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Modeling Preventive Maintenance in Complex Systems

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Approved by Major Professor(s): Karen Marais

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MODELING PREVENTIVE MAINTENANCE IN COMPLEX SYSTEMS

A Thesis

Submitted to the Faculty

of

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by

Jessica Rivas

In Partial Fulfillment of the

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of

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Dedicated to my parents.

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As always, I give many thanks to my other half; without his support and cheerfulness, I would have lost my sanity.

Thank you to my parents, who have worked so hard to give me every possible opportunity to succeed.

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NOMENCLATURE

λ	Failure rate in the Homogenous Poisson process. Indication of design quality.
θ	Repair level indicating the amount of effort put into performing maintenance.
$N_i(t)$	the total number of failures from time zero to the i^{th} interval
Δt	the length of the preventive maintenance interval
R	random structural resistance
S	the total random load effects
$f_R(r), f_S(s)$	Probability density functions
F_R	the cumulative distribution function of R
A,B,C,D,E,F	Constants
B	growth rate
α	characteristic life,
t	time
$m(t)$	Failure expression rate
V_n	System's Virtual age after nth repair

X_n	the additional age incurred between the $(n-1)^{th}$ and n^{th} repair
$R_n(t)$	Reliability as a function of time
n	periodic maintenance action
R_{min}	Minimum reliability level
ESL	Expected service life
r	reliability right before the maintenance action is performed
$Cost_{acq}$	acquisition cost and is assumed to be realized as a lump sum at the onset of operation
$Cost_{op}$	operating cost
$Cost_m$	maintenance cost
$Cost_{base}$	Base operating cost

ABSTRACT

Rivas, Jessica. M.S.A.A., Purdue University, May 2014. Modeling Preventive Maintenance in Complex Systems. Major Professor: Karen Marais.

This thesis presents an explicit consideration of the impacts of modeling decisions on the resulting maintenance planning. Incomplete data is common in maintenance planning, but is rarely considered explicitly. Robust optimization aims to minimize the impact of uncertainty—here, in contrast, I show how its impact can be explicitly quantified. Doing so allows decision makers to determine whether it is worthwhile to invest in reducing uncertainty about the system or the effect of maintenance.

The thesis consists of two parts. Part I uses a case study to show how incomplete data arises and how the data can be used to derive models of a system. A case study based on the US Navy's DDG-51 class of ships illustrates the approach. Analysis of maintenance effort and cost against time suggests that significant effort is expended on numerous small unscheduled maintenance tasks. Some of these corrective tasks are likely the result of deferring maintenance, and, ultimately decreasing the ship reliability. I use a series of graphical tests to identify the underlying failure characteristics of the ship class.

The tests suggest that the class follows a renewal process, and can be modeled as a single unit, at least in terms of predicting system lifetime.

Part II considers the impact of uncertainty and modeling decisions on preventive maintenance planning. I review the literature on multi-unit maintenance and provide a conceptual discussion of the impact of deferred maintenance on single and multi-unit systems. The single-unit assumption can be used without significant loss of accuracy when modeling preventive maintenance decisions, but leads to underestimating reliability and hence ultimately performance impacts in multi-unit systems. Next, I consider the two main approaches to modeling maintenance impact, Type I and Type II Kijima models and investigate the impact of maintenance level, maintenance interval, and system quality on system lifetime. I quantify the net present value obtained of the system under different maintenance strategies and show how modeling decisions and uncertainty affect how closely the actual system and maintenance policy approach the maximum net present value. Incorrect assumptions about the impact of maintenance on system aging have the most cost, while assumptions about design quality and maintenance level have significant but smaller impact. In these cases, it is generally better to underestimate quality, and to overestimate maintenance level.

CHAPTER 1. INTRODUCTION

1.1 Introduction

Maintenance refers to the actions intended to keep a system in, or restore it to, a state in which it can perform at least part of its intended function(s) [Dekker, 1996; Marais and Saleh, 2009]. There are two main types of maintenance: corrective and preventive [Pham and Wang, 1996]. Corrective maintenance restores system functionality after a failure; preventive maintenance occurs according to a plan while the system is still operational with the aim of preventing or delaying deterioration. When performed properly, maintenance not only ensures the proper functioning of the system, but proper maintenance can also reduce the total cost of ownership by extending a system's lifetime, when required by programmatic decisions, and by reducing the system's operating costs.

To fully understand the impact of maintenance, one needs a model of how the system degrades, a model of operating costs, a model of how maintenance affects the system, and, to optimize value, a model of revenues, or, in the case of unpriced systems, utility

[Marais and Saleh, 2009]. Many models of system deterioration and maintenance impacts, as well as the resulting optimal maintenance strategies, have been proposed [see Pham and Wang, 1996 and Wang, 2002 for reviews].

The focus of this thesis is the challenges associated with developing these models, as shown in Figure 1. First, all of these models call for the appropriate data which may not exist or may be difficult to obtain. Knowing the type of data available is important because a model can only be as detailed as the information that is provided. Second, it is often necessary to make large assumptions to simplify the model and the impact of maintenance. One major assumption is that most models assume that the system can be modeled as a single unit. This assumption simplifies the problem significantly and does lead to some useful results. For example, where there is little dependency between units in a system, the system can be modeled as a single unit system. However, when there is dependency between units, it is difficult to adapt these strategies to multi-unit systems [Zille et al., 2011; Dekker, 1996; Ozekici, 1996; Thomas, 1986]. As a result, the impact of maintenance tends to be simplified since the type of data available affects how this impact is quantified. All of these simplifications will determine how maintenance is modeled.

In Part I, I focus on the case study of the DDG-51 class of surface combatant ships and the available data to highlight the limitations of using incomplete data. In Part II, I focus on how to model preventive maintenance with incomplete data and the resulting impact on the maintenance policies.

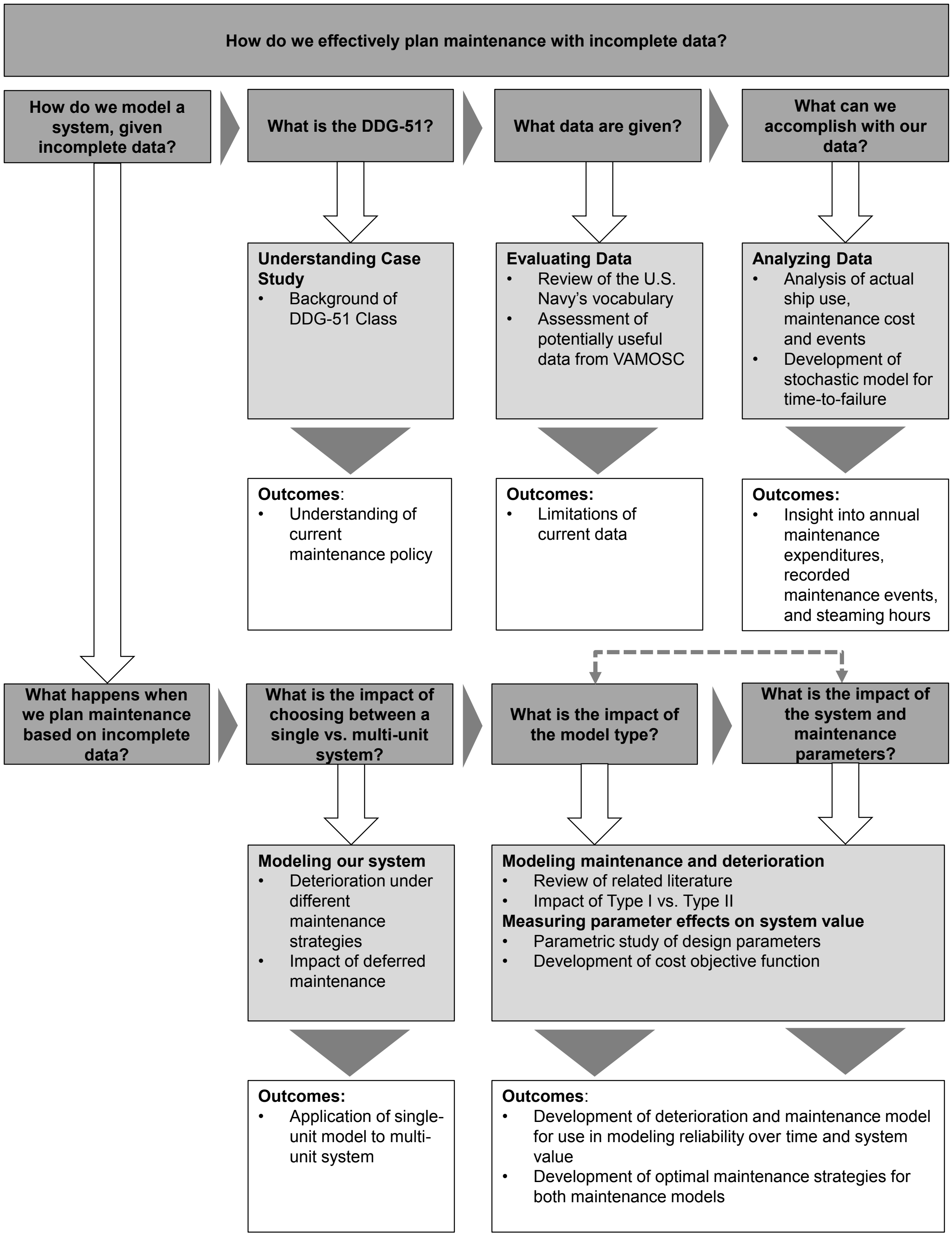

Figure 1. Research Roadmap

CHAPTER 2. INTRODUCTION: PART I[1]

Without maintenance, long-lived systems will deteriorate due to use or age. Maintenance is especially important for costly systems that are subjected to punishing tasks, such as Navy ships. When performed properly, maintenance not only ensures the proper functioning of the ships, but proper maintenance can also reduce the total cost of ownership by extending a ship's lifetime, when required by programmatic decisions, and by reducing the ship's operating costs. However, many United States Navy fleets are plagued with less than expected availability and shorter than hoped lifetimes, which increase Total Ownership Cost (TOC) [Koenig et al., 2008]. Recent decisions indicate that the Navy anticipates keeping some of the DDG-51 operating for up to 40 years because acquisition of a wholly-new designed destroyer is cost prohibitive.

In Part I, I focus on understanding the DDG-51 case study and the available data. Part I is structured as follows: Section 1 presents a background of the DDG-51 case study; Sections 2 and 3 present an evaluation and analysis of the given data. Part I is extracted from Marais et al. (2013).

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[1] Extracted from Marais et al., (2013)

CHAPTER 3. TYPES OF MAINTENANCE

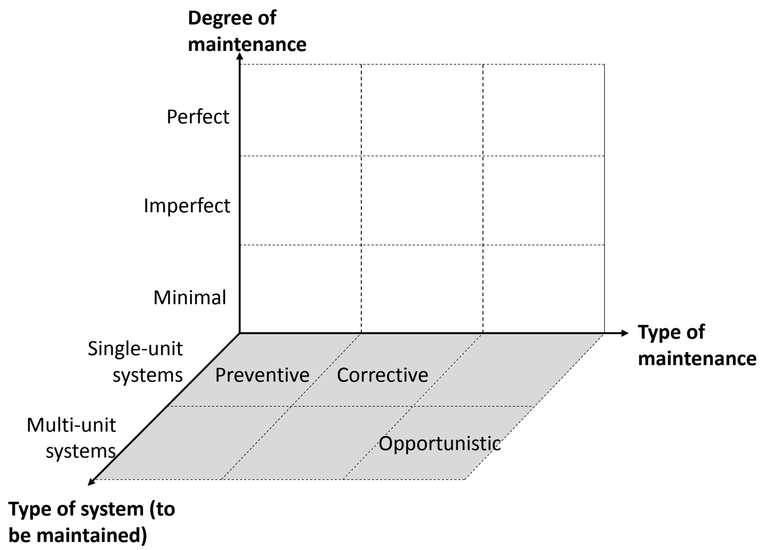

Figure 2. Types of Maintenance [Marais and Saleh, 2009]

Maintenance can be classified as preventive or corrective, as shown in Figure 2. Preventive or scheduled maintenance occurs while the system is still operational with the goal of preventing or delaying deterioration. Replacing engine oil is an example of preventive maintenance. Preventive maintenance can be further divided into scheduled, opportunistic, and condition-based maintenance. Scheduled maintenance includes for example aircraft engine overhauls, which occur after a pre-determined number of operating hours. Condition-based maintenance requires monitoring of the system and performing maintenance when the system has deteriorated to a certain state of wear, via visual inspection or other technique. These inspections seek to determine whether a deteriorating component must be replaced before the component fails, thus potentially incurring higher costs [Wireman, 2004]. For example, if inspection reveals that a vehicle's tires are worn beyond a certain limit, they will be replaced to prevent a more serious tire blowout failure. Opportunistic maintenance aims at restoring additional system components during scheduled maintenance; this type of maintenance can only occur for multi-unit systems. Corrective maintenance aims to restore system functionality when the system has failed, for example, fixing a flat tire is corrective maintenance.

The extent or degree of maintenance can be perfect, imperfect, or minimal. Minimal maintenance is when the least amount of maintenance is performed to fix the system. Perfect maintenance is fixing the system to be as good as new and imperfect maintenance is in between perfect and minimal maintenance. Figure 2 shows the relationship between type of maintenance, degree of maintenance, and system type.

CHAPTER 4. THE CASE STUDY: DDG-51 CLASS OF DESTROYERS

Many United States Navy fleets are plagued with less than expected availability and shorter than hoped lifetimes, which increase Total Ownership Cost (TOC) [Koenig et al., 2008]. Recent decisions indicate that the Navy anticipates keeping some of the DDG-51 operating for up to 40 years because acquisition of a wholly-new designed destroyer is cost prohibitive. I am seeking to develop practical models that can provide guidance on selecting an appropriate model in order to determine the best maintenance policy for a given system.

The program used in this study is the Arleigh Burke (DDG-51) class of guided missile destroyers. Each ship represents a highly complex system and, for the purposes of this study, is assumed to be identical to the other ships in its class. Since the commissioning of the first ship in 1991, the U.S. Navy has compiled maintenance and cost data for every ship in the DDG-51 class and has made such data available for this study. The DDG-51 case study represents an example of how a company might wish to improve an existing system's life span in an economically feasible way.

4.1 Background on DDG-51

The DDG-51s are “designed to operate as [either] an integral element in a Carrier Battle Group, independently, or as an amphibious, logistics force or MCM group escort, in multi-threat environments” [Stepanchick and Brown, 2007]. This study considers the existing two flight classes (Flight I, Flight II, and Flight IIA), comprising 60 ships (DDG-51 through DDG-110).

Figure 3. DDG-0083 in East China Sea (http://ipv6.navy.mil)

Naval historical support and operating cost and non-cost related information is available from the Visibility & Management of Operating & Support Costs (VAMOSC) database. For this project, I gathered cost and non-cost data for ships, DDG-51 through DDG-100 for the fiscal years 1992-2011. The database provides a variety of data—of interest to this work is the data about ship use and the time and funding spent on maintenance. Ship use is recorded in terms of [Ships User Manual, 2012; Detailed Ships User Manual, 2012]:

- Steaming hours, consisting of:
    - Hours Steaming Underway are counted when the ship is underway (moving) on its own power
    - Hours Steaming Not Underway are counted when the ship is not moving but is operational on its own power
    - Cold Iron (non-steaming hours) are counted when the ship is not operating on its own power (i.e., ship is docked in port and is being provided shore side electrical power)
    - Ship Age, the age of a ship from commissioning date

Maintenance effort is reported in several ways:

- Man-hours, broken down into:
    - Intermediate Maintenance-Afloat
    - Intermediate Maintenance-Ashore
    - Organizational Corrective Maintenance, which is maintenance performed by the ship's own crew

Note: There is a Depot level maintenance but no hours are reported for this level of maintenance. Depot level maintenance is "maintenance performed on material requiring major overhaul or a complete rebuild of parts, subassemblies and end items, including the manufacture of parts, modifications, testing, and reclamation" [Detailed Ships User Manual, 2012].

