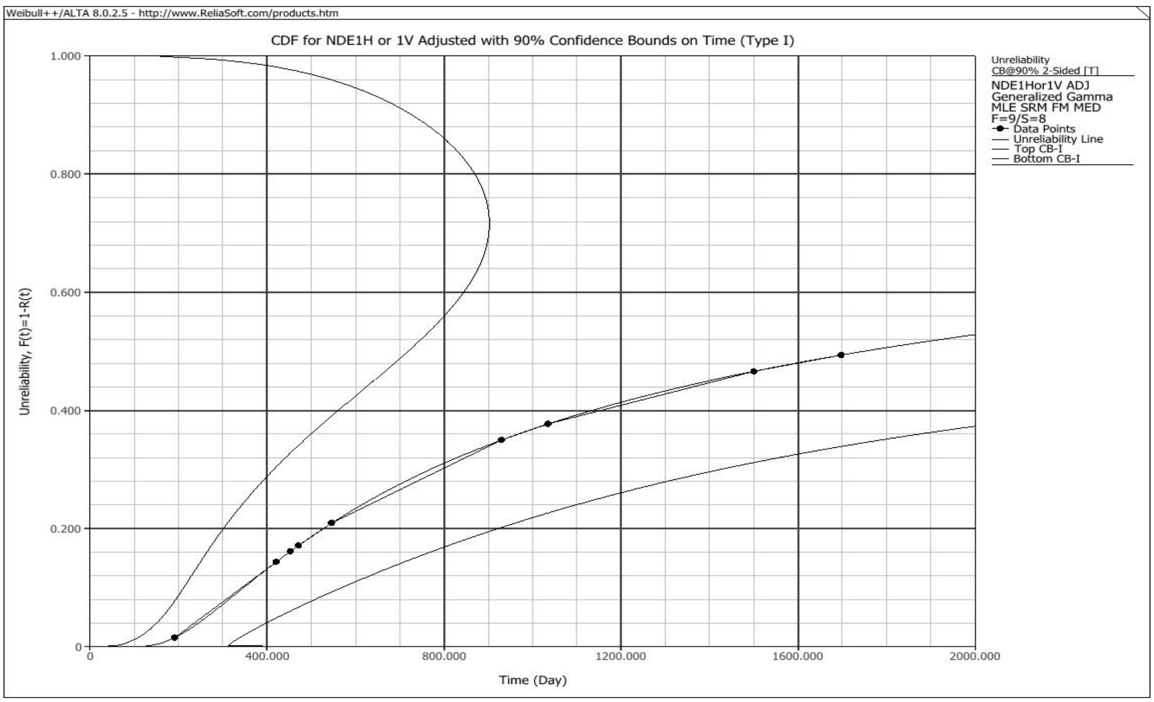


Figure 3-9 CDF Adjusted Data by Point – 90% Conf. Interval at NDE1H or 1V

3.5 Estimating Failure Time Using Two-Stage Method

Lu and Meeker [12] provided an example of the two-stage method of estimation which is demonstrated in this section. The measured vibration data for measurement point NDE3H or 3V was analyzed using Weibull++, and it is determined the best degradation path was a 3-parameter generalized gamma function. Instead of using the bootstrap simulation to generate data, the random number generator in SAS was used along with a variance-covariance matrix and the means of the three parameters estimated by Weibull++ to simulate additional data. Table 3-6 summarizes the simulated parameters and compares them to the adjusted measured data. The only comparable similarities were the factors Mu and sigma. The LK Values varied significantly (e.g., from -69 for the adjusted data, -2528, -6293 and -21494 for the simulated data). Other factors in the generalized gamma distribution varied significantly such as lambda which ranged from -0.014 for the adjusted data and -2.63 to -3.003 for the simulated data. This could be attributable to the relatively small amount of data that could be used in this study.

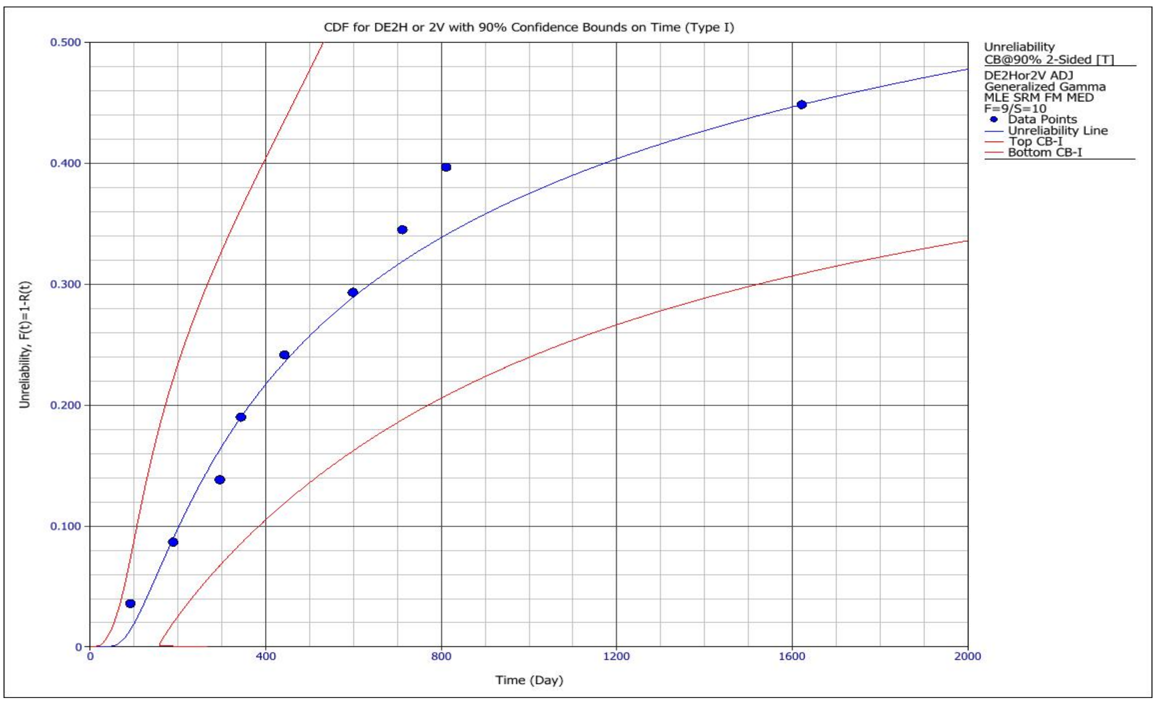


Figure 3-10 CDF Adjusted Data by Point – 90% Conf. Interval at DE2H or 2V

The two factors for the linear degradation function were simulated using this method. The results applying this method were encouraging. A CDF pertaining to measuring point DE3V or 3H shows the actual measured data and the simulated data for three different quantities of 500, 1250 and 2500 simulations in Figure 3-13. The discard of data with early failures for DE3V or 3H changes the time significantly for the first failure from approximately 0 days to 200 days.