- Cost, broken down into:
    - Scheduled maintenance
    - Non-scheduled maintenance
    - Fleet modernization
    - Equipment rework

Maintenance costs are also reported in terms of beginning and completion date of repairs in terms of availability type, and whether the repairs took place in a public shipyard, private shipyard, or shipyard repair facility; however this breakdown does not include the above classification. Finally, textual descriptions are also given for each maintenance event, though the level of detail varies significantly and in many cases this field is left open.

Unfortunately, these different types of descriptions are not linked. For example, depot level maintenance hours are not recorded. Therefore we cannot directly establish, for example, how much a particular maintenance event cost or how long it took. Nor can we directly determine how much was spent on scheduled vs. unscheduled maintenance.

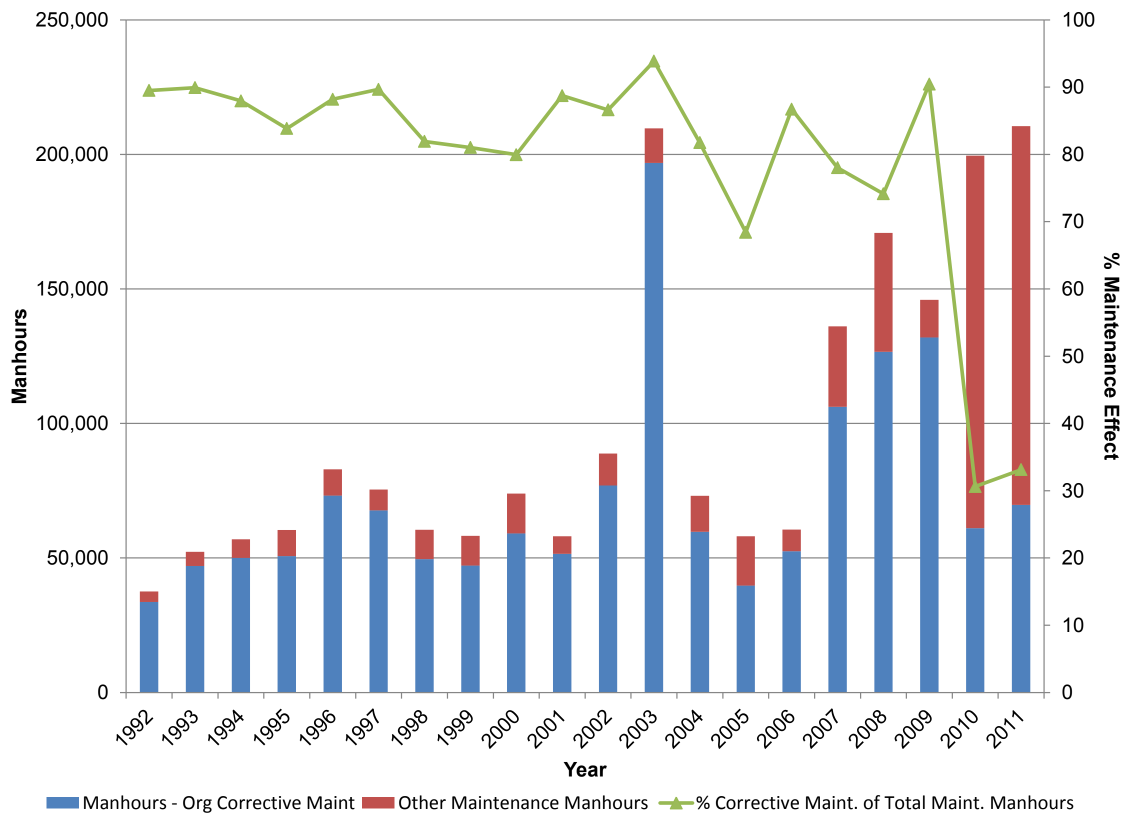

Figure 4. DDG-0051 Maintenance Hours Breakdown

Since none of the data provides a direct indication of the amount of deferred maintenance, I use the amount of corrective maintenance as an indicator, because deferring maintenance increases the reliance on corrective maintenance. Figure 4 shows how much effort has been expended on corrective maintenance over a particular ship's, the DDG-0051, lifetime. In most years, the majority of maintenance man-hours have been corrective.

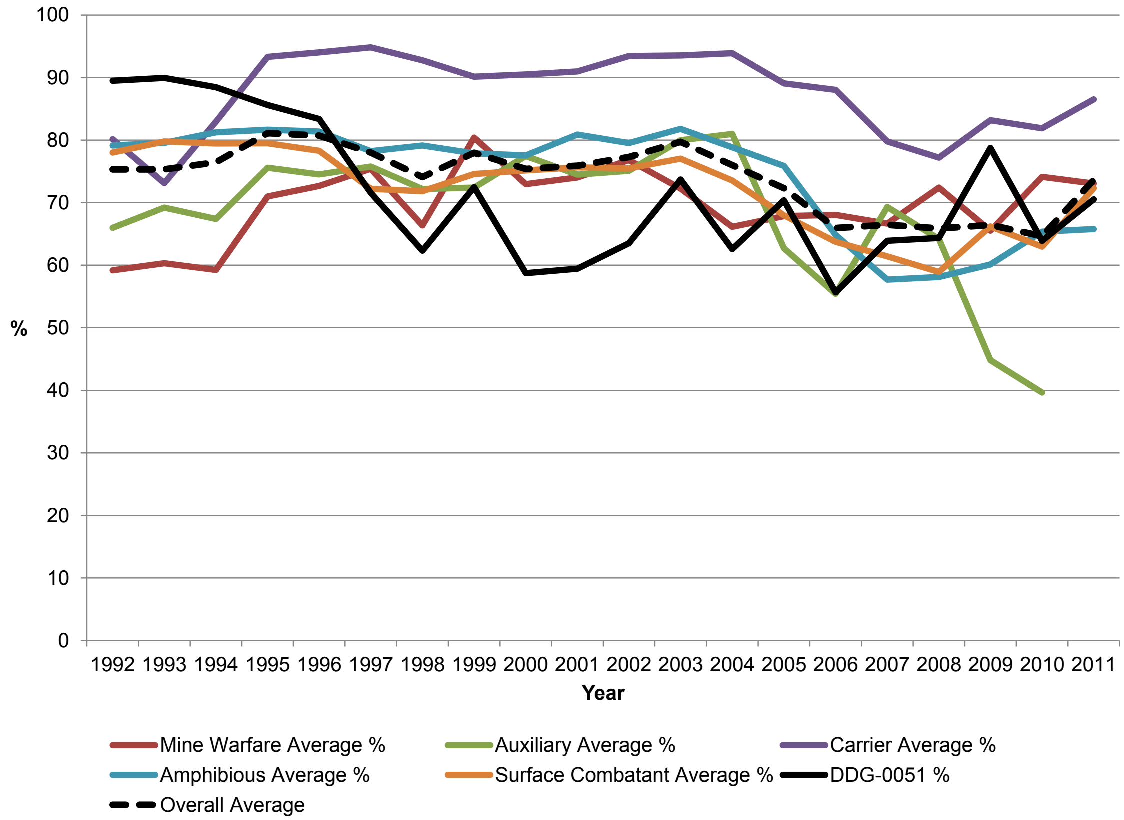

Figure 5. Comparison of Percentage of Corrective Maintenance Manhours on Surface Ships

This high proportion of corrective maintenance is not unusual. Figure 5 shows the percentage of corrective maintenance for different surface ship programs. The DDG-51 class is part of an overall pattern of reliance on corrective maintenance. In addition, there is a wide variation in the percentage of corrective maintenance performed each year, indicating that significant reductions in corrective maintenance are possible within current practices. Over the DDG-51 program lifetime, more than 70% of maintenance performed has been corrective. This high reliance on corrective maintenance increases the overall system cost, decreases expected service life (ESL), and may indicate that assumptions about system deterioration may be wrong or that the full impacts on ESL and cost are not being considered.

4.2 How is Ship Lifetime Determined?

Ship lifetime is a crucial aspect of TOC, but first it is necessary to understand exactly what is meant by lifetime. Many different terms are used, for example: the natural service life, the technical service life, the economic service life, and the expected service life [Xing et al., 2010].

The natural life is determined by the physical wear and tear of the ship, and is primarily determined by the hull structure [Keane, 2012]. The main stressors that affect the performance of the hull are corrosion, deterioration, and fatigue [Frangopol, et al., 2011]. Corrosion on ships is a chemical reaction that “eats” through the metal, thereby weakening the strength of the structure. This reaction can be detected via a visual check of the structure. Deterioration of a ship is the decline of the ship’s condition. Here, deterioration is referred to as the amount of ship use. In addition to corrosion, a visual inspection would help detect deterioration. Fatigue is structural damage caused by repeated loadings, which in the case of a ship would be sea loadings [Frangopol, et al., 2011]. Fatigue is associated with how much the ship is operated out at open sea and can be detected using special sensors.

Each of these stressors can be modeled; for example, the decay of the hull flexural capacity, or the hull bending strength, can be modeled using a corrosion model. Without adequate detection and preventive maintenance, these stressors can lead to potential system failure. Thus, the ship will not be as reliable and likely to deteriorate faster.

The technical service life is determined by the equipment life, which is a function of the deterioration of the equipment as well as its ability to deliver the desired functionality. For example, a much older version of an operating system, such as Windows XP, can still work with older software but might not be compatible with newer software made for operating systems such as Windows 8.

The economic service life is determined by the costs that the ship incurs over its lifetime—when the ship becomes too costly to operate, it is taken out of service [Xing et al, 2010]. Technical and economic service life are primarily driven by how much technology has progressed and by the allowable budget, however, neither can exceed the ship's natural life.

In the United States Navy, a ship's expected service life (ESL) is used to develop the ship class' scheduled maintenance plan. In contrast to the three types of service life discussed above, which depend primarily on physical condition and the ability to meet functional requirements, the ESL is based on the number of ships needed to achieve a given force structure [Koenig et al, 2008]. An ESL value is determined for each class of ship. The Navy has set a requirement to maintain a total fleet of 313 ships over the next thirty years; thus, the ESL is determined based on maintaining this fleet level [Koenig et al., 2008]. Ideally, the actual service life is a harmony of the natural, technical, and economic service life. However, like ESL, it is imposed “top down,” for example, a class may be retired because a new class is coming in.

Meanwhile, maintenance is performed to extend the natural, technical, and economic service lives. Figure 6 shows the different factors that affect the three types of service life and the ESL.

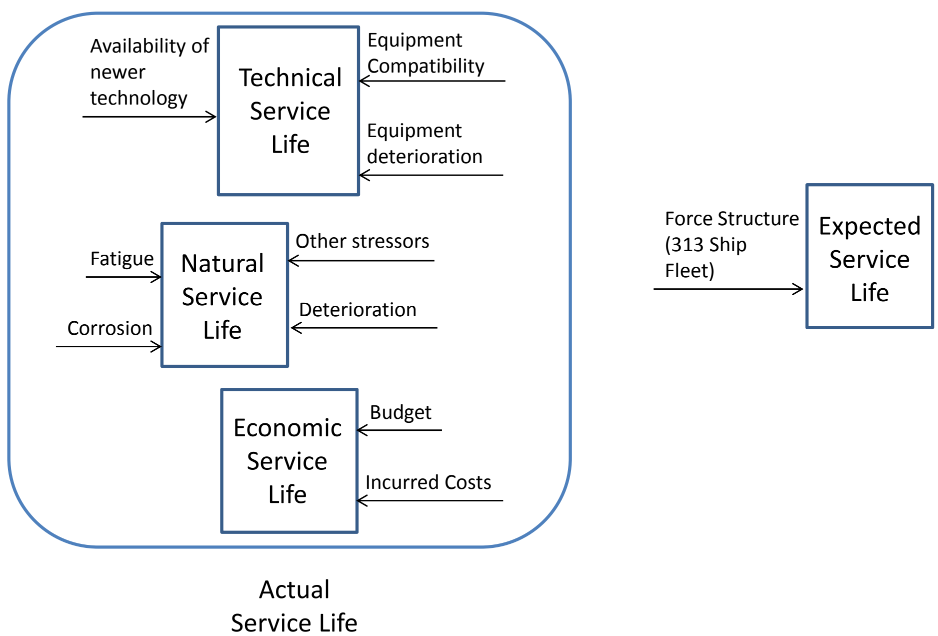

Figure 6. Aspects and Determinants of Ship Lifetime

Ideally, all ships should maintain their full expected service life. However, the Navy has found that many ships are being decommissioned before they have fulfilled their expected service life. Koenig et al. (2008) suggest that technical obsolescence and inadequate maintenance are the main reasons. Many older ships are being decommissioned in favor of newer, more technologically updated ships that are capable of accomplishing the same tasks as the older ships. For example, the Spruance class of destroyers was phased out to accommodate the newer Arleigh Burke class of destroyers. Other ships are decommissioned because they have deteriorated so much that they are too expensive to operate, often as a result of deferred maintenance.

4.3 Data Pre-processing

Upon examination of the detailed maintenance data provided in the VAMOSC database for the DDG-51 series of vessels, I was able to further analyze all reported maintenance costs incurred for each ship from their respective dates of commissioning until 2009. The VAMOSC maintenance tables provided a wealth of data, but gave more specific insight into annual maintenance expenditures, annual recorded maintenance events, and annual steaming hours for each vessel.

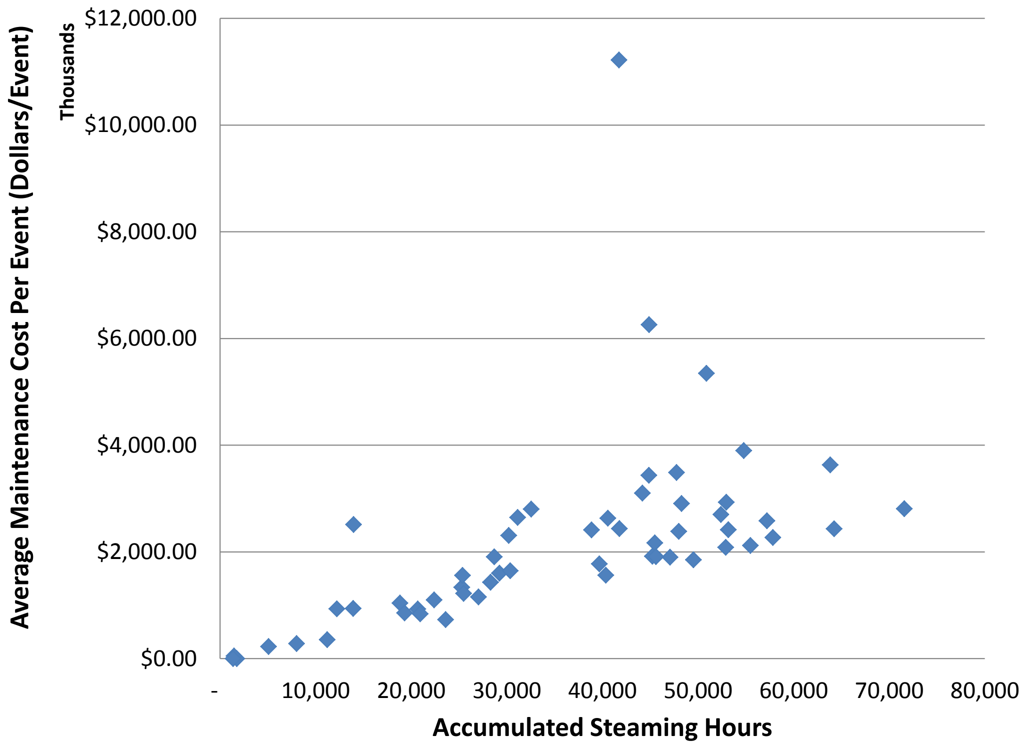

Figure 7. Average Maintenance Costs Per Event vs. Accumulated Steaming Hours

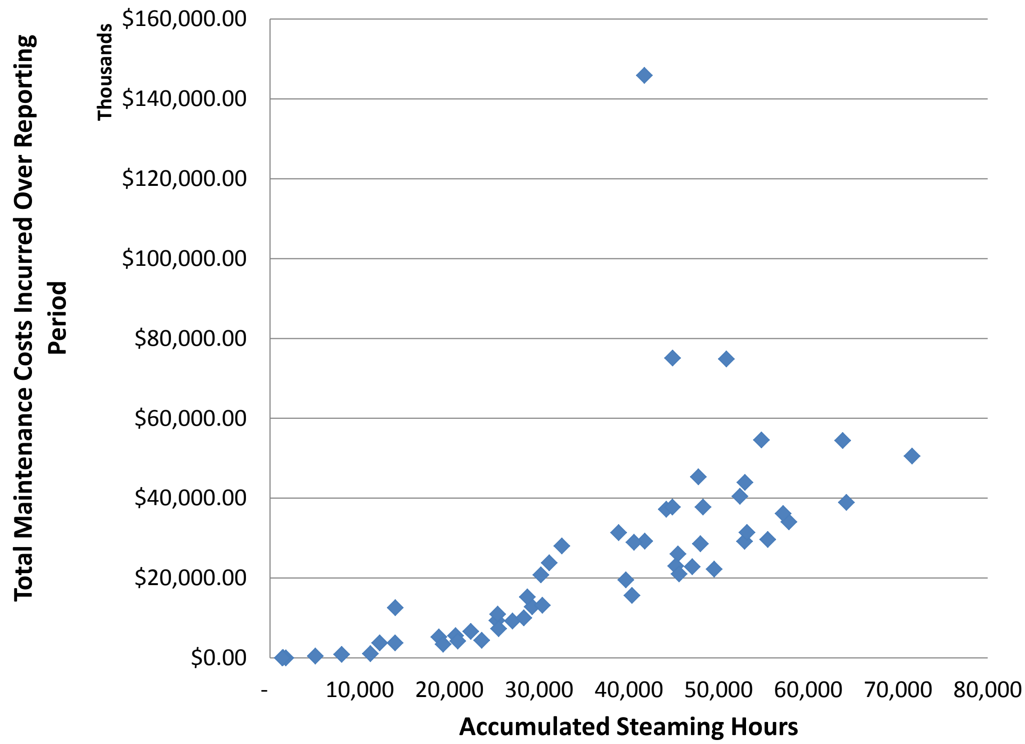

Figure 8. Total Maintenance Costs Incurred Over Reporting Period vs. Accumulated Steaming Hours

From this previously aggregated information, I was able to determine two key metrics: the total maintenance costs incurred over the reporting period for each ship, as well as the average maintenance cost per maintenance event. When plotting these two sets of information against the accumulated steaming hours, as in Figure 7 and Figure 8, I can make a few preliminary observations.

Excluding the data point representing DDG-067, which underwent significant corrective maintenance from an attack and is a clear outlier, one may note that average maintenance costs per event increases in a roughly linear manner as the ship's number of accumulated steaming hours increases, as one would expect. A similar pattern emerges when reviewing total maintenance costs incurred over the entire reporting period against accumulated steaming hours. The few spikes in average maintenance cost per event that occur on ships boasting a higher number of accumulated steaming hours may be attributable in part to a greater occurrence of more costly maintenance activities, or more frequent median cost maintenance events, or both.

CHAPTER 5. MODELING SHIP RELIABILITY BASED ON INCOMPLETE MAINTENANCE DATA

The first step in building a model of system behavior under maintenance is to build a model of system deterioration. Ideally, for a multi-unit system, I desire individual data on each unit’s deterioration; however, as discussed earlier, this level of resolution in the data is not available. I therefore begin by analyzing the ship class’s reliability at the system level.

5.1 Ship Maintenance Events

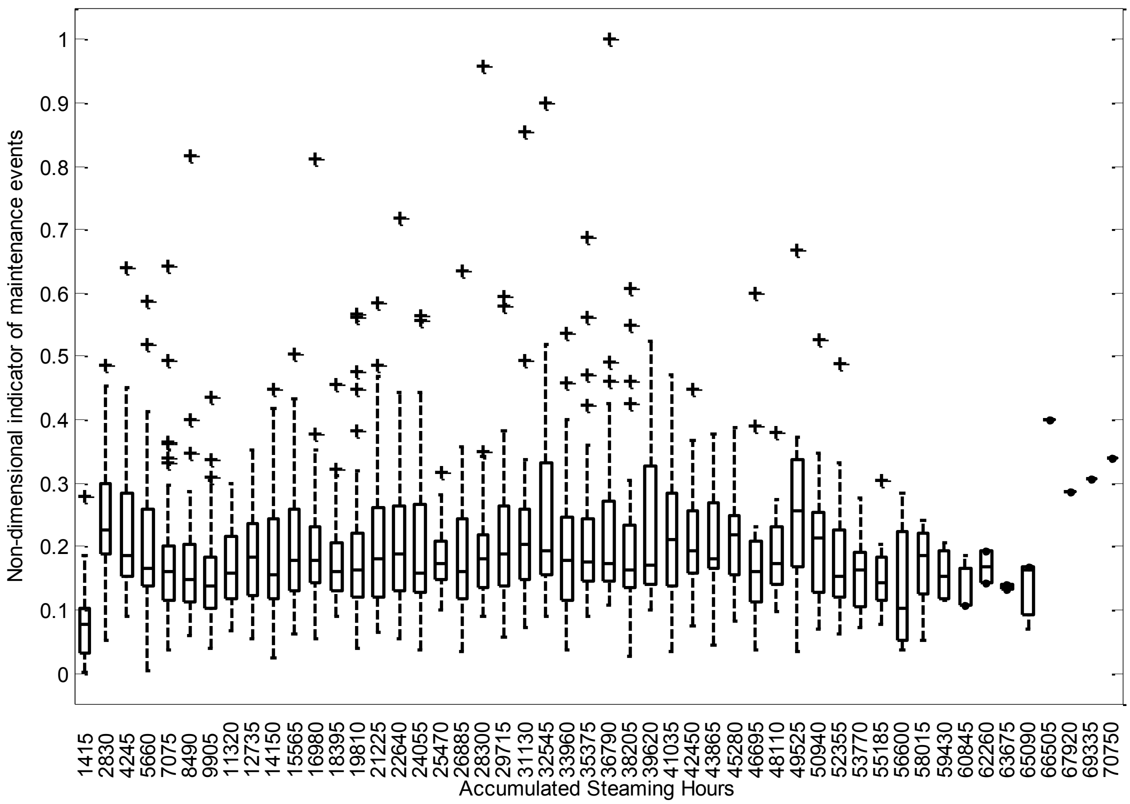

Figure 9. DDG 51-DDG 100 (1992-2009), 50 bins

First, I plotted the time and effort expended on maintenance. Along with the maintenance effort costs mentioned in Section 4, intermediate maintenance hours are included in the unscheduled and scheduled maintenance costs.

Figure 9 shows the normalized number of maintenance events per ship versus steaming hours. Here I use steaming underway and steaming not underway hours as a proxy for how much the ships are actively used. The accumulated steaming hours are separated into 50 bins with the x-axis denoting the middle value of each bin. The number of maintenance events is quite constant, suggesting that, as a class, the need for maintenance is quite constant over a ship's lifetime. However, this conclusion is subject to two caveats. First, the maintenance event count gives equal weight to each task, regardless of the effort involved. Therefore it may be possible, for example, that new ships have frequent "small" tasks, while in older ships these tasks are replaced by larger tasks. Second, the data has many outliers above the median values, suggesting that individual ships often require significantly more maintenance.

Figure 10 and Figure 11 show the maintenance effort in terms of cost versus ship age. In this case, the database does not provide data relative to steaming hours, so I use ship age as a proxy for how much the ships are actively used. On average, about 1.5 times more funding is expended on scheduled maintenance than on unscheduled maintenance. Once again, there are significant outliers on both graphs, again suggesting that individual ships often require significantly more maintenance. Based on my results, I surmise that some of these corrective tasks are the result of deferring maintenance which therefore decreases the ship reliability.

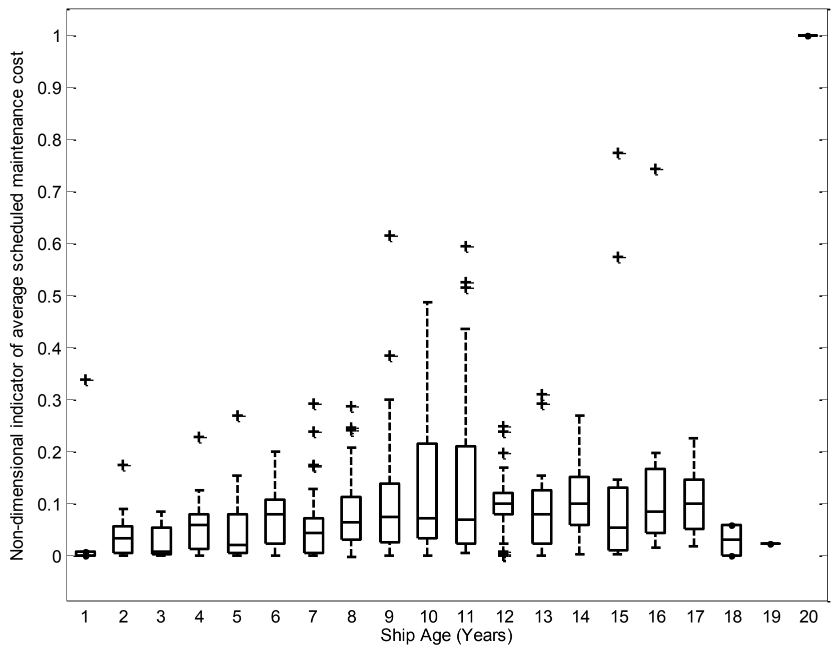

Figure 10. Average Scheduled Maintenance Cost for all ships over a 20 year time period

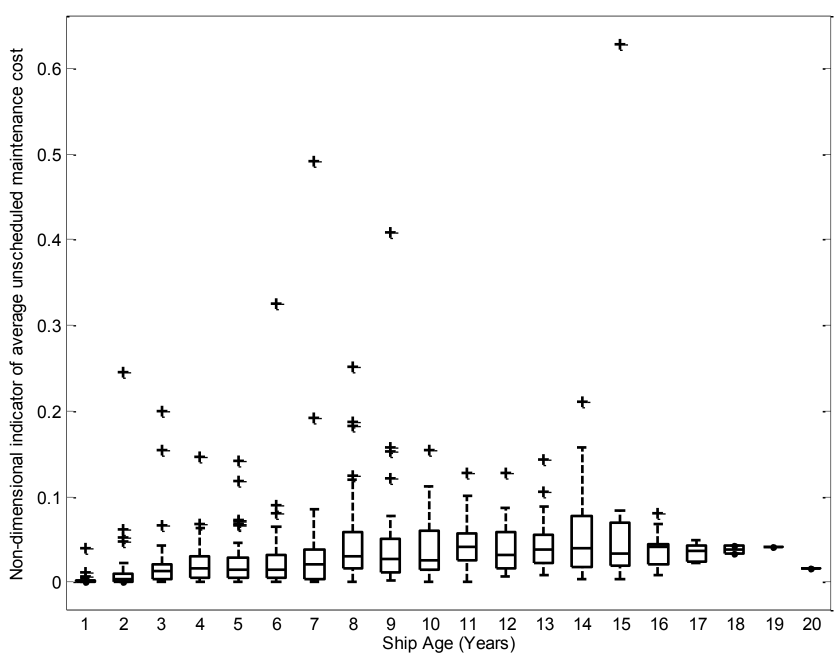

Figure 11. Average Un-Scheduled Maintenance Cost for all ships over a 20 year time period

CHAPTER 6. DETERMINING THE PROPER STOCHASTIC MODEL FOR TIME-TO-FAILURE

To properly model effects of maintenance on the total ownership cost, I must choose the proper model for the time-to-failure of the ship. For the DDG ships, I considered five stochastic models often used to describe repairable systems: the renewal process (RP), the homogeneous Poisson process (HPP), the branching Poisson process (BPP), the superposed renewal process (SRP), and the non-homogeneous Poisson process (NHPP) [Louit et al., 2009]. Given that the DDG ships are an extended service life system, I expect that their behavior would closely model a renewal process, wherein the ship is restored to a "like new" condition after each maintenance event. Modeling the ship as a renewal process allows the time to failure to be modeled via a statistical distribution, such as an exponential Weibull distribution.

Confirming that the DDG ships can be modeled as a renewal process is possible by several graphical tests using maintenance data from the VAMOSC Database. These tests, detailed by Louit et al. (2009), include examining plots of the cumulative failures over time, the average rate of occurrence of failures, and scatter plots of successive service lives.

Since the VAMOSC database does not record failure events, I used maintenance events as a proxy. I assumed that a ship "fails" if the number of maintenance events that occurred in a specified bin of steaming hours exceeds the median value of maintenance events over that same period. Two different sets of periods were used, one consisting of 50 time bins and another of 100 time bins; however, the results from using 100 time bins were more conclusive, so they are presented here. Whenever the behavior differed from that expected from a renewal process, I assume that reflects inadequate maintenance in two forms: (1) not extensive enough (i.e., the ship was not restored to "like new" condition), or (2) deferred maintenance.

6.1 Cumulative Failures over Time

For a renewal process to hold from given maintenance data, the cumulative failures over time should not have a trend and thus result in a linear plot [Louit et al., 2009].

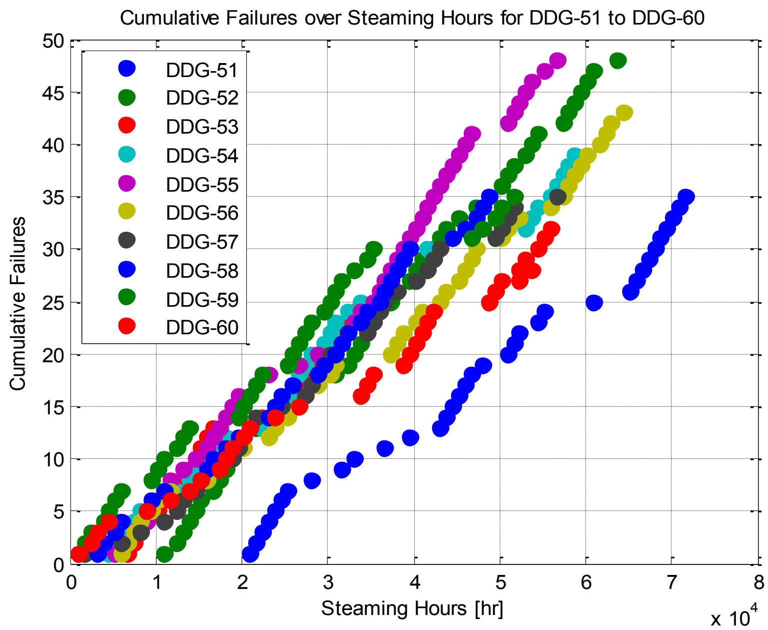

Figure 12. Cumulative Failures over time for DDG-51 to DDG-60

Figure 12 shows the cumulative failures over steaming hours for DDG-51 to DDG-60, using 100 time bins. A linear trend is evident in the plot.