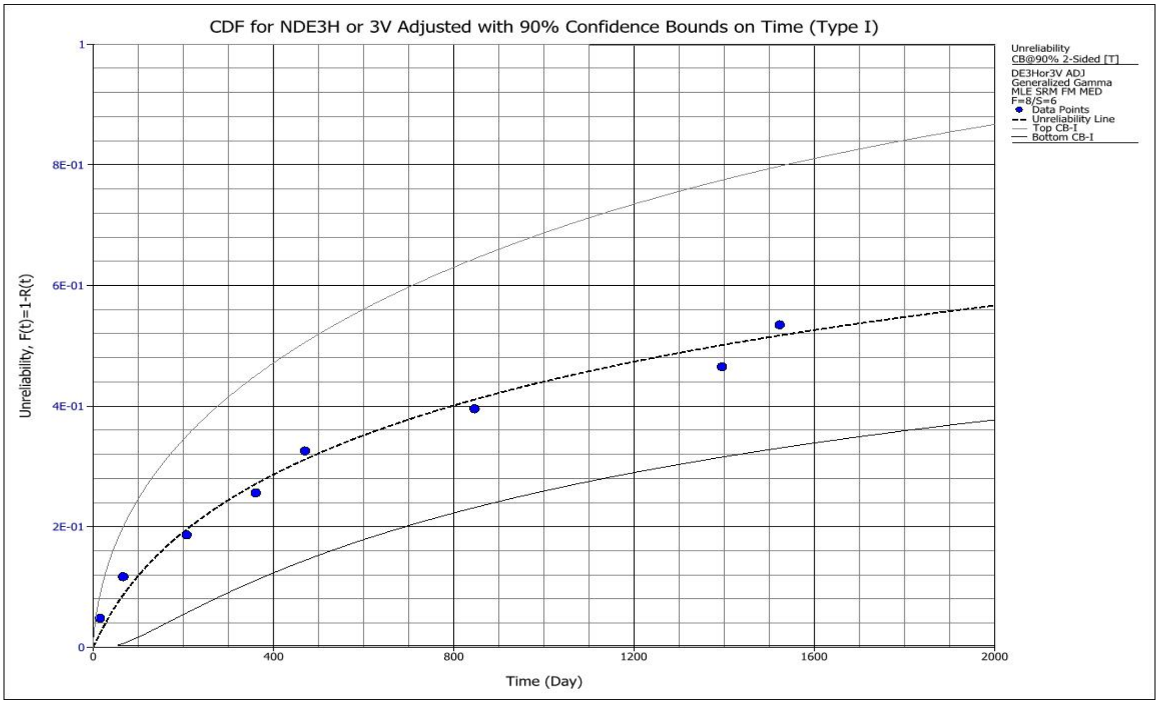


Figure 3-11 CDF Adjusted Data by Point – 90% Conf. Interval at NDE3H or 3V

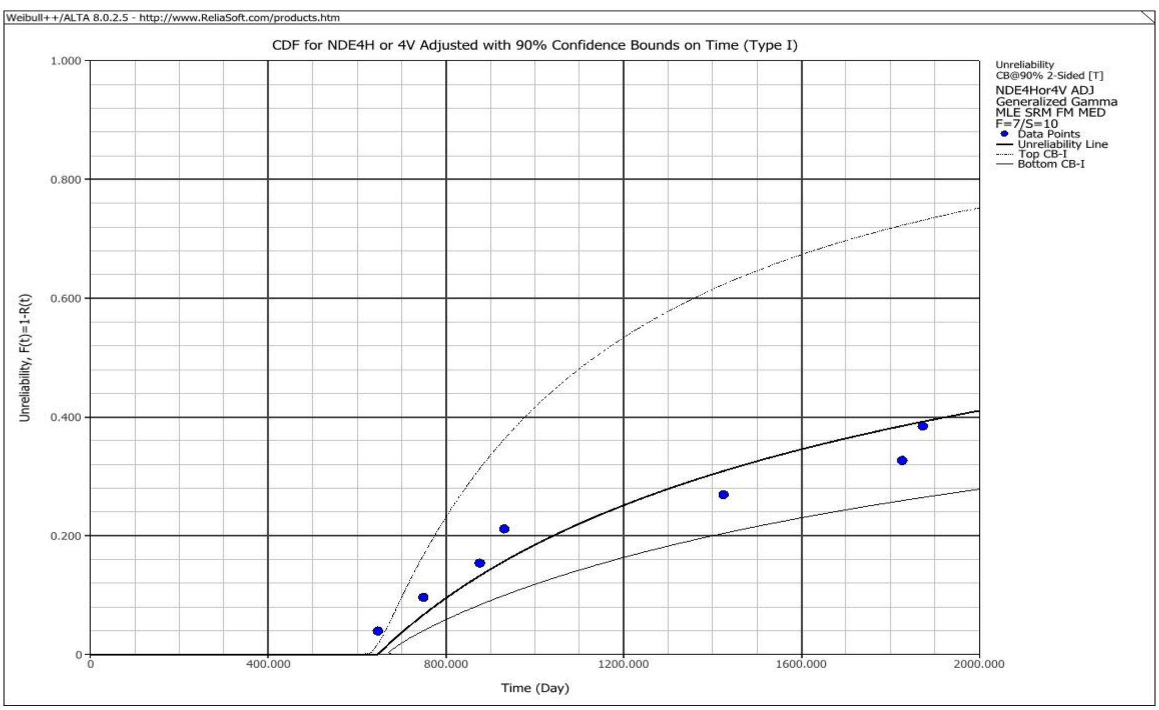


Figure 3-12 CDF Adjusted Data by Point – 90% Conf. Interval at NDE4H or 4V

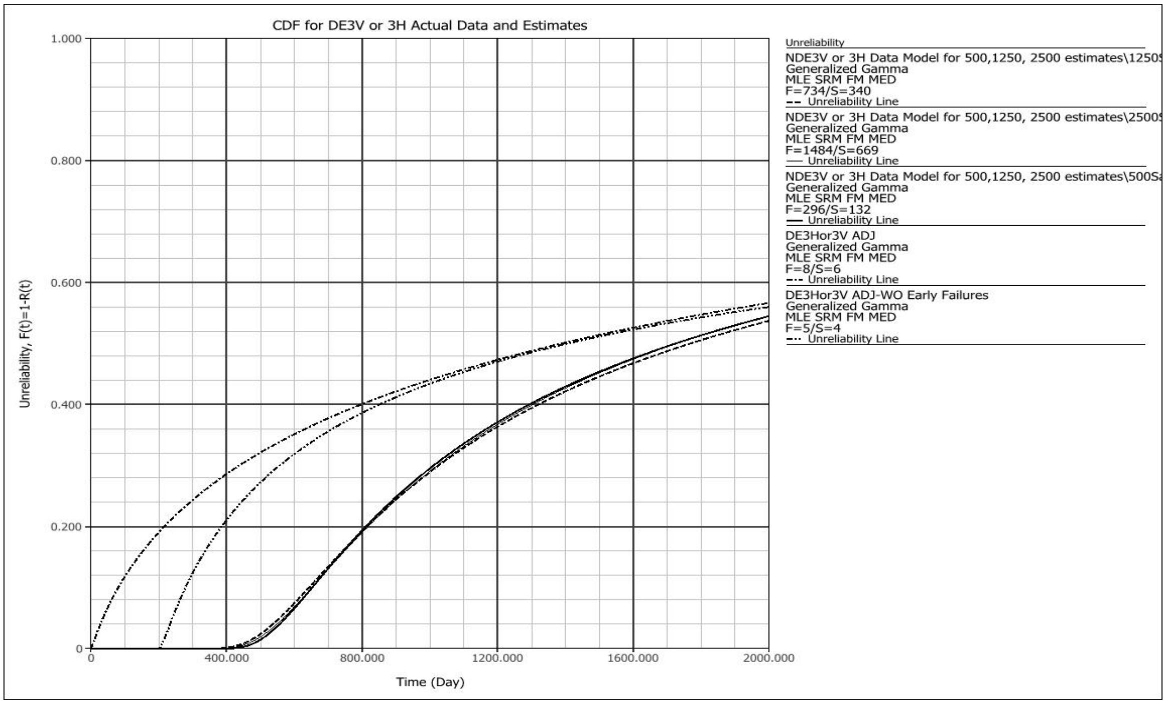


Figure 3-13 CDF Comparison of Measured Adjusted Data for DE3V or 3H and Estimated Data

Table 3-6 Summary of Parameters for NDE3H or 3V

	Combined	500 Random Numbers Generated	1250 Random Numbers Generated	2500 Random Numbers Generated	Adjusted Measured Data
Distribution:	G-Gamma-3P				
Analysis:	Maximum Likelihood Estimate				
CB Method:	Fisher Matrix				
Ranking:	Median				
Mu (Day)	6.710373	6.657803	6.714141	6.712131	7.418729
Sigma	0.583158	0.525047	0.604757	0.577656	2.324763
Lambda	-2.66795	-3.003754	-2.627409	-2.664791	-0.014227
LK Value	-21494.30045	-2528.160682	-6293.416263	-12670.2505	-68.857058
Failure \ Suspension	2514 \ 1141	296 \ 132	734 \ 340	1484 \ 669	8 \ 7
Variance-Mu	0.000283	0.002899	0.001008	0.000468	0.512178
CV Mean-Std	0.000127	0.001595	0.000444	0.00021	0.182702
CV Mean-Lambda	0.000869	0.012504	0.002923	0.001444	0.001333
Variance-Sigma	0.000126	0.001398	0.000445	0.000208	0.411114
CV Std-Lambda	0.000397	0.007306	0.001292	0.000658	-0.000187
Variance-Lambda	0.004827	0.078155	0.015635	0.008102	0.000819

Chapter 4
SUMMARY

The vibration analyses for three auxiliary boiler feed pumps from five ships were analyzed to determine if a mathematical function could be fitted to the measured degradation. One failure mode associated with the running speed of the motor-pump unit was selected for analysis. A function can be fitted and various estimates made concerning remaining time and reliability applying cumulative distribution function and confidence intervals. However, for a small population of units, even one failure occurring early on can skew the results dramatically as was the case. A comparison with the approach by Lu and Meeker was accomplished.

It is noted that the data files for these units are very large (160 MB for one year of data for the boiler feed pumps), so close cooperation with the ship operator will be necessary to select relevant equipment. For future research, it is recommended that several additional frequencies be analyzed such as several roller bearing frequencies to determine if a different degradation function is suitable. In addition to the distributions available on Weibull++™, a comparison of predicted survival times with the Bernstein Distribution may be of interest. Consideration of analyzing additional equipment types applying Tseng's et al., and Lu and Meeker's approaches is suggested and the results compared [40], [12].

REFERENCES

[1] American Bureau of Shipping, "Our Mission Page," November 2012. [Online]. Available: http://www.eagle.org/eagleExternalPortalWEB/appmanager/absEagle/absEagleDesktop?_nfpb=true&_pageLabel=abs_eagle_portal_our_mission_page. [Accessed 4 November 2012].

[2] American Bureau of Shipping, "Rules for Building and Classing Steel Vessels, 2012," 1 January 2012. [Online]. Available: http://www.eagle.org/eagleExternalPortalWEB/appmanager/absEagle/absEagleDesktop?_nfpb=true&_pageLabel=abs_eagle_portal_rules_guides_download_page&nodePath=%2FBEA+Repository%2FRules%26Guides%2FCurrent%2F2_SVR_2012. [Accessed 4 November 2012].

[3] American Bureau of Shipping, "Rules and Guides Downloads," November 2012. [Online]. Available: http://www.eagle.org/eagleExternalPortalWEB/appmanager/absEagle/absEagleDesktop?_nfpb=true&_pageLabel=abs_eagle_portal_rules_guides_do. [Accessed 4 November 2012].

[4] American Bureau of Shipping, "What We Do," November 2012. [Online]. Available: http://www.eagle.org/eagleExternalPortalWEB/appmanager/absEagle/absEagleDesktop?_nfpb=true&_pageLabel=abs_eagle_portal_whatwedo_page. [Accessed 4 November 2012].

[5] American Bureau of Shipping, Rules for Survey After Construction-Part 7, Houston: American Bureau of Shipping, 2012.

[6] American Bureau of Shipping, Rules for Building and Classing Steel Vessels, New York: American Bureau of Shipping, 1958.

[7] Society of Naval Architects and Marine Engineers, Guidelines for the Use of Vibration Monitoring for Preventive Maintenance, Jersey City: Society of Naval Architects and Marine Engineers, 1987.

[8] H. Pham and W. Li, "An Inspection-Maintenance Model for Systems With Multiple Competing Processes," *IEEE Transactions on Reliability,* vol. 54, no. 2, p. 320, June 2005.

[9] E. A. Elsayed, "Perspectives and challenges for research in quality and reliability engineering," *International Journal of Production Research,* vol. 38, no. 9, p. 1953 – 1976 , 2000.

[10] W. Nelson, "Analysis of Performance-Degradation Data from Accelerated Tests," *IEEE Transactions on Reliability,* Vols. R-30, no. 2, p. 149 – 155, June 1981.

[11] R. S. Mroczkowski and J. M. Maynard, "Estimating the Reliability of Electrical Connectors," *IEEE Transactions on Reliability,* vol. 40, no. 5, December 1991.

[12] C. J. a. M. W. Q. Lu, "Using Degradation Measures to Estimate a Time-to-Failure Distribution," *Technometrics,* vol. 35, no. 2, pp. 161-174, May 1993.

[13] R. G. Askin and W. Huang, "A Generalized SSI Reliability Model ConsideringStochastic Loading and Strength Aging Degradation," *IEEE Transactions on Reliability,* vol. 53, no. 1, p. 77 – 82, March 2004.

[14] W. Wang, "A model to predict the residual life of rolling element bearings given monitored condition information to date," *IMA Journal of Management Mathematics,* vol. 13, p. 3 – 16, 2002.

[15] N. Gebraeel, "Sensory-Updated Residual Life Distributions for Components with Exponential Degradation Patterns," *IEEE Transactions on Automation Science and Engineering,* vol. 3, no. 4, pp. 382-393, March 2006.

[16] M. A. L. R. L. a. J. K. R. Nagi Z. Gebraeel, "Residual-life distributions from component degradation signals: A Bayesian approach," *IIE Transactions,* vol. 37, p. 543–557, 2005.

[17] A. N. D. a. D. Acharya, "Age Replacement of Components During IFR Delay Time," *IEEE Transactions On Reliability,* vol. 53, no. 3, pp. 306-312, September 2004.

[18] J. B. D. M. a. P. M. T. G. S. Glinski, "A Diffusion Method for Reliability Prediction," *IEEE Transactions On Reliability,* Vols. R-18, no. 4, p. 149 – 156, November 1969.