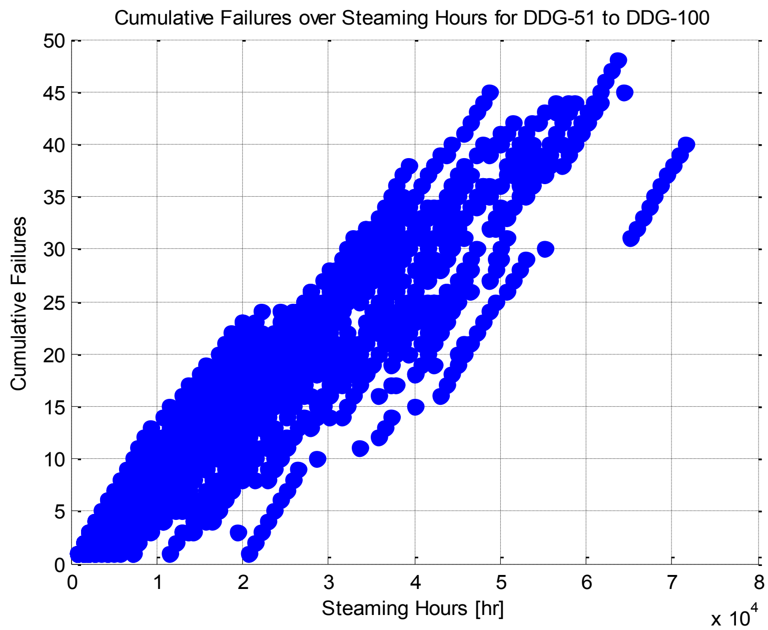

Figure 13. Cumulative Failures over time for DDG-51 to DDG-100

When the same analysis is extended to include ships DDG-51 to DDG-100, the same linear trend holds, as seen in Figure 13. Therefore I assume that the ship class does indeed follow a renewal process.

6.1.1 Average Rate of Occurrence of Failures

Another way to look for a trend in the data is to calculate the average rate of occurrence of failures. Louit et al. (2009) use the following formula:

$$\lambda_i(t) = \frac{N_i(t) - N_{i-1}(t)}{\Delta t} \; with \; (i-1)\Delta t \leq t \leq i\Delta t \qquad (1)$$

where $N_i(t)$ is the total number of failures from time zero to the i^{th} interval, and Δt is the length of each interval. Any trends in the data will be seen in successive values of $\lambda_i(t)$. For example, if the system is deteriorating, then successive values of $\lambda_i(t)$ will increase.

Figure 14 and Figure 15 show values of $\lambda_i(t)$ calculated using three different N_i values. In each figure, the top plot shows the results using the median and mean value of events for each bin, normalized by the number of ships (since there are fewer older ships). There is no noticeable trend in the plots. The second plot uses the sum of all events without "normalizing" it with the number of ships; because there is no normalizing, the data appears to trend downwards at the end, but this is merely a result of having fewer ships with a high number of steaming hours. Figure 14 shows the plots for DDG-51 to DDG-60, and Figure 15 gives results for DDG-51 to DDG-100.

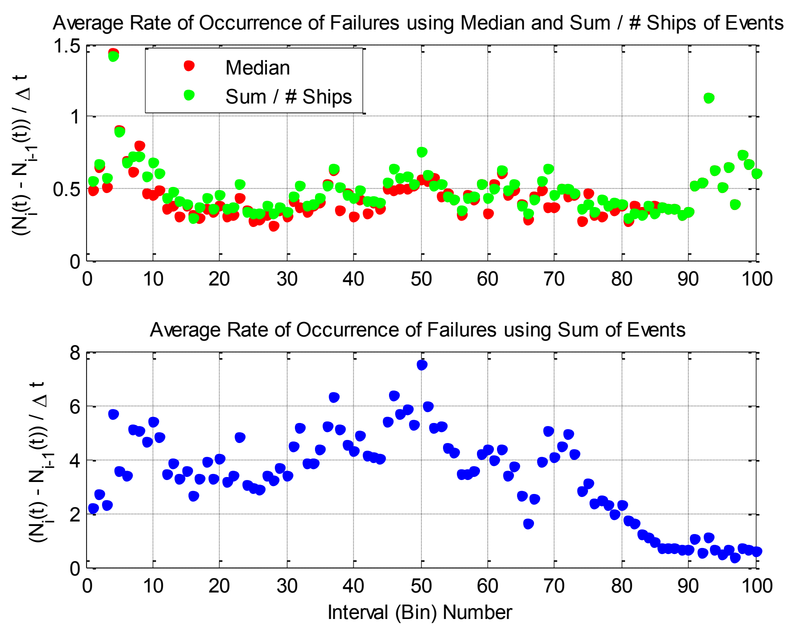

Figure 14. Average Rate of Occurrence of Failures for DDG-51 to DDG-60.

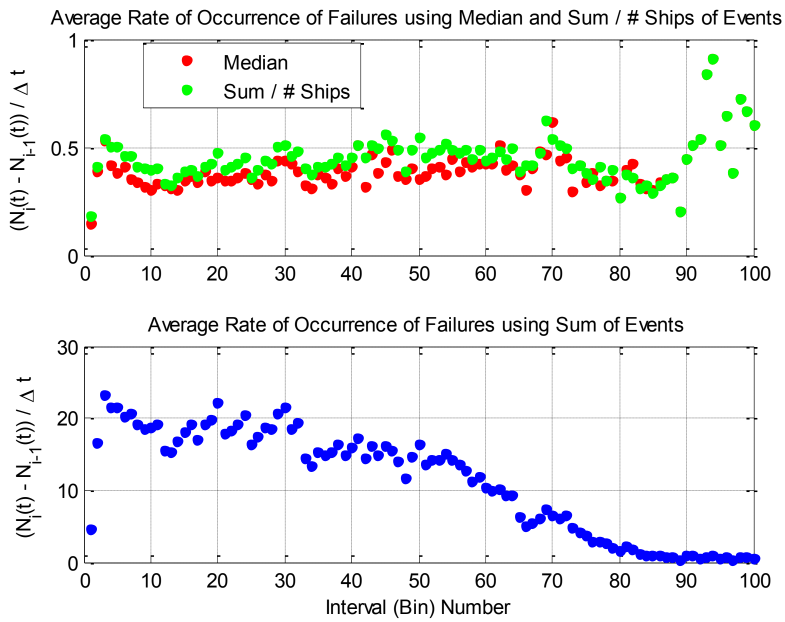

Figure 15. Average Rate of Occurrence of Failures for DDG-51 to DDG-100.

6.1.2 Scatter Plot of Successive Service Lives

The third test proposed by Louit et al. (2009) uses a plot of the service life of the i^{th} failure, against that of the $(i-1)^{th}$ failure. A plot with a single cluster represents a renewal process, while two or more clusters or linear plots indicate that the failure rate is not constant. Recall that a renewal process means that maintenance resets the system reliability to its initial value.

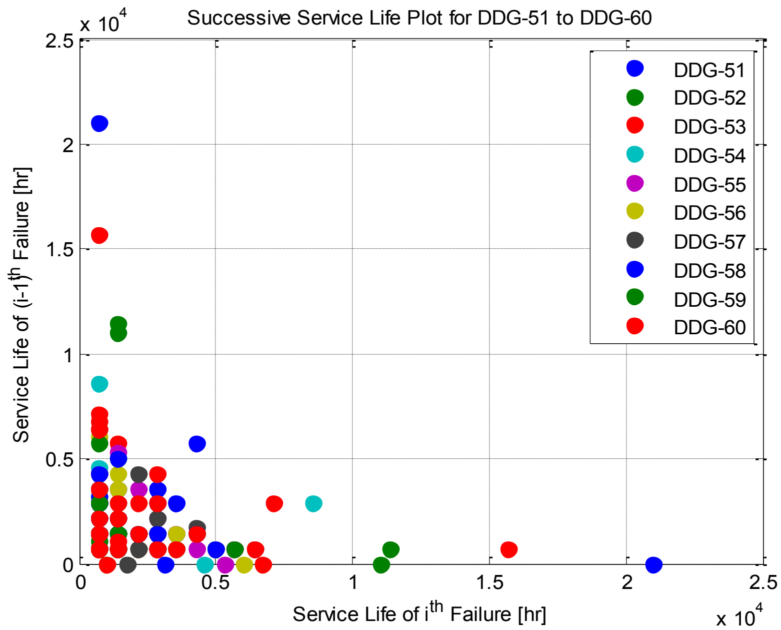

Figure 16. Scatter plot of successive service life for DDG-51 to DDG-60.

Figure 16 shows the scatter plot for DDG-51 to DDG-60. The figure clearly identifies a single cluster in the lower left hand corner, indicating a renewal process. There are several lone points, but these reflect occasional outlier values in the failure times.

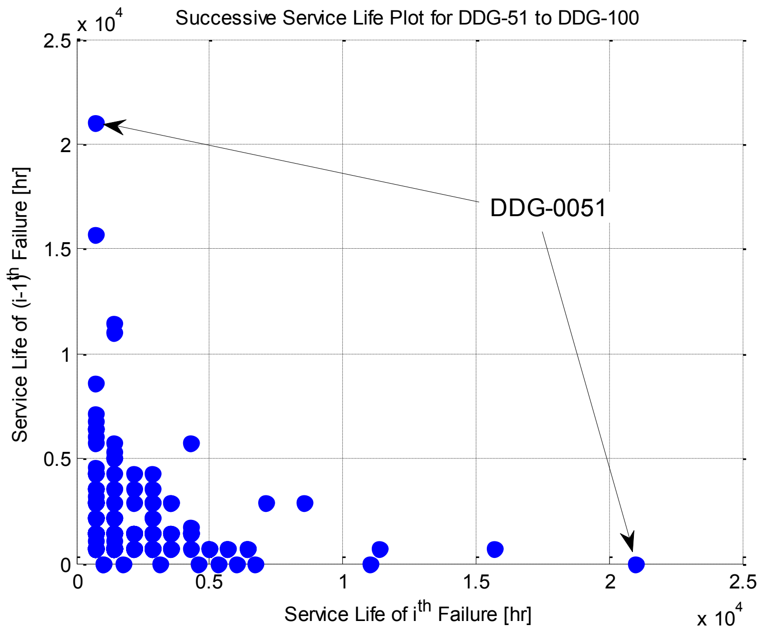

Figure 17. Scatter plot of successive service life for DDG-51 to DDG-100.

When this graphical test is applied to the larger set of ships (DDG-51 to DDG-100), as seen in Figure 17, the same conclusions hold. Figure 17 has a single cluster in the lower left hand corner, and the points outside of the cluster are assumed to be outliers in the failure times of the ships examined. For example, the two outermost points belong to the first ship, the DDG-0051. As the first built ship, there were still many unrealized flaws in the design. As each following ship was built, the overall design improved to account for these flaws.

CHAPTER 7. PART I CONCLUSION

Thus far, I have presented an overview of the DDG-51 case study to first, present an example of the motivation and application of this research and second, to build an understanding of how the U.S. Navy conducts maintenance. I have discovered that while preventive maintenance is intended to be scheduled on a regular basis, this is not currently the case as many ships undergo an extensive amount of corrective maintenance. The data available from the DDG-51 case study, while vast in amount, is far from being a complete set of data and does not directly provide the type of data that I want to use for building my model. As a result, I have used proxies to provide some preliminary analysis but this proves that in reality, there will be limitations to what is and is not available. Understanding these limitations is important for developing a maintenance and deterioration model for a given system.

Due to funding shortages, the U.S. Navy often finds the need to quantify the trade-off between maintenance and service life. With ship level data, I constructed a reliability model of a DDG-51 ship and presented a hypothesis about the model for time-to-failure.

Testing this hypothesis with two graphical tests, my hypothesis was confirmed: the DDG class of ships can be modeled as a single unit to nearly follow a renewal process. This development will pave the way for Part II, where modeling decisions will be based on the single unit and renewal process assumption. Then, with the resulting model, I can study the interaction between the model parameters. Knowing which parameters affect the service life most will help in obtaining the optimal maintenance strategy for the system.

CHAPTER 8. INTRODUCTION: PART II

Most work on maintenance optimization focuses on developing optimization algorithms for various contexts. For example, many cost-minimizing strategies for both preventive and corrective maintenance have been proposed. But in general the focus is always on one of three aspects: (1) showing that an optimal solution exists, (2) showing that the optimal solution, or a near-optimal solution can be found in a computationally feasible manner, (3) proposing a new way of modeling deterioration or maintenance and then deriving an optimal strategy.

To date there has been less emphasis on the impact of modeling decisions on the resulting optimizations, and, as a result, little discussion of how best to choose models for a particular context. In particular, I am concerned with how the deterioration model and maintenance model interact when an optimal maintenance policy is determined and with the ensuing result when the optimal maintenance policy is implemented on the real system. Figure 18 shows this interaction.

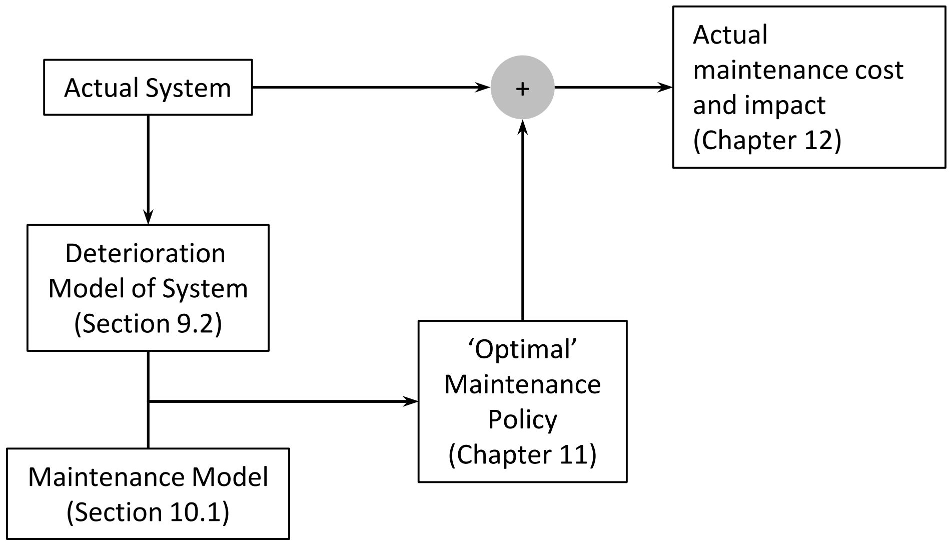

Figure 18. Interaction between system, deterioration and maintenance models, and resulting optimal maintenance policy

Inappropriate modeling decisions can have significant effects. Consider for example a simple single unit system that can be accurately modeled using a simple homogenous Poisson process (HPP), but for which the assumed failure rate is twice the actual failure rate. An 'optimal' maintenance policy is derived for this system over a given time period. For this argument, the basis of optimization is irrelevant (we assume that nonsensical cases like minimizing reliability or maximizing cost are not considered). It is obvious that the model will result in excessive preventive maintenance, as the optimization seeks to manage the "high" unreliability. The result is an excessively costly policy. In contrast, if the assumed failure rate is lower than the actual failure rate, the resulting policy will not yield the desired reliability.

In Part II, I explicitly consider the impact that decisions about how to model deterioration and the impact of maintenance have on the selection of optimal preventive maintenance strategies.[2] In Section 8, I begin by considering systems and how they deteriorate, and how that deterioration can be modeled. Next, in Section 9, I review the different types of maintenance models. In particular I consider single and multi-unit models, and different models of the impact of maintenance in aging. Then in Section 10, I review different bases for optimization; I focus on using a value-based optimization. Finally, in Section 11, I look at the impact of maintenance decisions on the optimal policy in terms of the net value obtained.

[2] Part II is an extension of work presented in Marais et al., (2014) and thus, has parts extracted from this report.

CHAPTER 9. SYSTEM DETERIORATION AND MODELS THEREOF

This section provides a review on deterioration and its mechanisms as well as the different types of maintenance that can address this deterioration.

9.1 Physical Deterioration

Complex engineering systems are subject to several different types of deterioration, which can be classified by their causes (also referred to as deterioration mechanisms) and progression over time, as shown in Table 1 [cf., Sanchez Silva et al., 2011; Harris, 2001].