[19] K. S. Park, "Optimal Wear-Limit Replacement with Wear -Dependent Failures," *IEEE Transactions On Reliability,* vol. 37, no. 3, p. 293 – 294., August 1988.

[20] Y. K. S. a. G. J. Savage, "A New Sample-Based Approach to Predict System Performance Reliability," *IEEE Transactions On Reliability,* vol. 57, no. 2, June 2008.

[21] P. W. T. K. a. C. B. Ethan Phelps, "Predicting Time to Failure Using the IMM and Excitable Tests," *IEEE Transactions On Systems, Man, And Cybernetics—Part A: Systems And Humans,* vol. 37, no. 5, September 2007.

[22] A. H. E. a. N. Z. Gebraeel, "Sensor-driven prognostic models for equipment replacement and spare parts inventory," *IIE Transactions,* vol. 40, p. 629–639, 2008.

[23] N. E. A. a. J. P. Gebraeel, "Residual Life Predictions in the Absence of Prior Degradation Knowledge," *IEEE Transactions on Reliability,* vol. 58, no. 1, pp. 106-117, March 2009.

[24] A. C. a. W. Wang, "A model of condition monitoring of a production plant," *International Journal of Production Research,* vol. 30, no. 9, pp. 2199 - 2211, 1992.

[25] W. Wang, "A model of to determine the optimal critical level and the monitoring intervals in condition-based maintenance," *International Journal of Production Research,* vol. 38, no. 6, pp. 1425 - 1436, 2000.

[26] H. S. a. P. K. Fran Barbera, "A Condition Based Maintenance Model with Exponential Failures and Fixed Inspection Intervals," *Journal of the Operational Research Society,* vol. 47, no. 8, pp. 1037-1045, August 1996.

[27] D. W. a. J. T. Coit, "Gamma distribution parameter estimation for field reliability data with missing failure times," *IIE Transactions,* vol. 32, no. 12, p. 1161 — 1166, 2000.

[28] N. G. M. A. L. Sze-jung Wu, "A Neural Network Integrated Decision Support System for Condition-Based Optimal Predictive Maintenance Policy," *IEEE Transactions on Systems, Man and Cybernetics – Part A: Systems and Humans,* vol. 37, no. 2, p. 226 – 236, March 2007.

[29] S. Y. a. M.-S. O. Alireza Ghasemi, "Parameter Estimation Methods for Condition-Based Maintenance with Indirect Observations," *IEEE Transactions On Reliability,* vol. 59, no. 2, June 2010.

[30] D. C. Swanson, "A General Prognostic Tracking Algorithm for Predictive Maintenance," in *0-Aerospace Conference, IEEE Proceedings*, 2001.

[31] H. L. a. X. W. Elsayed A. Elsayed, "An extended linear hazard regression model with application to time-dependent dielectric breakdown of thermal oxides," *IIE Transactions,* vol. 38, p. 329–340, 2006.

[32] E. Z. a. L. Podofillini, "Importance measures and genetic algorithms for designing a risk-informed optimally balanced system," *Reliability Engineering and System Safety,* vol. 92, p. 1435–1447, 2007.

[33] K. A. D. a. A. Hoyland, "Models for Variable-Stress Accelerated Life Testing Experiments Based on Wiener Processes and the Inverse Gaussian Distribution," *Technometrics,* vol. 34, no. 1, pp. 74-82, February 1992.

[34] S. L. A. a. D. M. M. Mohan Gopalakrishnan, "Maximizing the Effectiveness of a Preventive Maintenance System: An Adaptive Modeling Approach," *Management Science,* vol. 43, no. 6, pp. 827-840, June 1997.

[35] J. M. a. B. J. R. K B Goode, "Plant machinery working life prediction method utilizing reliability and condition-monitoring data," *Proceedings Institution of Mechanical Engineers,* vol. 214 Part E, 2000.

[36] D. L. a. V. Makis, "Recursive Filters for a Partially Observable System Subject To Random Failure," *Advances in Applied Probability,* vol. 35, no. 1, pp. 207-227, March 2003.

[37] C. a. G. R. Love, "Utilizing Weibull Rates in Repair Limit Analysis for Equipment Replacement/Preventive Maintenance Decisions," *The Journal of the Operational Research Society,* vol. 47, no. 11, pp. 1366-1376, November 1996.

[38] X. a. C. A. Jia, "A prototype cost model of functional check decisions in reliability-centered maintenance," *Journal of the Operational Research Society,* vol. 53, pp. 1380-1384, 2002.

[39] X. a. F. N. Zheng, "A Maintenance Policy For Repairable Systems Based On Opportunistic Failure-rate Tolerance," *IEEE Transactions on Reliability,* vol. 40, no. 2, pp. 237-244, June 1991.

[40] S.-T. Tseng, M. Hamada and C.-H. Chiao, "Using Degradation Data to Improve Flourescent Lamp Reliability," *Journal of Quality Technology,* vol. 27, no. No. 4, pp. 363 -369, October 1995.

[41] G. Donnesley, Interviewee, *Private telephone conversation.* [Interview]. 28 October 2010.

[42] BPG Engineering, "Measurement Point History," BPG Engineering, 1 April 2010.

[43] British Standard, Mechanical vibration-Evaluation of machine vibration by measurements on non-rotating parts Part 1: General guidelines, London: BSI, 1996.

[44] British Standard, Mechanical vibration-Evaluation of machine vibration by measurements on non-rotating parts-Part 3: Industrial machines with nominal power above 15 kW and nominal speeds between 120 r/min and 1500 r/min when measured in situ, London: BSI, 1998.

[45] American Bureau of Shipping, Guidance Notes on Reliability-Centered Maintenance, Houston: American Bureau of Shipping, 2004.

[46] P. J. a. V. S. Rousseeuw, "Robust estimation in very small samples," *Computational Statistics & Data Analysis,* vol. 40, pp. 741-758, 2002.

[47] Y. Amemiya, ""What Should Be Done When an Estimated Between Group Covariance Matrix is not Nonnegative Definite?"," *The American Statistician,* vol. 39, no. 2, pp. 112-117, 1985.

[48] SAS, SAS Help and Documentation, Cary: SAS Institute Inc., 2007.

[49] J. B. a. F. Kozin, Probabilistic Models of Cumulative Damage, New York: John Wiley & Sons, 1985.

[50] American Bureau of Shipping, "ABS Eagle Record," October 2010. [Online]. Available: ABS Eagle Record, http://www.eagle.org/eagleExternalPortalWEB/appmanager/absEagle/absEagleDesktop?_nfpb=true&_pageLabel=abs_eagle_portal_abseagle_record_page. [Accessed October 2010].

[51] American Bureau of Shipping, "ABS Record," October 2010. [Online]. Available: http://www.eagle.org/safenet/record/record_vesselsearch. [Accessed October 2010].

[52] American Bureau of Shipping, ABS Guide for Survey Based on Reliability-Centered Maintenance", Houston: American Bureau of Shipping, December 2003.

[53] C. E. Ebeling, An Introduction to Reliability and Maintainability Engineering, 1st ed., Long Grove: Waveland Press, Inc., 1995, pp. 374-380.

APPENDIX 1

BACKGROUND INFORMATION

A1. Ship Characteristics

Table A-1 lists the principal characteristics of the ships for which vibration data has been provided.

Table A-1 Ship Principal Characteristics Summary [50]

Vessel Type [51]	Length between Perpendiculars (m)	Molded Beam (m)	Molded Depth (m)	Displacement (tonnes)	Maximum Continuous Horsepower (kW)	Delivery Date
Roll-on Roll-off	177.9971 181.810	27.0 27.0	12.4 17.6	14826 15066	7079 5204	1977 1977
Tanker 1	192.024	27.4	16.3	43644	8504	1983
Tanker 2	233.000	42.0	21.3	105000	13560	2007
Products Carrier	186.766	32.3	18.3	48781	12682	1984 1983
Container Carrier	248.26	32.3	21.6	47014	20888	1985 Scrapped mid 2009 1984 Reported on way to breakers late 2009 1985 – Scrapped mid 2010

A2. Analyzed Equipment Characteristics

Table A-2 lists the vibration measuring points on the auxiliary boiler feed pumps.

Table A-2 Auxiliary Boiler Feed Pump Vibration Measurement Map

Measurement Point	Testing Performed
Motor NDE 1H	Vibration-Velocity
Motor DE 2H	Vibration-Velocity
Motor NDE 1V	Vibration-Velocity and Acceleration
Motor DE 2V	Vibration-Velocity and Acceleration
Pump DE 3V	Vibration-Velocity and Acceleration
Pump NDE 4V	Vibration-Velocity and Acceleration

APPENDIX 2

CONFIRMATION OF DEGRADATION MEASURES CALCULATIONS

B1. Fatigue Crack Growth Data

Table B-1 lists the fatigue crack growth data used to confirm Lu and Meeker's two-stage approach. The crack lengths published in Lu and Meeker through 1.60 inches were confirmed and the crack lengths and corresponding fatigue cycles were developed from Figure 4.5.2 on page 242 from Bogdanoff and Kozin [49]. A comparison was made and confirmed for the published fatigue cycles for the 1.60 inch crack length in Lu and Meeker and Bogdanoff and Kozin. The fatigue cycle comparisons are also shown in Table B-1.

From the data listed in Table B-1, Stage 1 estimates were determined and compared to the Stage 1 estimates in Table 3 in Lu and Meeker [12]. The resulting factors for each path were compared with the published calculations and determined to be acceptable. In Table B-4, the published fatigue cycles at 1.60 inches were compared to the resulting fatigue cycles with satisfactory results.

Table B-1 Fatigue Crack Growth Data from Bogdanoff and Kozin (1985)

Path	0.00	0.01[1]	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.11
1	0.902	0.95	1.00	1.05	1.12	1.19	1.27	1.35	1.48	1.64	1.93	
2	0.90	0.94	0.98	1.03	1.08	1.14	1.21	1.28	1.37	1.47	1.60	1.83
3	0.90	0.94	0.98	1.03	1.08	1.13	1.19	1.26	1.35	1.46	1.58	1.77
4	0.90	0.94	0.98	1.03	1.07	1.12	1.19	1.25	1.34	1.43	1.55	1.73
5	0.90	0.94	0.98	1.03	1.07	1.12	1.19	1.24	1.34	1.43	1.55	1.71
6	0.90	0.94	0.98	1.03	1.07	1.12	1.18	1.23	1.33	1.41	1.51	1.68
7	0.90	0.94	0.98	1.02	1.07	1.11	1.17	1.23	1.32	1.41	1.52	1.66
8	0.90	0.93	0.97	1.00	1.06	1.11	1.17	1.23	1.30	1.39	1.49	1.62
9	0.90	0.92	0.97	1.01	1.05	1.09	1.15	1.21	1.28	1.36	1.44	1.55
10	0.90	0.92	0.96	1.00	1.04	1.08	1.13	1.19	1.26	1.34	1.42	1.52
11	0.90	0.93	0.96	1.00	1.04	1.08	1.13	1.18	1.24	1.31	1.39	1.49
12	0.90	0.93	0.97	1.00	1.03	1.07	1.10	1.16	1.22	1.29	1.37	1.48
13	0.90	0.92	0.97	0.99	1.03	1.06	1.10	1.14	1.20	1.26	1.31	1.40
14	0.90	0.93	0.96	1.00	1.03	1.07	1.12	1.16	1.20	1.26	1.30	1.37
15	0.90	0.92	0.96	0.99	1.03	1.06	1.10	1.16	1.21	1.27	1.33	1.40
16	0.90	0.92	0.95	0.97	1.00	1.03	1.07	1.11	1.16	1.22	1.26	1.33
17	0.90	0.93	0.96	0.97	1.00	1.05	1.08	1.11	1.16	1.20	1.24	1.32
18	0.90	0.92	0.94	0.97	1.01	1.04	1.07	1.09	1.14	1.19	1.23	1.28
19	0.90	0.92	0.94	0.97	0.99	1.02	1.05	1.08	1.12	1.16	1.20	1.25
20	0.90	0.92	0.94	0.97	0.99	1.02	1.05	1.08	1.12	1.16	1.19	1.24
21	0.90	0.92	0.94	0.97	0.99	1.02	1.04	1.07	1.11	1.14	1.18	1.22

Notes: 1 Fatigue in millions of cycles

2 Fatigue crack (inches)

Table B-1 Fatigue Crack Growth Data from Bogdanoff and Kozin (1985) (continued)

Path	0.12	0.13	0.14	0.15	0.16	0.17	0.18	Cycles at Fracture Failure	Final Crack Length in.	Cycles at 1.60 in. Fracture	Cycles at 1.60 in. as published	Censored at 0.12 cycles
1								0.102	2.03	0.089	0.088	No
2								0.114	2.06	0.100	0.100	No
3								0.114	2.03	0.102	0.101	No
4								0.114	1.95	0.104	0.103	No
5								0.116	2.05	0.104	0.103	No
6								0.119	2.04	0.107	0.106	No
7								0.119	2.04	0.107	0.106	No
8	1.90							0.122	2.04	0.108	0.109	No
9	1.72							0.123	2.04	0.114	0.113	No
10	1.67							0.129	2.04	0.117	0.115	No
11	1.65	1.96						0.132	2.07	0.119	0.118	No
12	1.64	1.87						0.133	2.12	0.120	0.118	No
13	1.52	1.62	1.86					0.143	2.04	0.128	0.129	Yes
14	1.45	1.52	1.64	1.82				0.154	2.04	0.132	0.133	Yes
15	1.49	1.58	1.75	1.82				0.157	2.04	0.137	0.138	Yes
16	1.40	1.48	1.57	1.71				0.159	2.08	0.142	0.144	Yes
17	1.38	1.46	1.55	1.67	1.92					0.145	0.146	Yes
18	1.35	1.41	1.50	1.59	1.74	2.03				0.152	0.151	Yes
19	1.31	1.36	1.42	1.50	1.60	1.71	1.90			0.162	0.160	Yes
20	1.29	1.34	1.40	1.45	1.53	1.62	1.74			0.168	0.167	Yes
21	1.27	1.32	1.37	1.42	1.50	1.59	1.69			0.172	0.170	Yes

Table B-2 Stage 1 Estimates Comparisons with Table 3 of Lu and Meeker

Path	m_i	$\widehat{\Theta}_1$	$\widehat{\Theta}_2$	Lu and Meeker (LM)		Std Error		Std Error (LM)		Est Measurement Error Std Deviation	
				$\widehat{\Theta}_1$	$\widehat{\Theta}_2$	$s_{\widehat{\Theta}_1}$	$s_{\widehat{\Theta}_2}$	$s_{\widehat{\Theta}_1}$	$s_{\widehat{\Theta}_2}$	$\hat{\sigma}_\varepsilon$	$\hat{\sigma}_\varepsilon$(LM)
1	10	5.158	1.600	5.32	1.229	0.09130	0.11090	0.06948	0.1087	0.00507	0.00679
2	11	4.566	1.537	4.66	1.257	0.05440	0.08240	0.01618	0.0309	0.00337	0.00193
3	12	4.469	1.534	4.47	1.533	0.03940	0.06450	0.04461	0.0734	0.00239	0.00624
4	12	4.387	1.515	4.39	1.515	0.04380	0.07700	0.04936	0.0873	0.00265	0.00690
5	12	4.387	1.470	4.39	1.470	0.04260	0.07600	0.04765	0.0852	0.00256	0.00663
6	12	4.323	1.416	4.32	1.416	0.05710	0.10870	0.06410	0.1228	0.00340	0.00877
7	12	4.265	1.481	4.27	1.481	0.03500	0.06870	0.03864	0.0761	0.00210	0.00549
8	12	4.049	1.850	4.17	1.480	0.06120	0.10390	0.03071	0.0657	0.00491	0.00447
9	13	3.964	1.574	3.96	1.574	0.03630	0.07270	0.04046	0.0813	0.00265	0.00663
10	13	3.798	1.711	3.80	1.711	0.02480	0.05620	0.02722	0.0616	0.00187	0.00476
11	13	3.692	1.780	3.69	1.780	0.02980	0.07380	0.03334	0.0832	0.00231	0.00586
12	13	3.511	2.129	3.51	2.129	0.03620	0.10040	0.04084	0.1142	0.00302	0.00792
13	13	3.383	1.784	3.38	1.784	0.04060	0.14170	0.04456	0.1570	0.00329	0.00833
14	13	3.532	0.851	3.53	0.851	0.02880	0.09990	0.03059	0.1064	0.00192	0.00482
15	13	3.481	1.426	3.48	1.426	0.02390	0.07970	0.02528	0.0842	0.00177	0.00447
16	13	3.037	1.991	3.04	1.991	0.02160	0.11420	0.02240	0.1175	0.00199	0.00505
17	13	3.053	1.569	3.05	1.569	0.03340	0.18170	0.03502	0.1918	0.00289	0.00726
18	13	2.920	1.623	2.92	1.623	0.02560	0.16680	0.02658	0.1738	0.00237	0.00595
19	13	2.717	1.957	2.72	1.957	0.00745	0.06490	0.00764	0.0667	0.00080	0.00201
20	13	2.697	1.621	2.70	1.621	0.01100	0.10060	0.01121	0.1023	0.00114	0.00287
21	13	2.603	1.592	2.60	1.601	0.01070	0.11340	0.01084	0.1161	0.00117	0.00292

Table B-3 Stage 1 Summaries of Estimates Comparisons with Table 3 of Lu and Meeker

	$\widehat{\Theta}_1$	$\widehat{\Theta}_2$	Lu and Meeker (LM)		Std Error		Std Error (LM)		Est Measure-ment Error Std Deviation	
			$\widehat{\Theta}_1$	$\widehat{\Theta}_2$	$s_{\widehat{\Theta}_1}$	$s_{\widehat{\Theta}_2}$	$s_{\widehat{\Theta}_1}$	$s_{\widehat{\Theta}_2}$	$\hat{\sigma}_\varepsilon$	$\hat{\sigma}_\varepsilon(\mathrm{LM})$
Mean (Theta-cap)	3.714	1.620	3.732	1.571			Avg Std Error		0.003	0.006
		Mean Std Error (Sigma-cap)			0.036	0.098	0.034	0.100		
Covariance	-0.04612	-0.04612	-0.09373	-0.09373						
Covariance reported by Lu/Meeker			-0.09554	-0.09554						
Variance	0.50861	0.06844	0.54652	0.07808						
Variance reported by Lu/Meeker			0.54560	0.06654						
Standard error	0.71317	0.26161	0.73927	0.27944						

Table B-4 Fatigue Crack Length of 1.60 inches Compared to Checked and Reported Fatigue Cycles

Avg With Censored Data (inches)	0.108	0.107
Avg With All Data (inches)	0.125	0.125
Std Deviation	0.024	0.024

Table B-5 lists the regression analyses applied to the fatigue crack growth data and their relative ranking. Weibull++ software was used to obtain the results. The data were plotted and the results are shown in Appendix 2.

Table B-5 Fatigue Crack Growth Regression Analysis Ranking Comparison

Regression analysis function	Relative Rank
Degradation	
Exponential, 1-Parameter	9
Exponential, 2-Parameter	2
Gamma	7
G-Gamma	1
Gumbel	8
Logistic	5
Loglogistic	3
Log Normal	4
Normal	6
Weibull, 2-Parameter	6
Weibull, 3-Parameter	2