Table 1. Deterioration causes and progression

	Gradual	Sudden
Structural	Sagging can affect structures such as the hull of the ship by redistributing the weight loads, thereby, weakening the structure.	Cracking in load bearing, non-metal components, such as a concrete wall, will weaken a structure, possibly leading to sudden failure.
Thermal	Systems with materials that expand or contract when subjected to large temperature variations could undergo permanent deformation.	When subjected to large temperature variations, bonded materials may suffer "de-bonding".
Hygroscopic	Liquid absorption causes materials to endure abnormal stress concentrations and possible deformation.	When the absorbed moisture becomes frozen, the absorbing material could fracture as a result of the liquid expanding to become a solid.
Chemical	Typically affecting metals, corrosion will "eat" away at a material. Systems in or around salt water will encounter this type of deterioration.	N/A

9.2 Models of Deterioration

Deterioration is generally modeled from two main viewpoints: a physical or bottom-up view that combines the system's structural characteristics and the load characteristics to estimate the probability of failure, and an actuarial or top-down view that uses population statistics to estimate the probability of failure over time. In the physical view, the probability of failure is modeled by assuming that the random structural resistance, R, and the total random load effects, *S*, can be described by their probability density functions $f_R(r)$ and $f_S(s)$, respectively. Failure occurs when R ≤ S and its probability is given by:

$$P_f = \int_0^\infty F_R(s) f_s(s) ds \tag{2}$$

where F_R is the cumulative distribution function of R [Frangopol and Maute, 2003].

Although closed form solutions exist when both R and S are normal or log-normal, in general, a closed form solution does not exist and numerical methods are used to evaluate the integral. This model only accounts for a single failure mode of a single component—for a system consisting of many components with many failure modes, advanced reliability techniques that can accommodate the computational challenges of state explosion are necessary.

In the actuarial view, the probability of failure is typically estimated using some kind of arrival process. There are three main failure models: the Homogenous Poisson Process (HPP), the Non-homogenous Poisson Process (NHPP) with Power Law, and the Non-homogenous Poisson Process with Exponential Law, as shown in Table 2 [cf., NIST, 2014]. When selecting an optimal maintenance strategy, the choice of deterioration model will affect how well the modelled optimal strategy reflects the true optimal strategy. The two NHPP models are generally used for reliability growth modelling and are not considered a good fit for our purpose. Within the HPP process, the failure rate can be decreasing, constant, or increasing. Here, I focus on systems with a constant failure rate. Varying failure rates are left for future work.

The actuarial approach to modeling sacrifices the understanding of the structural resistance and the load applied to it, but is significantly simpler and easier to implement, provided credible and adequate population statistics are available. The physical approach is better in infrastructure reliability analysis, where the systems (e.g., bridges) consist of relatively few, large, and often bespoke, components. On the other end of the scale, the actuarial approach is better for electronic systems, which typically consist of many, often off-the-shelf, elements. Complex engineering systems lie between these two extremes. For example, on a ship it is most appropriate to model hull reliability using the physical approach (see, for example, Frangopol et al, 2011; Guedes Soares and Garbatov, 1999), while the ship radar's reliability should be modeled using the actuarial approach.

Table 2. Deterioration Models

Deterioration Model	**Failure Rate Expression**	**Parameters**	**Application**
HPP	$m(t) = C$	C = constant	Used to evaluate reliability for repairable systems, this model follows the middle portion of the Bathtub curve by defining the time-to-failure of a system if failures are independent and identically distributed (constant failure rate).

Table 2 continued

Deterioration Model	Failure Rate Expression	Parameters	Application
NHPP w/ Power Law	$m(t) = \alpha t^{-B}$	B = growth rate, α = characteristic ife, t = time	Also known as the Duane Model, this model is used for assessing reliability growth and reliability improvement tests by using the Poisson process to define the time-to-failure of a system. The model can simulate both increasing and decreasing failure rates as well as simulate “incorporated fixes” to prevent same failures. This model includes the HPP as a special case.
NHPP w/ Exponential Law	$m(t) = e^{\alpha + Bt}$	B = growth rate, α = characteristic ife, t = time	This log-linear model is used to simulate the exponential decay of a repairable system’s reliability by defining the time-to-failure of a system that allows for the application of linear regression. In reality, a system cannot behave in an exponential manner indefinitely; therefore, this model can only be used within a defined boundary. This model includes the HPP as a possible case.

9.3 System Lifetime

Section 4.2 discussed the different ways the Navy defines service life. Most definitions are based on high-level economic and political needs, rather than the performance and reliability of individual systems. For example, ship lifetime may be defined by when the

Navy plans to have a new fleet available: the "old" ships must last till the "new" ships are available.

In contrast, most maintenance modeling bases lifetime on performance, reliability, or operating cost. Thus when the system performance or reliability become too low, or the operating cost becomes too high, the system is considered to be at the end of its lifetime. Or, the lifetime is assumed to be imposed externally, and the system operating cost must be minimized (or the reliability maximized). Here, I assume that a minimum acceptable level of reliability exists, and that this level defines the maximum possible lifetime. Shorter lifetimes may result in practice for example when operating cost becomes too high, or when there is no longer a need for the system. In practice, the real-time reliability may be estimated based on the number of failures, in a similar manner to that discussed in Part I.

CHAPTER 10. MAINTENANCE IMPACT MODELS

Maintenance impact models can be divided into those that consider the system as a single unit, as I did for the DDG-51 in Part I, or those that consider the system as consisting of two or more units. Most research focuses on the single-unit assumption, either by assuming the entire system is a single unit, or by considering subsystems and their maintenance in isolation. Here, I review the research on single and multi-unit maintenance modeling, and discuss the implications of modeling complex systems as single units.

10.1 Single-Unit Maintenance Models

Wu and Zuo (2010) review preventive maintenance models and suggest that they can all be reduced to age reduction models or ageing alteration models. Age reduction models assume that preventive maintenance returns the system to an earlier age. Thus perfect maintenance is an instance of age reduction, in this case to zero. Different models are created by using different parameters to determine the virtual age reduction. Ageing alteration models assume that preventive maintenance alters the future ageing of the model, either slowing it down or accelerating it.

Kijima (1989) proposed that for a single unit system, the effect of repair could be modeled as reducing the system's virtual age and then using a g-renewal function to determine the optimal time between replacements. He let V_n be the system's virtual age after the n^{th} repair, X_n the additional age incurred between the $(n-1)^{th}$ and n^{th} repair, and ϑ_n the level of repair. In his Type I model, the n^{th} repair cannot remove the damages incurred before the $(n-1)^{th}$ repair. Thus, after the n^{th} repair the virtual age of the system becomes:

$$V_n = V_{n-1} + \theta_n X_n \qquad (3)$$

Note that if we start with a new system (and the replacement systems are also always new) at t = 0, the system virtual age will therefore always be less than or equal to the clock time. The Type I model is therefore an age reduction model, which allows maintenance to make systems "as good as old".

The Type II model allows repair to remove damage caused by prior failures too. After the nth repair, the virtual age of the system becomes [Kijima, 1989]:

$$V_n = \theta_n (V_{n-1} + X_n) \qquad (4)$$

The Type II model is therefore an ageing alteration model which allows maintenance to make systems "as good as new". Both model types implicitly assume that the maintenance action is successful—in other words the age improvement is proportional to the repair level (ϑ). Thus for example, a "worse than" repair is not covered by this approach.

Table 3 shows examples of preventive maintenance models in both categories.

Table 3. Categorization of Preventive Maintenance Models

	Age Reduction Models	**Ageing Alteration Models**
Principle	Preventive maintenance returns the system to a younger age.	Preventive maintenance slows/speeds future ageing.
Examples		
	Malik (1979)	
	Nakagawa 1	Nakagawa 2
	Kijima Type I	Kijima Type II
	Canfield	
	Proportional age reduction (PAR), Martorell et al. (1999)	Proportional age setback (PAS), Martorell et al. (1999)
	Repair reduces failure intensity gained since last repair (Doyen and Gaudoin, 2004)	Repair reduces total failure intensity gain (Doyen and Gaudoin, 2004)

In reality, modeling preventive maintenance for a system might include using a combination of both Type I and Type II models. For example, it would be most appropriate to use the Type II model to model the effects of preventive maintenance such as an engine overhaul. In essence, an overhaul resets the condition of the component to a "like new" condition. Thus, most damage endured over the lifetime of the component is undone. When a repair is performed to remove damage from a specific failure, the most appropriate model to use is the Type I model. The damage from a specific failure is repaired while any other damage to the system remains.

Figure 19 shows conceptually the deterioration of a system's reliability with periodic preventive maintenance. The figure reads as follows. The horizontal dotted line represents the minimum acceptable reliability. Below this reliability, the system experiences failures (e.g., leaks) so frequently that performance is excessively affected. Thus the time where the reliability reaches this line corresponds to the natural life. The solid red line shows the reliability deterioration when no maintenance is performed. The dashed-black curve shows the reliability when periodic preventive maintenance is performed. Between maintenance intervals the reliability deteriorates; each maintenance action creates a step increase in reliability. The solid blue curve shows the effective reliability achieved using this nominal preventive maintenance program.

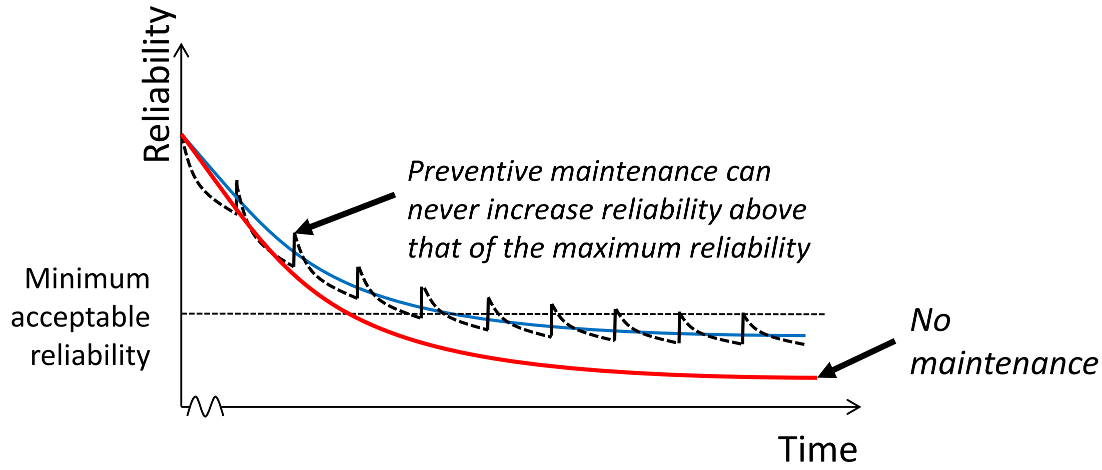

Figure 19. Nominal Reliability Trajectory for System overlaid with Periodic Preventive Maintenance

In Chapter 11, I introduce a value-based optimization to determine how to choose the PM policy.

10.2 <u>Multi-Unit Maintenance Models</u>

Maintenance planning in multi-unit systems is harder because (1) these systems are more complex, providing both opportunity (e.g., doing opportunistic preventive maintenance on subsystems when the system is down for other corrective maintenance), and challenge, specifically in the form of interdependencies between systems.

For the maintenance problem, dependencies in multi-unit systems can be classified into three types: economic, structural, and stochastic [Thomas, 1986; Dekker et al., 1997].

In economic dependence, costs can be saved by performing joint maintenance (e.g., if a unit is difficult to access, other co-located units should be maintained at the same time) or simultaneous downtime is undesirable and maintenance must be spread out over time. Most research on dependence assumes economic dependence, and focuses on preventive maintenance [for reviews see Cho and Parlar, 1991; Dekker et al., 1997].

In structural dependence, units structurally form a part, therefore when one component is maintained, other parts must be maintained too, or the possibility of opportunistic maintenance should be considered. Thomas (1983, 1985, 1986) and Haurie and L'Ecuyer (1983) provide early discussions of this dependence and suggest simple suboptimal policies that avoid the complex optimization challenges posed by these problems. Most subsequent research has focused on the opportunistic maintenance aspect, in which case the dependence can be modeled as economic [e.g., Ozekici, 1988].

In stochastic dependence, failure of one unit affects the other unit(s), or, the units experience common-cause failures. I focus here on the first case. For the first case, failure of the first unit can increase the deterioration of the remaining units because the remaining units must work harder because of the failure, or by directly affecting the remaining units. This second mechanism can be modeled at the extremes as "shocking" the remaining units (e.g., failure of a cooling pump causes another unit to overheat), or as accelerating the deterioration of the remaining units (e.g., failure of a cooling pump results in hot fluid, which corrodes the surfaces of the remaining units) [Nakagawa and Murthy, 1993].

Most work on failure interaction has used simple two-unit systems and then derived cost- or reliability-optimal maintenance strategies. For example, Nakagawa and Murthy (1993) present a two-unit system where the first unit's failure damages the second unit and model the interaction as (1) an induced failure with a conditional failure probability, and (2) shock damage with a damage distribution. Sun et al. (2006, 2009) propose a model to quantify the impact of interaction on unit failure probability and then to calculate the system reliability. Most recently, Golmakani and Moakedi (2012) found an optimal finite horizon cost minimizing inspection interval for a simple system with hard failures (cause the system to stop) and soft failures (increase operating costs, only detected through inspection).

10.3 Impact of the Single-Unit Assumption on Multi-Unit Systems

This section provides a conceptual discussion of the impact of deferring preventive and corrective maintenance, and explores the applicability of applying single-unit models to multi-unit systems. I focus on stochastic dependence, specifically of the first kind (failure of one unit increases the deterioration of the other units).

10.3.1 Preventive Maintenance

Consider first the impact of deferring scheduled maintenance on a single-unit system, as shown in Figure 20. The dashed gray lines show the notional expected reliability over time in the absence of maintenance[3]. The rate of deterioration is exaggerated for clarity. Preventive maintenance shifts the reliability curve to a higher reliability level; the solid black line demonstrates this. If maintenance is not performed, the system continues deteriorating (decreasing in reliability); the dashed gray lines depict this. Deferring maintenance means that a larger reliability improvement is necessary to regain the same level of reliability, as shown by the solid gray arrows; the longer length of the arrow on the right illustrates this. With the assumption that cost is proportional to the amount of reliability improvement, then deferred maintenance is more expensive. For example, if the ship's engines are not lubricated at some minimum interval, the engines, deteriorate more rapidly and are likely to fail earlier or more frequently, requiring corrective maintenance. The engine performance may also be affected; for example, it may become less fuel efficient. Instead of a simple oil change at the prescribed or initially indicated, the engines may now require a major overhaul. Therefore, deferring preventive maintenance has three main effects: (1) the system deteriorates more rapidly, bringing the time at which failures are unacceptably frequent earlier in the system's life; (2) it increases the cost of bringing the system back to the desired

[3] I assume that any infant mortality failures have already occurred or have been mitigated through burn-in, since preventive maintenance is not appropriate for infant mortality.

reliability; and (3) it may result in reduced performance. Thus deferring preventive maintenance can increase TOC and decrease expected service life.

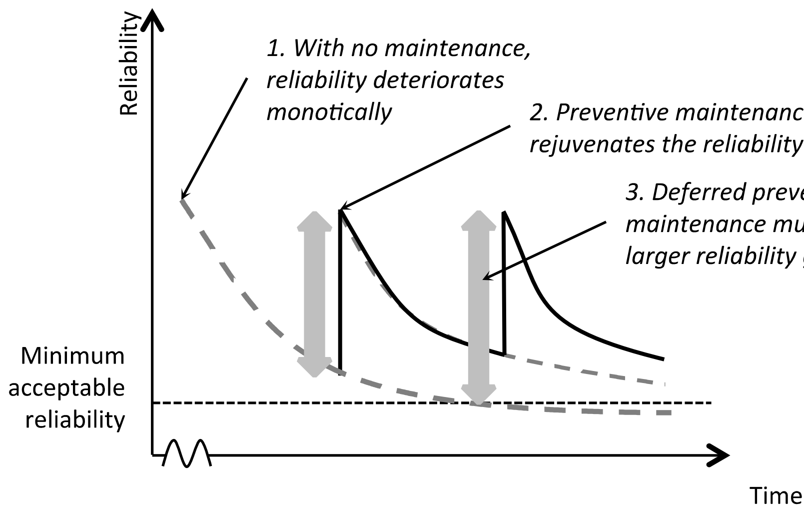

Figure 20. The impact of deferring preventive maintenance is the same for single and multi-unit systems

For a multi-unit system, deferring scheduled maintenance has similar effects as for a single-unit system. The multi-unit system's no-maintenance curve (dashed gray in Figure 20) would incorporate any deterioration and failure interaction effects between units, and the effort to restore the system through unit maintenance would also account for all effected units. Deferring maintenance in a multi-unit system may save immediate cost, but it could lead to higher total ownership cost.

10.3.2 Corrective Maintenance

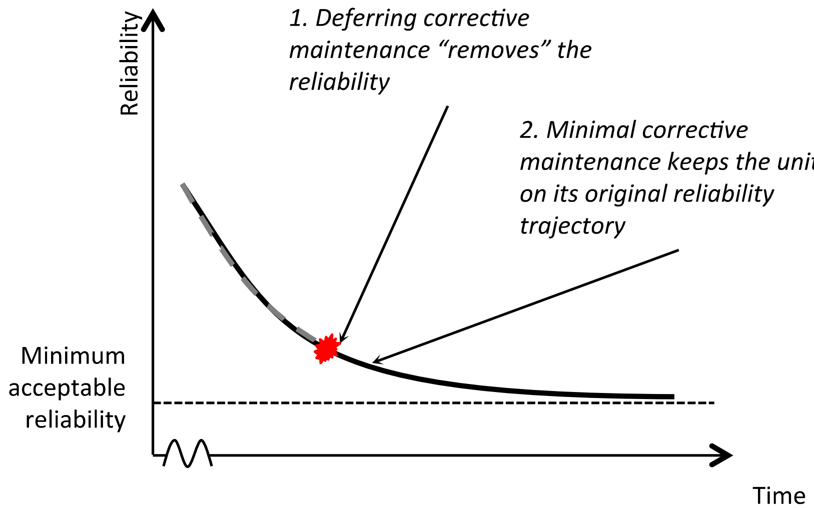

Figure 21. Impact of Deferring Corrective Maintenance on a Single-Unit System

The impact of deferring corrective maintenance for a single-unit system is obvious—the system is not available and performance goes to zero. Once the unit has failed, reliability no longer has any meaning if it is not repaired, as indicated by the dashed gray line dropping to zero reliability in Figure 21[4].

[4] For clarity, the figures assume that the corrective maintenance is minimal.

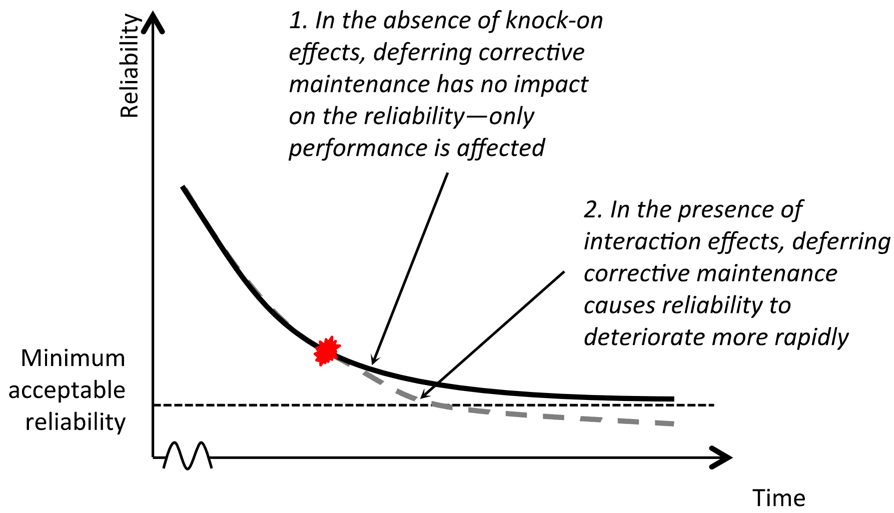

Figure 22. Impact of Deferring Corrective Maintenance on a Multi-Unit System

In contrast, consider the impact of deferring corrective maintenance on a multi-unit system, as shown in Figure 22. By definition, corrective maintenance is needed when a unit has failed. Ignoring for the moment the possibility of redundant backup units, deferring corrective maintenance of a failed unit results in system performance loss caused by the failure continuing, but the system may still be functioning and have an associated level of reliability. If the failure of the unit does not affect the remaining units, the reliability of the system is not affected—as shown by the solid black line—only the performance is reduced. In contrast, if other units are affected, either by deteriorating more rapidly as a result of the failure or by having to work harder to compensate for the failure, those units and, hence, the system becomes less reliable, as shown by the dashed gray line. These units may therefore also be more likely to fail and require corrective maintenance. Therefore, the impact of deferring corrective maintenance depends on the coupling in the system: (1) where the failed unit is isolated, deferring maintenance causes only the decrease in performance associated with that unit; (2) where the failure of the unit causes other units to work harder, deferring maintenance also results in the remainder of the system becoming less reliable.

Therefore, the single-unit assumption can be used when modeling preventive maintenance decisions, but leads to underestimating reliability and hence ultimately performance impacts in multi-unit systems.

10.4 Deterioration under Different Maintenance Strategies: Type I Model

This section introduces the impact of the modeling parameters on the system reliability over time.

Under the Type I assumption, preventive maintenance can reset aging up to the last repair. If the system deterioration follows a Homogenous Poisson process (see Table 2), reliability (*R*) as a function of time (*t*) is given by:

$$R_n(t) = e^{-\lambda\left(t-n\Delta t(1-\theta)\right)} \tag{5}$$

where *n* represents the periodic maintenance actions, *Δt* is the periodic maintenance interval, ϑ is the repair level, and λ is the mean time between failures. This equation represents the periodic "jumps" in reliability with each maintenance action; note that ϑ, Δt, and n depend on the maintenance program, while λ depends on the system characteristics (λ is usually interpreted as the mean time between failures (MTBF)).

For the parametric study, I focus on the relationship between each of the model parameters and the effect on service life. Figure 23 depicts this relationship. The preventive maintenance interval (Δt) defines the time between each maintenance action. The repair level (ϑ) defines the amount of effort put into each maintenance action. Lower repair levels denote more effort, while higher repair levels denote less effort. The system quality (λ) defines the quality of the system design. Lower system quality values represent better designed systems while higher quality values represent worse designed systems. Both the repair level and PM interval represent the type of maintenance policy chosen while λ represents the system design.

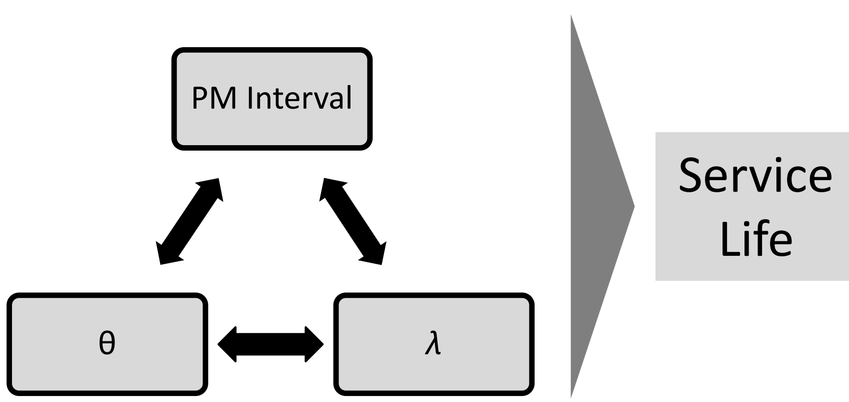

Figure 23. Interaction of model parameters

10.4.1 Nominal Case—Type I

Table 4 defines the variables for the nominal case.

Table 4. Type I Nominal Case Parameters and Results

Parameter	Symbol	Nominal Value
Deterioration model		HPP
Maintenance interval	Δt	1.0 year
Repair level	ϑ	0.75
MTBF	λ	0.5
Minimum reliability	R_{min}	0.5
Results		
Service life without maintenance	*ESL*	1.4 years
Service life with nominal PM	*ESL*	1.64 years

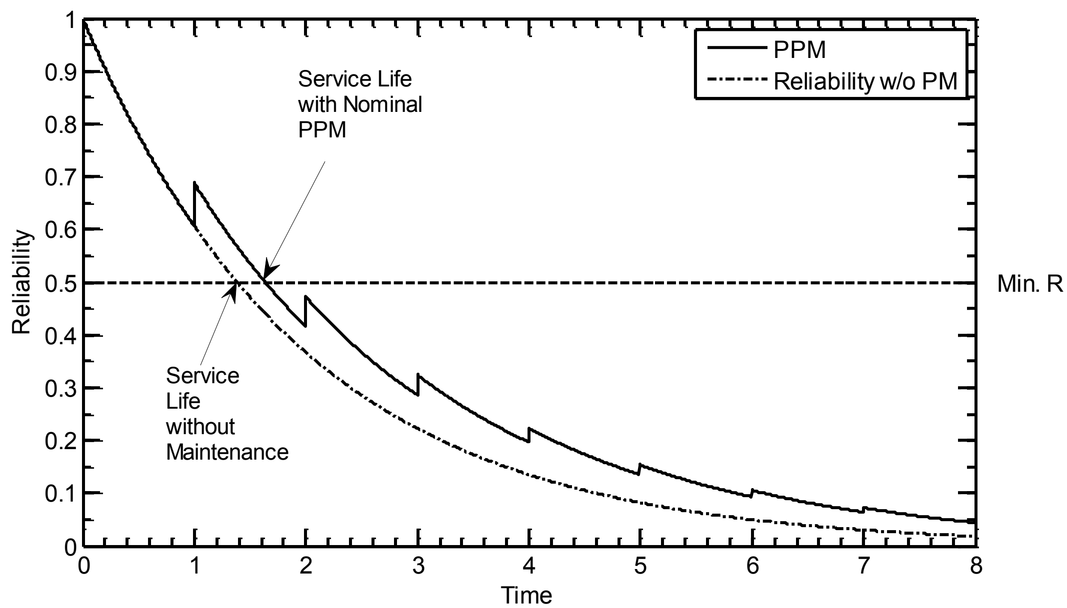

Figure 24. Type I PPM Nominal Case

Figure 24 displays the nominal case for the Type I model. The dotted line shows the deterioration of the reliability in the absence of maintenance; the solid line shows the reliability trajectory for periodic preventive maintenance. For the purposes of this study, the service life is defined as the point at which the reliability reaches a minimum acceptable level; in this case, I chose a minimum reliability level of 0.50. Essentially, a system operating at this threshold would have a 50% chance of being able to successfully perform on a given day. Choosing the minimum reliability was based on the assumption that 50% probability of failure is a practical level for a general system. A higher level would not enable us to show the progression of the effects of preventive maintenance under the Type I and Type II assumptions. Later, I consider the impact of varying the end-of-life reliability. Under preventive maintenance, the service life for the nominal case is extended from approximately 1.4 years to 1.64 years.

Finally, note that the reliability increments become smaller with time due to the interaction between the Homogenous Poisson process (HPP) and the Type I assumption. Under the HPP, the rate of reliability deterioration decreases with time—in other words the amount of aging during each successive fixed interval decreases. Under the Type I assumption, a fixed proportion of aging is removed in each action, resulting in the reliability increment decreasing with time.

10.4.2 Maintenance Interval—Type I

Consider next the effect of structurally modifying the way in which maintenance is conducted. First, consider the impact of extending or shortening the interval between preventive maintenance actions, as shown in Figure 25 and Figure 26. In these figures, Δt is varied while ϑ and λ remain constant.

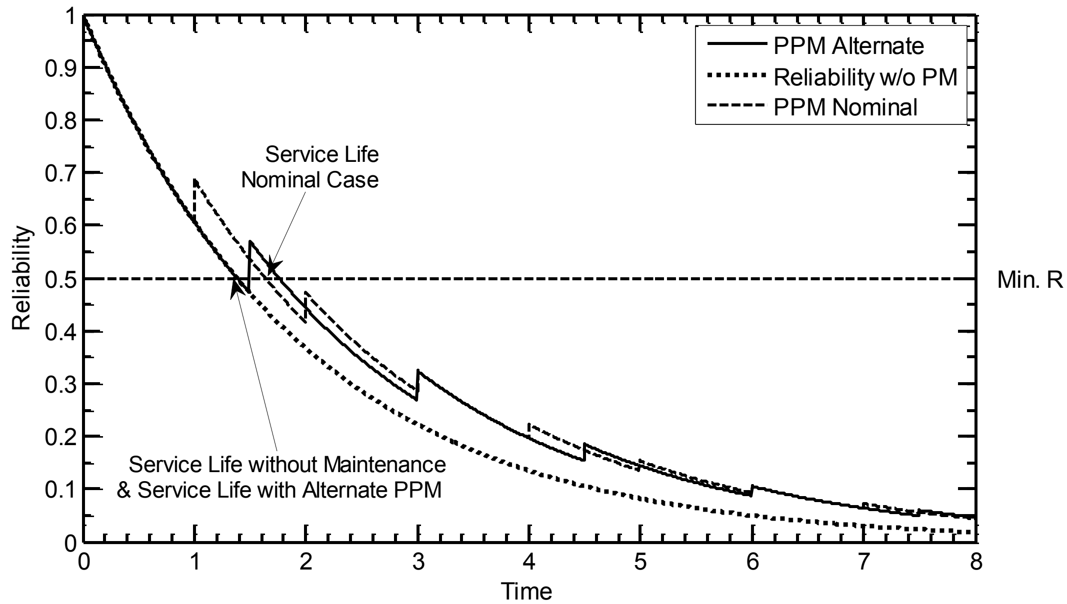

Figure 25. Type I PPM (Δt_{var} = 1.5)

In Figure 25, the maintenance interval is increased by 50% to 1.5 years. The expected service life (ESL) decreases from 1.64 years to 1.4 years (i.e. the system reaches minimum reliability level before the first scheduled maintenance action). These results are expected, as increasing the time interval between preventive maintenance actions allows for greater system deterioration during this period, resulting in a shorter ESL.

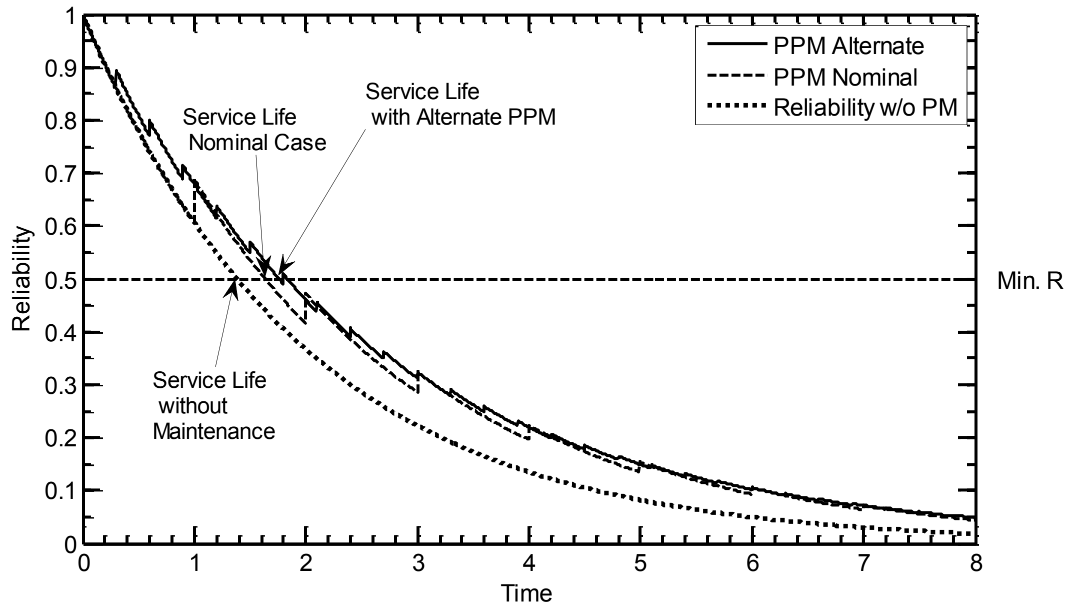

Figure 26. Type I PPM (Δt_{var} = 0.3)

In contrast, as shown in Figure 26, decreasing the maintenance interval to 0.3 years yields a slight increase in service life; but this increase requires five times as many preventive maintenance actions. The ESL slightly increases from 1.64 years to 1.76 years. This result suggests that there is an upper bound to how many preventive maintenance actions can be performed before the return on investment is no longer economically advantageous. A later section explores this idea further.