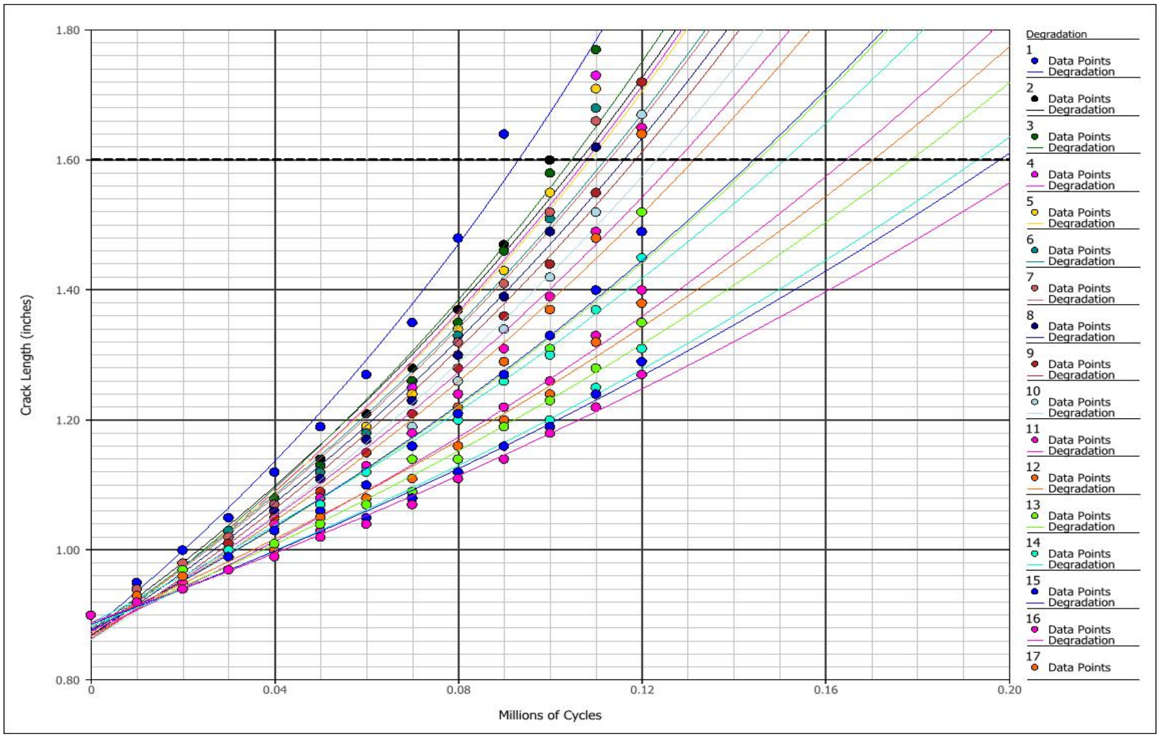


Figure B-1 Lu and Meeker Degradation Data with Censoring at 0.12 Million Cycles

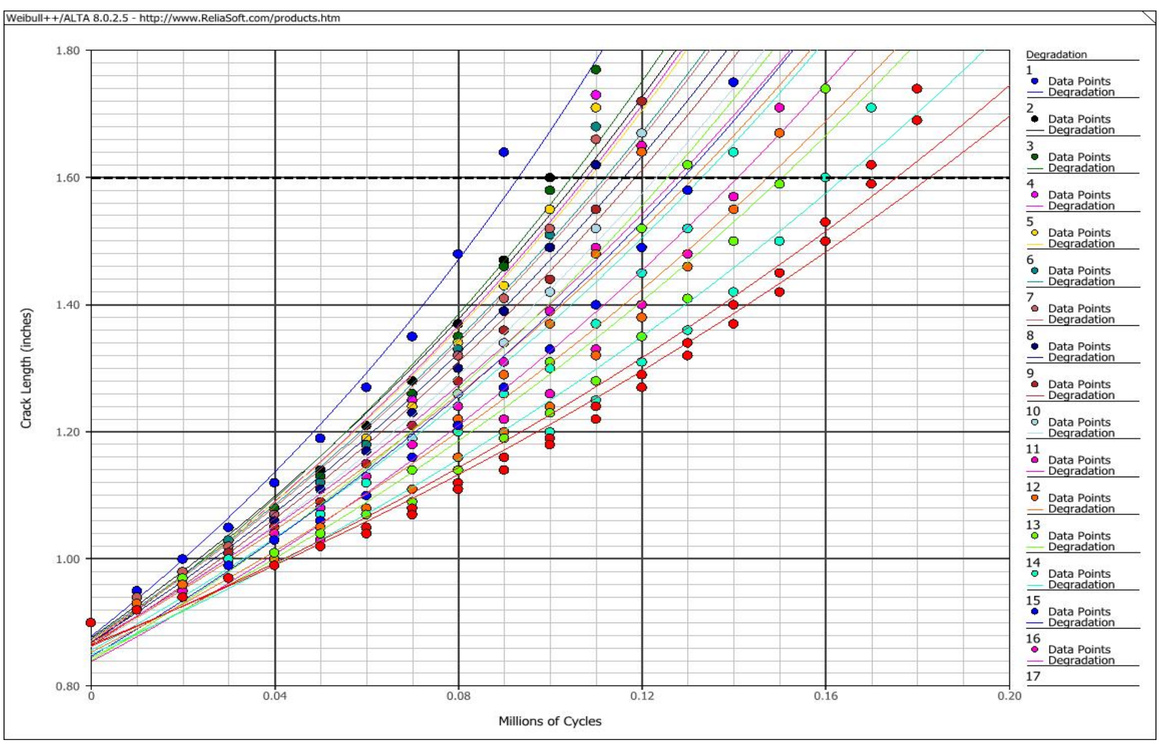


Figure B-2 Lu and Meeker Degradation Data without Censoring

APPENDIX 3

DEGRADATION CALCULATIONS FOR SHIP DATA

C1. Vibration Test Data

At 59.5 Hz, the degradation path can be modeled linearly in the form $y = at + b$ where t is in days. These coefficients were calculated using Weibull++'s *Degradation Model Wizard* which compares six degradation models and ranks them with respect to one another. Tables C-1 through C-5 list the linear coefficients a and b and their standard deviations for each degradation path by ship.

Those degradation paths with a negative a coefficient are not used in the analyses indicated as "adjusted" because degradation should increase over time. A negative coefficient implies the equipment is improving with time.

Table C-1 Degradation Fit Results for Tanker 101

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_101_NDE1H_1_59.5_A	0.002419	0.000569	0.076660	0.017667
30702040918_101_NDE1H_1_59.5_B	0.000252	0.000519	0.118618	0.033906
30702040918_101_NDE1H_1_59.5_C	0.000153	0.000122	0.070068	0.024489
30702040918_101_NDE1H_1_59.5_D	-0.000024	0.000059	0.152321	0.027180
30702040918_101_NDE1H_2_59.5_A	-0.000010	0.000019	0.062398	0.005760
30702040918_101_NDE1H_3_59.5_A	0.000146	0.000077	0.007741	0.015106
30702040918_101_NDE1H_3_59.5_B	0.000147	0.000164	0.050983	0.017148
30702040918_101_NDE1H_3_59.5_C	0.000390	0.000126	0.087105	0.011903
30702040918_101_DE2H_1_59.5_A	0.001284	0.002080	0.130467	0.070293
30702040918_101_DE2H_1_59.5_B	0.002130	0.001220	0.102804	0.086032
30702040918_101_DE2H_1_59.5_C	0.000061	0.000140	0.142304	0.028094
30702040918_101_DE2H_1_59.5_D	-0.001096	0.000349	0.226297	0.014112
30702040918_101_DE2H_2_59.5_A	-0.000011	0.000025	0.048740	0.007273
30702040918_101_DE2H_3_59.5_A	0.000092	0.000055	0.022192	0.010668
30702040918_101_DE2H_3_59.5_B	0.000087	0.000150	0.060694	0.015682
30702040918_101_DE2H_3_59.5_C	-0.000042	0.000092	0.124675	0.021703
30702040918_101_DE3V_1_59.5_A	-0.000185	0.000249	0.038062	0.007737
30702040918_101_DE3V_1_59.5_B	0.000077	0.000097	0.022265	0.007839
30702040918_101_DE3V_1_59.5_C	0.000118	0.000076	0.022082	0.014366
30702040918_101_DE3V_1_59.5_D	-0.000529	0.000865	0.066029	0.034985
30702040918_101_DE3V_3_59.5_A	0.000073	0.000022	0.024314	0.007802
30702040918_101_NDE4V_1_59.5_A	0.000734	0.000506	0.016288	0.015720
30702040918_101_NDE4V_1_59.5_B	0.000035	0.000027	0.029221	0.002168
30702040918_101_NDE4V_1_59.5_C	0.000015	0.000024	0.027644	0.004483
30702040918_101_NDE4V_1_59.5_D	0.000000	0.000000	0.030000	0.000000
30702040918_101_NDE4V_2_59.5_A	-0.000029	0.000016	0.023945	0.004828
30702040918_101_NDE4V_3_59.5_A	-0.000017	0.000016	0.030352	0.005467

Table C-2 Degradation Fit Results for Tanker 102

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_102_NDE1H_1_59.5_A	-0.000020	0.000568	0.047706	0.035493
30702040918_102_NDE1H_1_59.5_B	0.000042	0.000290	0.108760	0.010565
30702040918_102_NDE1H_1_59.5_C	-0.000257	0.000238	0.076442	0.019155
30702040918_102_NDE1H_1_59.5_D	0.000098	0.000103	0.045053	0.006613
30702040918_102_NDE1H_2_59.5_A	-0.000147	0.000185	0.093291	0.024048
30702040918_102_NDE1H_2_59.5_B	0.000979	0.000217	0.098104	0.004419
30702040918_102_NDE1H_2_59.5_C	-0.000112	0.000317	0.079387	0.026810
30702040918_102_NDE1H_3_59.5_A	0.000048	0.000025	0.021040	0.006195
30702040918_102_DE2H_1_59.5_A	-0.000020	0.000568	0.137706	0.035493
30702040918_102_DE2H_1_59.5_B	-0.000248	0.000157	0.151242	0.005729
30702040918_102_DE2H_1_59.5_C	-0.000216	0.000069	0.178103	0.005574
30702040918_102_DE2H_1_59.5_D	-0.000370	0.000448	0.133590	0.028866
30702040918_102_DE2H_2_59.5_A	-0.000321	0.000231	0.143738	0.026445
30702040918_102_DE2H_2_59.5_B	-0.000216	0.000691	0.136224	0.014090
30702040918_102_DE2H_2_59.5_C	0.000014	0.000166	0.098969	0.014018
30702040918_102_DE2H_3_59.5_A	0.000065	0.000030	0.030766	0.007260
30702040918_102_DE3H_1_59.5_A	-0.017119	0.001587	1.726413	0.099216
30702040918_102_DE3H_1_59.5_B	-0.000521	0.000845	0.283227	0.030728
30702040918_102_DE3H_1_59.5_C	-0.000417	0.000280	0.252384	0.022499
30702040918_102_DE3H_1_59.5_D	-0.000838	0.000198	0.269609	0.012761
30702040918_102_DE3H_2_59.5_A	0.000496	0.000564	0.120247	0.064532
30702040918_102_DE3H_2_59.5_B	0.001538	0.005794	0.253476	0.118215
30702040918_102_DE3H_2_59.5_C	-0.000334	0.000408	0.295191	0.034462
30702040918_102_DE3H_3_59.5_A	0.000169	0.000044	0.042122	0.010689
30702040918_102_NDE4H_1_59.5_A	-0.000038	0.000343	0.048615	0.021425
30702040918_102_NDE4H_1_59.5_B	-0.000368	0.000377	0.046739	0.013698
30702040918_102_NDE4H_1_59.5_C	0.000201	0.000159	0.012823	0.012792
30702040918_102_NDE4H_1_59.5_D	-0.000021	0.000074	0.018563	0.004797
30702040918_102_NDE4H_2_59.5_A	0.000052	0.000035	0.022644	0.004012
30702040918_102_NDE4H_2_59.5_B	0.000384	0.002296	0.050869	0.046841

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_102_NDE4H_2_59.5_C	-0.000166	0.000242	0.042409	0.016852
30702040918_102_NDE4H_3_59.5_A	-0.000026	0.000009	0.025739	0.002275