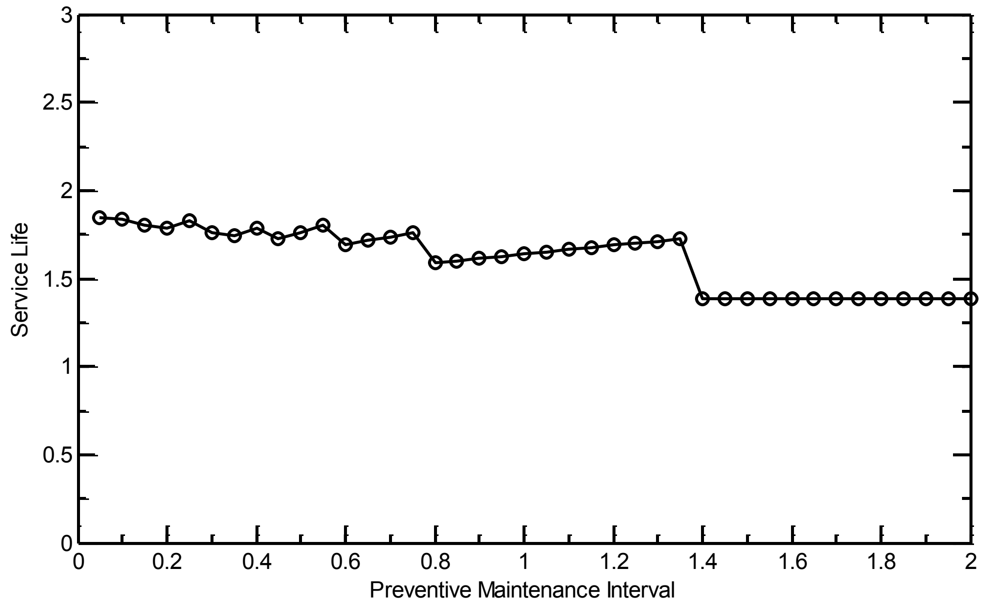

Figure 27. Service Life vs. Preventive Maintenance Interval, Type I

Figure 27 shows a plot of the preventive maintenance interval and its effect on service life in a Type I model with the nominal parameters given in Table 4. Generally, as the preventive maintenance interval increases, the service life decreases. At a preventive maintenance interval of 1.4, the service life stops decreasing due to the preventive maintenance interval being larger than the time it takes for the system's reliability to reach the minimum reliability level.

Due to an artifact of the model setup, the service life decreases in a "stair step" fashion with the slight increase in service life at each step (as shown in Figure 28b). This is due to the type of deterioration model chosen combined with the use of periodic preventive maintenance (PPM). A slight increase in the PM interval shifts the PPM reliability trajectory just enough, giving the illusion that the service life is extended when a longer PM interval is chosen (as shown in Figure 28a). When the PM interval is too long (depicted by point 3 in Figure 28), the PPM trajectory reaches the minimum reliability before another maintenance action can be performed. Thus, the service life drops sharply, creating a “stair step” trend. This trend will be seen in both the Type I and Type II models. This artifact of the model should be taken into consideration when making any maintenance decisions.

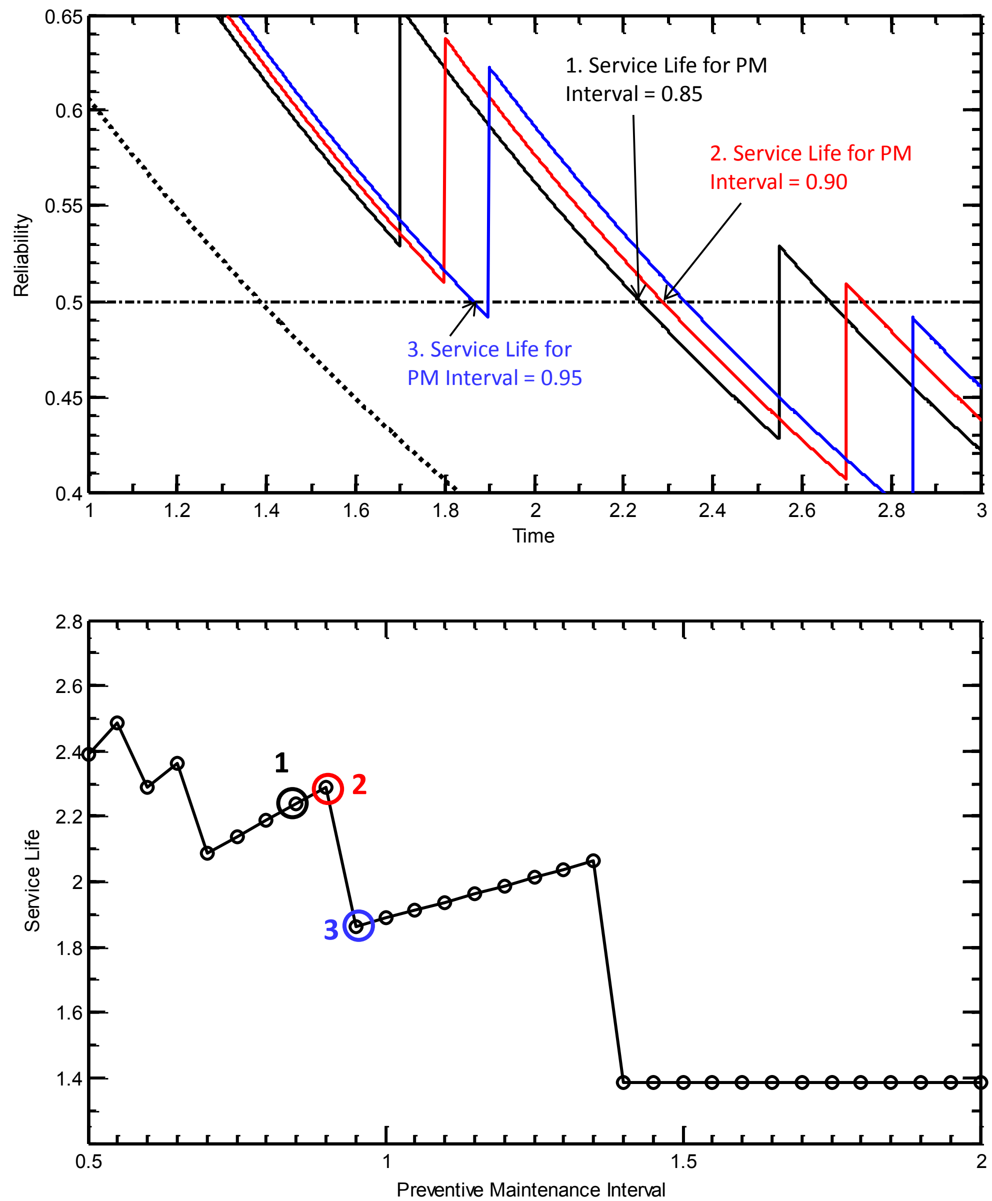

Figure 28. (a) Reliability vs Time, (b) Service Life vs Preventive Maintenance Interval

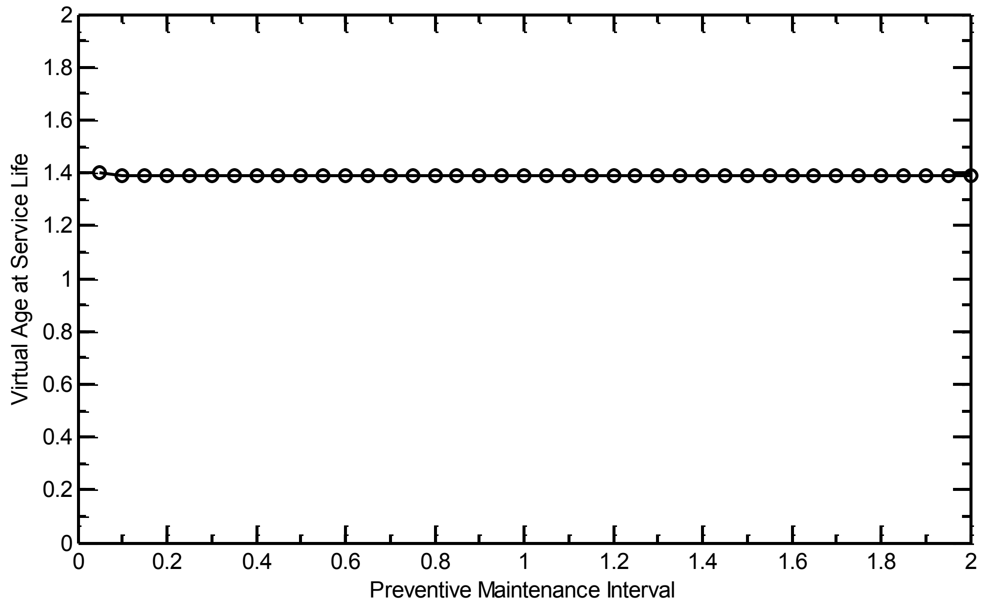

Figure 29. Virtual Age vs. Preventive Maintenance Interval, Type I

As mentioned in Section 10.1, the virtual age of a system is a function of the system's calendar age and extent of repair. Unlike the calendar age of the system, the virtual age of the system can be reset by an amount determined by the deterioration model used and the repair extent (see Section 6.2). As mentioned previously, the virtual age of the system will be less than or equal to the system's clock time (calendar age). As seen in Figure 29, the virtual age at service life stays constant regardless of the preventive maintenance interval used. Since the virtual age at service life is defined as the point where the system's reliability crosses the minimum acceptable reliability level, the virtual age is expected to be the same regardless of the parameters chosen.

10.4.3 Repair Level—Type I

Next, consider the impact of changing the repair level, ϑ. The repair level is a measure of how much maintenance is performed during any single action. By convention, a high value of ϑ corresponds to a low level of maintenance effort, and vice versa. As stated earlier, the repair level is used to determine the total preventive maintenance cost.

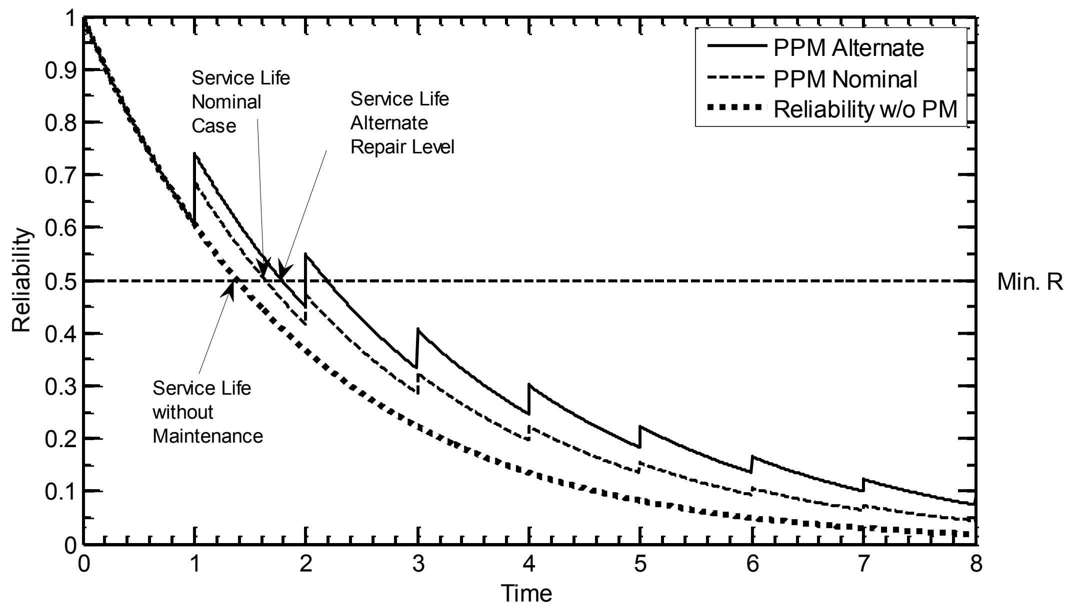

Figure 30. Type I PPM (ϑ_{var} = 0.6)

Figure 30 shows that increasing the maintenance effort (lower ϑ) increases the expected service life. By performing "better" maintenance, the service life increased by 9.8% to 1.80 years.

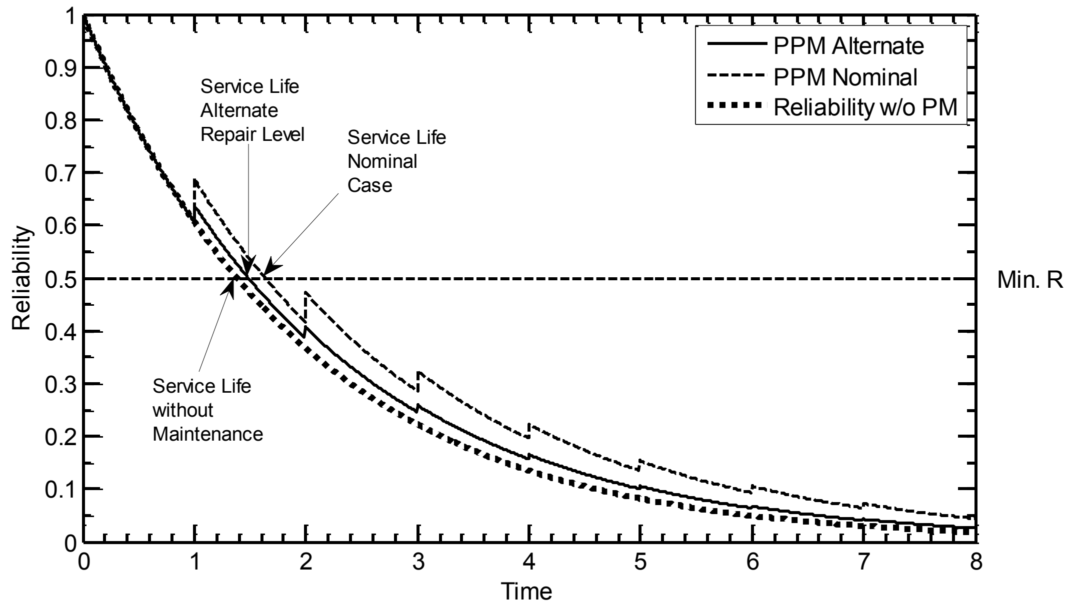

Figure 31. Type I PPM (ϑ_{var} = 0.9)

In contrast then, decreasing the maintenance effort (higher ϑ), decreases the service life, as shown in Figure 31. The ESL decreased by 9.1% to 1.49 years.