Table C-3 Degradation Fit Results for Tanker 103

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_103_NDE1H_1_59.5_A	-0.000173	0.000238	0.116852	0.036856
30702040918_103_NDE1H_2_59.5_A	0.000136	0.000039	0.024858	0.007406
30702040918_103_NDE1H_3_59.5_A	-0.000103	0.000058	0.073115	0.010456
30702040918_103_NDE1H_3_59.5_B	0.001181	0.000365	0.040189	0.011524
30702040918_103_DE2H_1_59.5_A	-0.000087	0.000101	0.139259	0.015598
30702040918_103_DE2H_2_59.5_A	0.000342	0.000114	0.056490	0.021669
30702040918_103_DE2H_3_59.5_A	-0.000077	0.000076	0.097294	0.013593
30702040918_103_DE2H_3_59.5_B	-0.000150	0.000315	0.086280	0.012163
30702040918_103_DE3H_1_59.5_A	0.000192	0.000219	0.209331	0.033984
30702040918_103_DE3H_2_59.5_A	0.000213	0.000109	0.119239	0.020831
30702040918_103_DE3H_3_59.5_A	0.000047	0.000041	0.027134	0.007354
30702040918_103_DE3H_3_59.5_B	-0.000144	0.000113	0.045146	0.003971
30702040918_103_NDE4H_1_59.5_A	0.000133	0.000110	0.056576	0.017042
30702040918_103_NDE4H_2_59.5_A	0.000325	0.000169	-0.003093	0.032152
30702040918_103_NDE4H_3_59.5_A	-0.000034	0.000033	0.050926	0.005945
30702040918_103_NDE4H_3_59.5_B	-0.000198	0.000292	0.055667	0.011303

Table C-4 Degradation Fit Results for Tanker 104

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_104_NDE1H_1_59.5_A	0.001534	0.000393	0.005971	0.032388
30702040918_104_NDE1H_1_59.5_B	0.000426	0.000649	0.120581	0.035562
30702040918_104_NDE1H_1_59.5_C	-0.000286	0.000175	0.126916	0.030316
30702040918_104_NDE1H_1_59.5_D	0.000228	0.000232	0.088117	0.034853
30702040918_104_NDE1H_1_59.5_E	-0.000136	0.000309	0.128093	0.042578
30702040918_104_NDE1H_1_59.5_F	0.000597	0.000206	0.029433	0.019396
30702040918_104_NDE1H_2_59.5_A	0.000034	0.000219	0.070696	0.031672
30702040918_104_NDE1H_2_59.5_B	0.000267	0.000174	0.023141	0.035112
30702040918_104_NDE1H_2_59.5_C	-0.000014	0.000087	0.085807	0.024465
30702040918_104_NDE1H_3_59.5_A	0.000566	0.000213	0.033063	0.020658
30702040918_104_NDE1H_3_59.5_B	0.000048	0.000022	0.076553	0.008709
30702040918_104_DE2V_2_59.5_A	0.000398	0.000219	0.061379	0.027942
30702040918_104_DE2V_2_59.5_B	0.000130	0.000085	0.026613	0.017269
30702040918_104_DE2V_2_59.5_C	0.000038	0.000054	0.057436	0.015280
30702040918_104_DE2V_3_59.5_A	0.000582	0.000303	0.041858	0.029351
30702040918_104_DE2V_3_59.5_B	0.000129	0.000022	0.090170	0.011432
30702040918_104_DE3H_1_59.5_A	0.003659	0.001374	0.050487	0.113197
30702040918_104_DE3H_1_59.5_B	0.000916	0.000610	0.173089	0.110362
30702040918_104_DE3H_1_59.5_C	-0.000233	0.000751	0.273219	0.129705
30702040918_104_DE3H_1_59.5_D	0.000365	0.000762	0.223616	0.114350
30702040918_104_DE3H_1_59.5_E	-0.001351	0.000594	0.471208	0.089931
30702040918_104_DE3H_1_59.5_F	-0.000533	0.000167	0.113308	0.011357
30702040918_104_DE3H_2_59.5_A	-0.000033	0.000098	0.099910	0.011734
30702040918_104_DE3H_2_59.5_B	0.000070	0.000114	0.056399	0.024546
30702040918_104_DE3H_2_59.5_C	0.000100	0.000047	0.072607	0.013231
30702040918_104_DE3H_3_59.5_A	0.000180	0.000171	0.048854	0.016541
30702040918_104_DE3H_3_59.5_B	-0.000006	0.000015	0.051385	0.007654
30702040918_104_NDE4H_1_59.5_A	0.000358	0.000180	0.031081	0.014849
30702040918_104_NDE4H_1_59.5_B	0.000167	0.000302	0.030497	0.054574
30702040918_104_NDE4H_1_59.5_C	0.000033	0.000260	0.082940	0.044885

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_104_NDE4H_1_59.5_D	0.000136	0.000059	0.044409	0.008845
30702040918_104_NDE4H_1_59.5_E	-0.000162	0.000086	0.076191	0.012958
30702040918_104_NDE4H_1_59.5_F	0.000105	0.000090	0.032249	0.006118
30702040918_104_NDE4H_2_59.5_A	0.000037	0.000052	0.037481	0.006214
30702040918_104_NDE4H_2_59.5_B	-0.000072	0.000064	0.061195	0.013768
30702040918_104_NDE4H_2_59.5_C	0.000083	0.000023	0.045131	0.006610
30702040918_104_NDE4H_3_59.5_A	0.000323	0.000200	0.016249	0.019378
30702040918_104_NDE4H_3_59.5_B	0.000021	0.000012	0.031897	0.006140

Table C-5 Degradation Fit Results for Tanker 105

Unit ID	Parameter a	Std - a	Parameter b	Std - b
30702040918_105_DE2H_1_59.5_A	0.000822	0.000357	0.067884	0.020071
30702040918_105_DE2H_1_59.5_B	-0.000231	0.000222	0.113590	0.009333
30702040918_105_DE2H_1_59.5_C	0.000022	0.000060	0.081498	0.013368
30702040918_105_DE2H_1_59.5_D	-0.002000	N/A	0.060000	N/A
30702040918_105_DE2H_2_59.5_A	0.000005	0.000047	0.080593	0.011418
30702040918_105_DE2H_3_59.5_A	0.000469	N/A	0.020000	N/A
30702040918_105_DE2H_3_59.5_B	0.000394	0.000336	0.005520	0.034412
30702040918_105_DE2H_3_59.5_C	0.000073	0.000022	0.038847	0.007643
30702040918_105_DE3H_1_59.5_A	0.002509	0.001007	0.041415	0.056636
30702040918_105_DE3H_1_59.5_B	0.002692	0.001643	0.062564	0.069068
30702040918_105_DE3H_1_59.5_C	-0.000032	0.000034	0.121978	0.007466
30702040918_105_DE3H_1_59.5_D	-0.018000	N/A	0.170000	N/A
30702040918_105_DE3H_2_59.5_A	-0.000015	0.000024	0.061228	0.005770
30702040918_105_DE3H_3_59.5_A	0.000000	N/A	0.040000	N/A
30702040918_105_DE3H_3_59.5_B	0.000520	0.000693	0.023169	0.071102
30702040918_105_DE3H_3_59.5_C	-0.000012	0.000020	0.036098	0.006933
30702040918_105_NDE1H_1_59.5_A	0.000513	0.000294	0.028708	0.016510
30702040918_105_NDE1H_1_59.5_B	-0.000385	0.000178	0.084872	0.007467
30702040918_105_NDE1H_1_59.5_C	-0.000022	0.000027	0.040463	0.005541

30702040918_105_NDE1H_1_59.5_D	0.000000	N/A	0.020000	N/A
30702040918_105_NDE1V_2_59.5_A	0.000026	0.000021	0.054571	0.005089
30702040918_105_NDE1V_3_59.5_A	0.000469	N/A	0.010000	N/A
30702040918_105_NDE1V_3_59.5_B	-0.000087	0.000178	0.050454	0.018193
30702040918_105_NDE1V_3_59.5_C	-0.000033	0.000017	0.034101	0.005653
30702040918_105_NDE4V_1_59.5_A	-0.000265	0.000155	0.050252	0.008713
30702040918_105_NDE4V_1_59.5_B	0.000346	0.000244	0.042949	0.010267
30702040918_105_NDE4V_1_59.5_C	0.000032	0.000012	0.008040	0.002613
30702040918_105_NDE4V_1_59.5_D	0.000000	N/A	0.010000	N/A
30702040918_105_NDE4V_2_59.5_A	0.000015	0.000024	0.042018	0.005788
30702040918_105_NDE4V_3_59.5_A	0.000313	N/A	0.020000	N/A
30702040918_105_NDE4V_3_59.5_B	-0.000156	0.000169	0.049197	0.017349
30702040918_105_NDE4V_3_59.5_C	-0.000001	0.000010	0.022602	0.003333

Tables C-6 through C-12 list the various degradation paths by Unit ID followed and organized by the four measurement location factors. This information is used for the development of the Stage 1 estimates applied by Lu and Meeker in Section 5 [12].

The check calculation results for the residuals for the degradation paths are listed in Table C-13. Among various checks are autocorrelation checks for white noise and residuals. Correlation checks of the parameter estimates were found satisfactory.

Table C-6 Degradation Fit Results for Measurement Location NDE1H and NDE1V

Unit ID	RUN	DF Model	DF Error	m_i	SSE	MSE	Root MSE	R-Square	Adj R-Sq	Durbin Watson
30702040918_101_NDE1H_1_59.5_C	1	2	10	12	0.0215	0.00215	0.0464	0.1363	0.05	1.1228
30702040918_101_NDE1H_3_59.5_A	2	2	11	13	0.00834	0.000758	0.0275	0.2441	0.1754	0.6821
30702040918_101_NDE1H_3_59.5_B	3	2	5	7	0.00256	0.000512	0.0226	0.1381	-0.0343	1.2556
30702040918_101_NDE1H_3_59.5_C	4	2	4	6	0.000965	0.000241	0.0155	0.7061	0.6326	2.9937
30702040918_102_NDE1H_1_59.5_D	5	2	2	4	0.000137	0.000068	0.00828	0.315	-0.0274	2.1856
30702040918_102_NDE1H_3_59.5_A	6	2	19	21	0.00436	0.000229	0.0151	0.1585	0.1142	2.0632
30702040918_103_NDE1H_2_59.5_A	7	2	7	9	0.00102	0.000145	0.012	0.637	0.5852	1.8585
30702040918_104_NDE1H_1_59.5_A	8	2	6	8	0.0137	0.00229	0.0478	0.7173	0.6702	0.9392
30702040918_104_NDE1H_1_59.5_B	9	2	5	7	0.022	0.00441	0.0664	0.0795	-0.1046	2.8969
30702040918_104_NDE1H_1_59.5_D	10	2	6	8	0.0188	0.00313	0.0559	0.1381	-0.0056	1.7619
30702040918_104_NDE1H_1_59.5_F	11	2	4	6	0.00263	0.000658	0.0256	0.6766	0.5957	2.3163
30702040918_104_NDE1H_2_59.5_A	12	2	8	10	0.0178	0.00222	0.0472	0.0031	-0.1216	2.7774
30702040918_104_NDE1H_2_59.5_B	13	2	6	8	0.017	0.00283	0.0532	0.2829	0.1633	2.8622
30702040918_104_NDE1H_3_59.5_A	14	2	5	7	0.00529	0.00106	0.0325	0.585	0.502	2.7333
30702040918_104_NDE1H_3_59.5_B	15	2	23	25	0.019	0.000828	0.0288	0.1712	0.1352	2.3151
30702040918_105_NDE1V_2_59.5_B	16	2	10	12	0.00154	0.000154	0.0124	0.445	0.3895	3.409

Table C-6 Degradation Fit Results for Measurement Location NDE1H and NDE1V (continued)

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx Pr > |t|	Parameter b Estimate	Approximate Std Error	t Value	Approx Pr > |t|	Covariances	
									a	b
1	0.000153	0.000122	1.26	0.2375	0.070068	0.0245	2.86	0.0169	1.487E-08	-2.501E-06
									-2.501E-06	5.997E-04
2	0.000146	0.000077	1.88	0.0861	0.062401	0.0151	0.51	0.6185	5.981E-09	-1.008E-06
									-1.008E-06	2.282E-04
3	0.000147	0.000164	0.9	0.4117	0.050	0.0171	2.97	0.031	2.684E-08	-2.435E-06
									-2.435E-06	2.940E-04
4	0.00039	0.000126	3.1	0.0362	0.087105	0.0119	7.32	0.0019	1.579E-08	-1.266E-06
									-1.266E-06	1.417E-04
5	0.000098	0.000103	0.96	0.4387	0.045053	0.00661	6.81	0.0209	1.054E-08	-5.295E-07
									-5.295E-07	4.370E-05
6	0.000048	0.000025	1.89	0.0739	0.02104	0.0062	3.4	0.003	6.407E-10	-1.326E-07
									-1.326E-07	3.840E-05
7	0.000136	0.000039	3.5	0.0099	0.024858	0.00741	3.36	0.0121	1.515E-09	-2.421E-07
									-2.421E-07	5.480E-05
8	0.001534	0.000393	3.9	0.008	0.005971	0.0324	0.18	0.8598	2.000E-07	-1.090E-05
									-1.090E-05	1.049E-03

Table C-6 Degradation Fit Results for Measurement Location NDE1H and NDE1V (continued)

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx Pr > |t|	Parameter b Estimate	Approximate Std Error	t Value	Approx	Covariances a	Covariances b
9	0.000426	0.000649	0.66	0.5401	0.120581	0.0356	3.39	0.0194	4.000E-07	-1.630E-05
									-1.630E-05	1.265E-03
10	0.000228	0.000232	0.98	0.3648	0.088117	0.0349	2.53	0.0448	5.399E-08	-6.668E-06
									-6.668E-06	1.215E-03
11	0.000597	0.000206	2.89	0.0444	0.029433	0.0194	1.52	0.2037	4.254E-08	-3.368E-06
									-3.368E-06	3.762E-04
12	0.000034	0.000219	0.16	0.8795	0.070627	0.0317	2.23	0.0563	4.809E-08	-6.127E-06
									-6.127E-06	1.003E-03
13	0.000267	0.000174	1.54	0.1749	0.023141	0.0351	0.66	0.5343	3.019E-08	-5.151E-06
									-5.151E-06	1.233E-03
14	0.000566	0.000213	2.65	0.0452	0.033063	0.0207	1.60	0.1704	4.548E-08	-3.541E-06
									-3.541E-06	4.268E-04
15	0.000048	0.000022	2.18	0.0398	0.076553	0.00871	8.79	<.0001	4.818E-10	-1.434E-07
									-1.434E-07	7.580E-05
16	0.000079	0.000028	2.83	0.0178	0.041127	0.00705	5.83	0.0002	7.727E-10	-1.689E-07
									-1.689E-07	4.970E-05
Mean	0.000306063			Mean	0.04971625					
Variance	1.30901E-07			Variance	0.001004627					

Table C-7 Degradation Fit Results for Measurement Location NDE2H and NDE2V

Unit ID	RUN	DF Model	DF Error	mi	SSE	MSE	Root MSE	R-Square	Adj R-Sq	Durbin Watson
30702040918_101_DE2H_1_59.5_B	17	2	5	7	0.0834	0.0167	0.1291	0.5127	0.4152	1.6338
30702040918_101_DE2H_1_59.5_C	18	2	10	12	0.0283	0.00283	0.0532	0.0184	-0.0797	1.8156
30702040918_101_DE2H_3_59.5_A	19	2	11	13	0.00416	0.000378	0.0194	0.2049	0.1327	0.8781
30702040918_101_DE2H_3_59.5_B	20	2	5	7	0.00214	0.000428	0.0207	0.063	-0.1245	2.6595
30702040918_102_DE2H_2_59.5_C	21	2	5	7	0.002	0.000399	0.02	0.0015	-0.1982	1.5392
30702040918_102_DE2H_3_59.5_A	22	2	19	21	0.00599	0.000315	0.0178	0.2033	0.1614	1.8747
30702040918_103_DE2H_2_59.5_A	23	2	7	9	0.0087	0.00124	0.0353	0.5625	0.5000	1.9644
30702040918_104_DE2V_1_59.5_A	24	2	6	8	0.022	0.00367	0.0605	0.583	0.5135	0.8125
30702040918_104_DE2V_1_59.5_B	241	2	6	8	0.015	0.0025	0.05	0.2155	0.0848	1.2074
30702040918_104_DE2V_1_59.5_D	25	2	6	8	0.0121	0.00201	0.0449	0.3361	0.2255	1.7678
30702040918_104_DE2V_1_59.5_F	26	2	4	6	0.0136	0.00341	0.0584	0.4705	0.3381	1.6866
30702040918_104_DE2V_2_59.5_A	27	2	6	8	0.00969	0.00162	0.0402	0.3539	0.2463	1.998
30702040918_104_DE2V_2_59.5_B	28	2	6	8	0.00411	0.000685	0.0262	0.2775	0.1571	2.277
30702040918_104_DE2V_2_59.5_C	29	2	13	15	0.0162	0.00124	0.0353	0.0361	-0.038	1.9335
30702040918_104_DE2V_3_59.5_A	30	2	5	7	0.0107	0.00213	0.0462	0.4243	0.3092	2.4718
30702040918_104_DE2V_3_59.5_B	31	2	28	30	0.0445	0.00159	0.0399	0.5494	0.5333	1.4214
30702040918_105_DE2H_1_59.5_C	32	2	9	11	0.00657	0.00073	0.027	0.0152	-0.0942	1.7522
30702040918_105_DE2H_2_59.5_B	33	2	10	12	0.00627	0.000627	0.025	0.0899	-0.0011	1.1653
30702040918_105_DE2H_3_59.5_C	34	2	11	13	0.00121	0.00011	0.0105	0.5006	0.4552	2.035

Table C-8 Degradation Fit Results for Measurement Location NDE2H and NDE2V

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx Pr > |t|	Estimate	Approximate Std Error	t Value	Approx Pr > |t|	Covariances a	Covariances b
17	0.002386	0.00104	2.29	0.0703	0.078804	0.0679	1.16	0.2984	1.100E-06	-4.910E-05
									-4.910E-05	4.614E-03
18	0.000061	0.00014	0.43	0.6739	0.142304	0.0281	5.07	0.0005	1.957E-08	-3.291E-06
									-3.291E-06	7.893E-04
19	0.000092	0.000055	1.68	0.1203	0.022191	0.0107	2.08	0.0617	2.983E-09	-5.028E-07
									-5.028E-07	1.138E-04
20	0.000087	0.00015	0.58	0.5873	0.060694	0.0157	3.87	0.0118	2.245E-08	-2.036E-06
									-2.036E-06	2.459E-04
21	0.000014	0.000166	0.09	0.9338	0.098969	0.014	7.06	0.0009	2.755E-08	-1.960E-06
									-1.960E-06	1.965E-04
22	0.000065	0.00003	2.2	0.0402	0.030766	0.00726	4.24	0.0004	8.798E-10	-1.812E-07
									-1.821E-07	5.270E-05
23	0.000342	0.000114	3	0.0199	0.05649	0.0217	2.61	0.0351	1.297E-08	-2.073E-06
									-2.073E-06	4.695E-04
24	0.001441	0.000498	2.9	0.0275	0.026256	0.041	0.64	0.5455	2.000E-07	-1.740E-05
									-1.740E-05	1.680E-03
241	0.000567	0.000442	1.28	0.2465	0.131787	0.0267	4.93	0.0026	1.951E-07	-8.847E-06
									-8.847E-06	7.140E-04

Table C-8 Degradation Fit Results for Measurement Location NDE2H and NDE2V (continued)

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx	Estimate	Approximate Std Error	t Value	Approx	Covariances	
				Pr > |t|				Pr > |t|	a	b
25	0.000325	0.000186	1.74	0.132	0.036144	0.0279	1.29	0.2435	3.472E-08	-4.287E-06
									-4.287E-06	7.810E-04
26	0.000885	0.00047	1.89	0.1325	-0.00508	0.0442	-0.12	0.9139	2.000E-07	-1.750E-05
									-1.750E-05	1.950E-03
27	0.000398	0.000219	1.81	0.1198	0.061379	0.0279	2.2	0.0704	4.817E-08	-5.300E-06
									-5.300E-06	7.808E-04
28	0.00013	0.000085	1.52	0.1798	0.026613	0.0173	1.54	0.1742	7.303E-09	-1.246E-06
									-1.246E-06	2.982E-04
29	0.000038	0.000054	0.7	0.4976	0.057436	0.0153	3.76	0.0024	2.941E-09	-6.656E-07
									-6.656E-07	2.335E-04
30	0.000582	0.000303	1.92	0.113	0.041858	0.0294	1.43	0.2132	9.180E-08	-7.147E-06
									-7.147E-06	8.615E-04
31	0.000129	0.000022	5.84	<.0001	0.09017	0.0114	7.89	<.0001	4.896E-10	-1.950E-07
									-1.950E-07	1.307E-04
32	0.000022	0.00006	0.37	0.7176	0.081498	0.0134	6.1	0.0002	3.601E-09	-6.360E-07
									-6.360E-07	1.787E-04
33	0.000056	0.000056	0.99	0.3437	0.066961	0.0143	4.7	0.0008	3.156E-09	-6.899E-07
									-6.899E-07	2.031E-04
34	0.000073	0.000022	3.32	0.0068	0.049238	0.0049	10.05	<.0001	4.789E-10	-8.614E-08
									-8.614E-08	2.400E-05

Table C-9 Degradation Fit Results for Measurement Location DE3H and DE3V

Unit ID	RUN	DF Model	DF Error	mi	SSE	MSE	Root MSE	R-Square	Adj R-Sq	Durbin Watson
30702040918_101_DE3V_1_59.5_B	35	2	5	7	0.000837	0.000167	0.0129	0.1125	-0.065	1.8928
30702040918_101_DE3V_1_59.5_C	36	2	9	11	0.00591	0.000656	0.0256	0.2116	0.124	1.0527
30702040918_101_DE3V_3_59.5_A	37	2	11	13	0.00172	0.000156	0.0125	0.0009	-0.0899	2.2064
30702040918_101_DE3V_3_59.5_B	38	2	5	7	0.000637	0.000127	0.0113	0.1431	-0.0283	3.0938
30702040918_102_DE3H_2_59.5_A	39	2	7	9	0.06980	0.00997	0.0998	0.0996	-0.0291	1.7813
30702040918_102_DE3H_3_59.5_A	40	2	19	21	0.0130	0.000683	0.0261	0.4413	0.4119	1.8515
30702040918_103_DE3H_1_59.5_A	41	2	5	7	0.0152	0.00304	0.0551	0.1332	-0.0402	2.8551
30702040918_103_DE3H_2_59.5_A	42	2	7	9	0.00804	0.00115	0.0339	0.3516	0.2589	2.5013
30702040918_103_DE3H_3_59.5_A	43	2	8	10	0.00141	0.000176	0.0133	0.1392	0.0316	1.7211
30702040918_104_DE3H_1_59.5_B	44	2	22	24	0.5869	0.0267	0.1633	0.0684	0.026	2.3776
30702040918_104_DE3H_2_59.5_C	45	2	21	23	0.0211	0.001	0.0317	0.1452	0.1045	2.1213
30702040918_104_DE3H_3_59.5_A	46	2	5	7	0.00339	0.000678	0.026	0.1816	0.0179	1.7461

Table C-10 Degradation Fit Results for Measurement Location DE3H and DE3V

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx Pr > |t|	Estimate	Approximate Std Error	t Value	Approx Pr > |t|	Covariances a	Covariances b
35	0.000077	0.000097	0.8	0.4621	0.022265	0.00784	2.84	0.0362	9.458E-09	-5.959E-07
									-5.959E-07	6.140E-05
36	0.000118	0.000076	1.55	0.1545	0.022082	0.0144	1.54	0.1586	5.771E-09	-9.202E-07
									-9.202E-07	2.064E-04
37	3.53E-06	0.000035	0.1	0.9217	0.03402	0.00686	4.96	0.0004	1.235E-09	-2.081E-07
									-2.081E-07	4.710E-05
38	0.000075	0.000082	0.91	0.4028	0.040372	0.00855	4.72	0.0052	6.671E-09	-6.052E-07
									-6.052E-07	7.310E-05
39	0.000496	0.000564	0.88	0.4082	0.120247	0.0645	1.86	0.1047	3.000E-07	-3.120E-05
									-3.120E-05	4.164E-03
40	0.000169	0.000044	3.87	0.001	0.042122	0.0107	3.94	0.0009	1.907E-09	-3.948E-07
									-3.948E-07	1.142E-04
41	0.000192	0.000219	0.88	0.4209	0.209331	0.034	6.16	0.0016	4.818E-08	-5.892E-06
									-5.892E-06	1.155E-03
42	0.000213	0.000109	1.95	0.0924	0.119239	0.0208	5.72	0.0007	1.198E-08	-1.916E-06
									-1.916E-06	4.339E-04
43	0.000047	0.000041	1.14	0.2883	0.027134	0.00735	3.69	0.0061	1.689E-09	-2.481E-07
									-2.481E-07	5.410E-05
44	0.000639	0.000503	1.27	0.2172	0.250818	0.0534	4.7	0.0001	3.000E-07	-2.100E-05
									-2.100E-05	2.847E-03

Table C-10 Degradation Fit Results for Measurement Location DE3H and DE3V (continued)

Run	Parameter a Estimate >0.0	Approx Std Err	t Value	Approx	Estimate	Approx Std Err	t Value	Approx Pr > |t|	Covariances	
									a	b
45	0.000082	0.000043	1.89	0.0728	0.071726	0.0112	6.43	<.0001	1.885E-09	-3.901E-07
									-3.901E-07	1.244E-04
46	0.00018	0.000171	1.05	0.3404	0.048854	0.0165	2.95	0.0318	2.916E-08	-2.270E-06
									-2.270E-06	2.736E-04

Table C-11 Degradation Fit Results for Measurement Location DE4H and DE4V

Unit ID	RUN	DF Model	DF Error	mi	SSE	MSE	Root MSE	R-Square	Adj R-Sq	Durbin Watson
30702040918_101_NDE4V_1_59.5_B	47	2	5	7	0.000064	0.000013	0.00358	0.2535	0.1041	1.641
30702040918_101_NDE4V_1_59.5_C	48	2	16	18	0.00318	0.000199	0.0141	0.0785	0.0209	2.0327
30702040918_102_NDE4H_2_59.5_A	49	2	7	9	0.00027	0.000039	0.00621	0.2417	0.1333	2.5139
30702040918_102_NDE4H_2_59.5_B	50	2	2	4	0.005	0.0025	0.05	0.0138	-0.4793	1.8807
30702040918_103_NDE4H_1_59.5_A	51	2	5	7	0.00382	0.000765	0.0277	0.2264	0.0716	1.8285
30702040918_103_NDE4H_2_59.5_A	52	2	7	9	0.0192	0.00274	0.0523	0.346	0.2526	1.9972
30702040918_104_NDE4H_1_59.5_A	53	2	6	8	0.00289	0.000481	0.0219	0.397	0.2965	1.7931
30702040918_104_NDE4H_1_59.5_C	54	2	3	5	0.00704	0.00235	0.0484	0.0055	-0.326	2.0732
30702040918_104_NDE4H_1_59.5_D	55	2	6	8	0.00121	0.000202	0.0142	0.4713	0.3831	2.2518
30702040918_104_NDE4H_1_59.5_F	56	2	3	5	0.000193	0.000064	0.00803	0.3099	0.0799	2.4236
30702040918_104_NDE4H_2_59.5_A	57	2	7	9	0.000828	0.000118	0.0109	0.0688	-0.0642	2.8464
30702040918_104_NDE4H_2_59.5_C	58	2	13	15	0.00302	0.000233	0.0152	0.4928	0.4538	1.9351
30702040918_104_NDE4H_3_59.5_A	59	2	5	7	0.00465	0.000931	0.0305	0.3433	0.212	2.3546

Table C-11 Degradation Fit Results for Measurement Location DE4H and DE4V (continued)

Run	Parameter a Estimate >0.0	Approximate Std Error	t Value	Approx Pr > |t|	Estimate	Approximate Std Error	t Value	Approx Pr > |t|	Covariances a	Covariances b
47	0.000035	0.000027	1.3	0.2494	0.029221	0.00217	13.48	<.0001	7.233E-10	-4.557E-08
									-4.557E-08	4.699E-06
48	0.00004	0.000034	1.17	0.2602	0.02344	0.00535	4.38	0.0005	1.174E-09	-1.000E-07
									-1.436E-07	2.860E-05
49	0.000052	0.000035	1.49	0.1789	0.022644	0.00401	5.64	0.0008	1.227E-09	-1.000E-07
									-1.204E-07	1.610E-05
50	0.000384	0.0023	0.17	0.8824	0.050869	0.0468	1.09	0.3909	5.300E-06	-9.090E-05
									-9.090E-05	2.194E-03
51	0.000133	0.00011	1.21	0.2805	0.056576	0.017	3.32	0.021	1.212E-08	-1.500E-06
									-1.482E-06	2.904E-04
52	0.000325	0.000169	1.92	0.0957	-0.00309	0.0322	-0.1	0.9261	2.854E-08	-4.600E-06
									-4.564E-06	1.034E-03
53	0.000358	0.00018	1.99	0.094	0.031081	0.0148	2.09	0.0812	3.249E-08	-2.300E-06
									-2.283E-06	2.205E-04
54	0.000033	0.00026	0.13	0.9057	0.08294	0.0449	1.85	0.1618	1.000E-07	-1.020E-05
									-1.020E-05	2.015E-03
55	0.000136	0.000059	2.31	0.0601	0.044409	0.00885	5.02	0.0024	3.478E-09	-4.000E-07
									-4.295E-07	7.820E-05
56	0.000105	0.00009	1.16	0.3297	0.032249	0.00612	5.27	0.0133	8.114E-09	-4.000E-07
									-4.462E-07	3.740E-05
57	0.000037	0.000052	0.72	0.4954	0.037481	0.00621	6.03	0.0005	2.680E-09	-3.000E-07
									-2.613E-07	3.860E-05
58	0.000083	0.000023	3.55	0.0035	0.045131	0.00661	6.83	<.0001	5.503E-10	-1.000E-07
									-1.245E-07	4.370E-05
59	0.000323	0.0002	1.62	0.1669	0.016249	0.0194	0.84	0.44	4.002E-08	-3.100E-06
									-3.116E-06	3.755E-04

Table C-12 Check Calculations for Residuals for Degradation Paths

Mean of Working Series		0.082891							
Standard Deviation		0.076866							
Number of Observations		685							
Autocorrelation Check for White Noise									
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	947.02	6	<.0001	0.556	0.529	0.516	0.435	0.456	0.348
12	1273.21	12	<.0001	0.358	0.377	0.252	0.258	0.208	0.158
18	1327.27	18	<.0001	0.169	0.071	0.141	0.092	0.069	0.101
24	1343.97	24	<.0001	0.066	0.037	0.046	0.082	0.064	0.069
Maximum Likelihood Estimation									
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag				
MU	0.08314	0.005498	15.12	<.0001	0				
AR1,1	0.55642	0.03183	17.48	<.0001	1				
Constant Estimate		0.036877							
Variance Estimate		0.004091							
Std Error Estimate		0.063963							
AIC		-1820.43							
SBC		-1811.37							
Number of Residuals		685							

Table C-12 Check Calculations for Residuals for Degradation Paths (continued)

Correlations of Parameter										
Estimates										
Parameter	MU	AR1,1								
MU	1	0.005								
AR1,1	0.005	1								
Autocorrelation Check of Residuals										
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations						
6	102.6	5	<.0001	-0.177	0.141	0.201	0.044	0.234	0.005
12	157.01	11	<.0001	0.097	0.224	-0.035	0.118	0.06	-0.005
18	197.12	17	<.0001	0.136	-0.115	0.134	0.006	-0.025	0.082
24	200.93	23	<.0001	0.015	-0.02	-0.01	0.067	-0.002	-0.01
30	221.08	29	<.0001	0.055	0.024	0.059	0.054	-0.013	0.134
36	228.31	35	<.0001	-0.012	0.035	0.063	0.002	0.066	0.017
42	231.13	41	<.0001	0.044	0.029	0	0.024	-0.019	-0.011
48	234.61	47	<.0001	-0.001	0.007	-0.014	-0.008	-0.064	-0.018
Model for variable Yest									
Estimated Mean		0.083135							
Autoregressive Factors									
Factor 1:	1 - 0.55642 B**(1)								