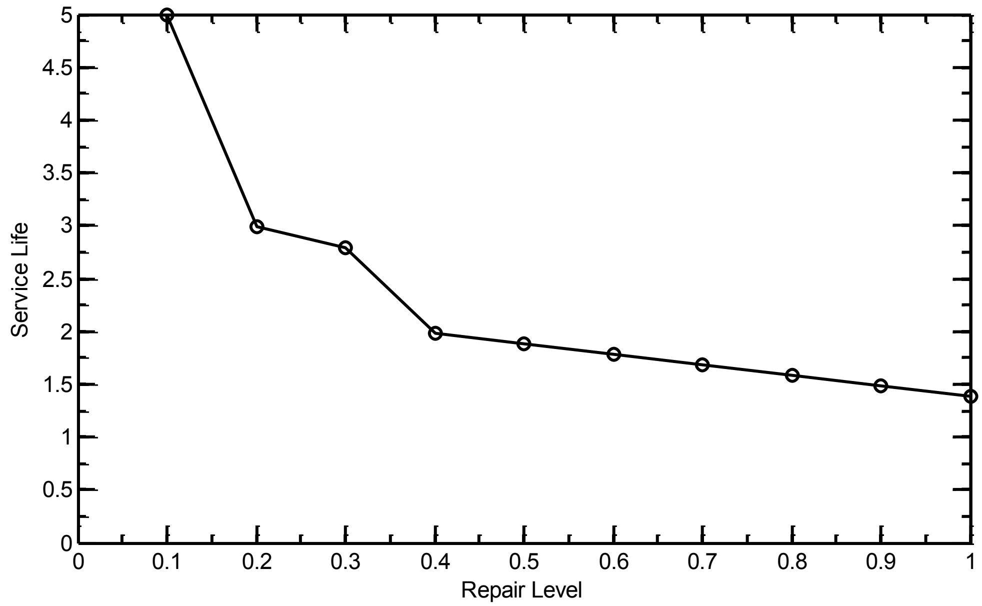

Figure 32. Service Life vs. Repair Level, Type I

Figure 32 shows the effects of the repair level on service life, with the PM interval and system quality at the nominal values. The service life is 4.98 years at a good repair level of 0.1 then sharply decreases to a service life of 2.95 years at a repair level of 0.2. As expected, performing more maintenance results in a longer service life but the gain in service life decreases when a larger repair level is reached; there is a gain of about 2 years in service life between the repair levels of 0.2 and 0.1 but only a gain of about half a year between the repair levels of 0.6 and 0.9.

Thus far I have assumed that the repair level is constant. In some cases it may make sense to vary the repair level as the system ages. For example, to obtain the same revenue, better repair is necessary as the system ages so that the system reliability maintains a high level.

I model the variable repair level as:

$$\theta(t) = e^{-Cnr} \tag{6}$$

where C is a constant, *n* represents the maintenance action, and *r* is the reliability immediately before the maintenance action is performed. Thus the repair level decreases as the reliability decreases, and decreases as more maintenance actions are performed.

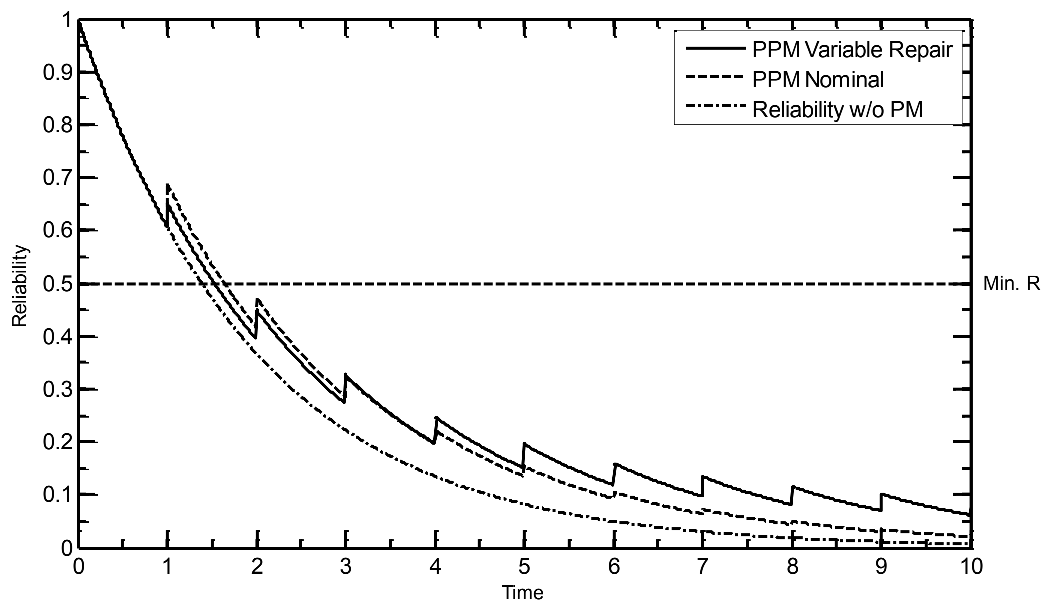

Figure 33. Reliability vs. Time for Variable Repair Level, Type I

Figure 33 shows the effect on reliability when a variable repair level is applied to the Type I model. As the system ages, the PPM with a variable repair level obtains a higher reliability level than the nominal PPM case.

10.4.4 Parametric Study—Type I

Next, I determined the relative sensitivity of the service lifetime by varying all three parameters (ϑ, Δt, λ) using a parametric study. The variables were varied as shown in Table 5. The ranges of values were chosen in order to demonstrate the possible range of behavior. Upper and lower bounds were based upon the amount of viable data resulting from the design trials.

Table 5. Type I Parameter Range

Parameter	**Symbol**	**Value Range**
Maintenance interval	Δt	0.05 – 5.0
Repair level	ϑ	0.05 – 0.95
System MTBF	λ	0.05 – 0.95

First, consider the case where the PM interval and λ vary while ϑ is kept to the nominal value.

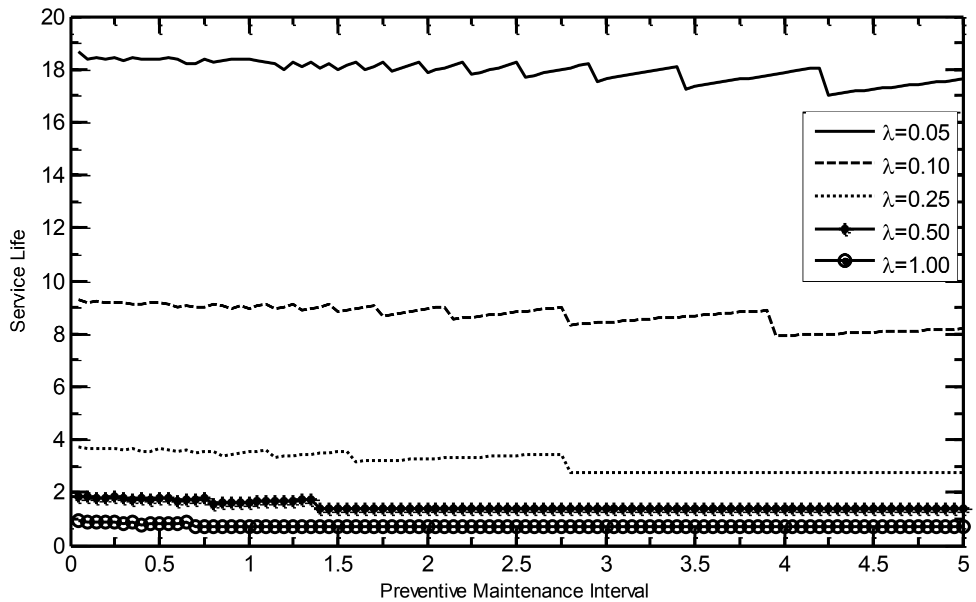

Figure 34. Service Life vs. PM Interval, ϑ = 0.75, Type I

The service life for multiple values of λ is shown for a range of PM intervals in Figure 34. Better quality systems (smaller λ) result in longer service lives and provide a wider choice of PM intervals. For example, if λ = 0.10, a PM interval as long as 4 years will still result in a larger service life than λ = 0.25 with the smallest PM interval. Note that as the system quality improves, there is a larger gain in service life.

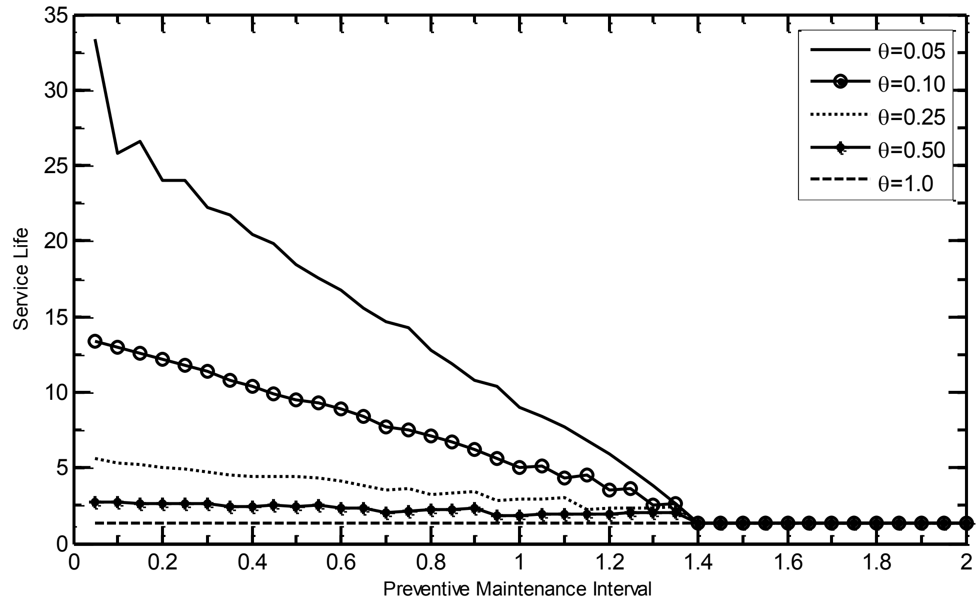

Figure 35. Service Life vs. PM Interval, λ = 0.5, Type I

Figure 35 shows how service life varies with PM interval and repair level when the system quality is kept constant. Poor repairs (high ϑ) result in low service lives, as expected. As the repair is improved, the service life increases exponentially, as shown explicitly in Figure 36.

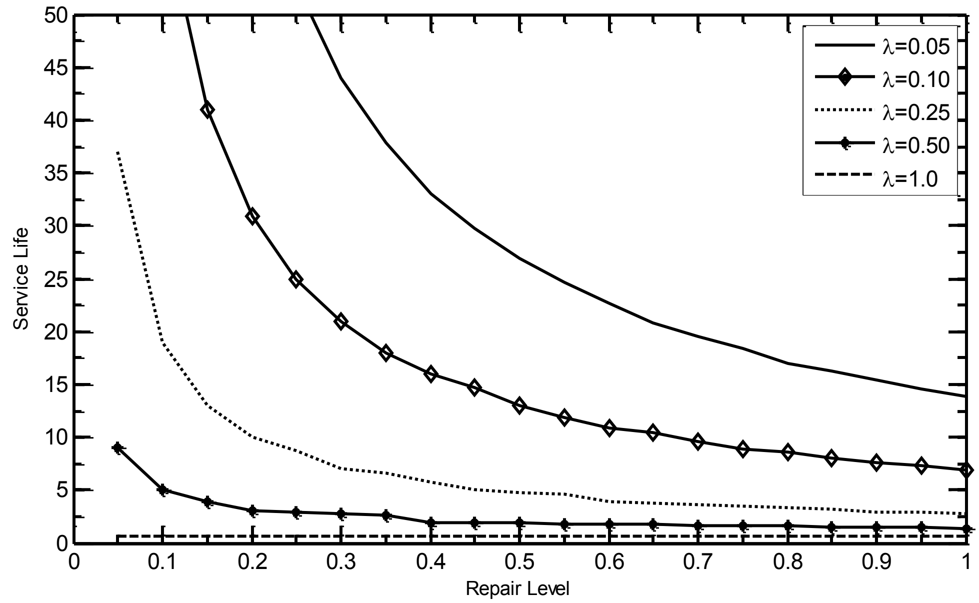

Figure 36. Service Life vs. Repair Level, PM Interval = 1, Type I

Figure 36 shows the variation in service life with system quality and repair level. When the system quality is very low (high λ), performing better repairs has little impact on the service life, which remains low and near to its no-maintenance value of 1.4 years. No matter how good the maintenance is, long service lives cannot be obtained with low quality systems, if the Type I assumption is correct. In contrast, high quality systems respond well to better repair, as shown by the curve for $\lambda = 0.05$.

10.5 Deterioration under Different Maintenance Strategies: Type II Model

In a Type II repair model, maintenance can reset the virtual age back to zero. Under the Type II model, for the HPP, reliability as a function of time is given by:

$$R_n(t) = e^{-\lambda\left(t-\Delta t\left(n-\theta^n-\theta^{n-1}-\theta^{n-2}\ldots-\theta\right)\right)} \tag{7}$$

10.5.1 Nominal Case—Type II

Table 6 shows the parameters for the nominal case.

Table 6. Type II Nominal Case Parameters and Results

Parameter	Symbol	Nominal Value
Deterioration model		HPP
Maintenance interval	Δt	1.0 year
Repair level	ϑ	0.75
MTBF	λ	0.50
Minimum reliability	R_{min}	0.5
Results		
Service life without maintenance	*ESL*	1.4 years
Service life with nominal PM	*ESL*	1.6 years

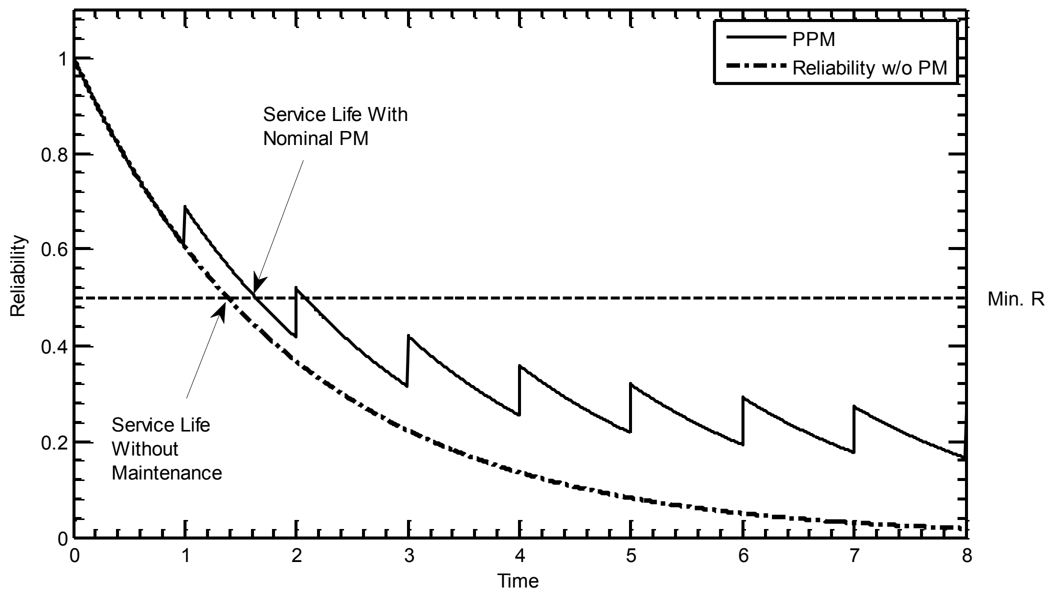

Figure 37. Type II PPM Nominal Case

Figure 37 shows the nominal case for the Type II model. As with the Type I analysis, the no-maintenance service life is 1.4 years. The solid line shows the reliability trajectory for Type II periodic preventive maintenance. Maintenance extends the service life to t = 1.6 years. Similar to the Type I assumption, the reliability increments become smaller with time, but do not decrease as significantly as seen in the Type I case.

10.5.2 Maintenance Interval—Type II

Figure 38 and Figure 39 show the impact of modifying the PM interval while ϑ and λ are kept to the nominal case values.

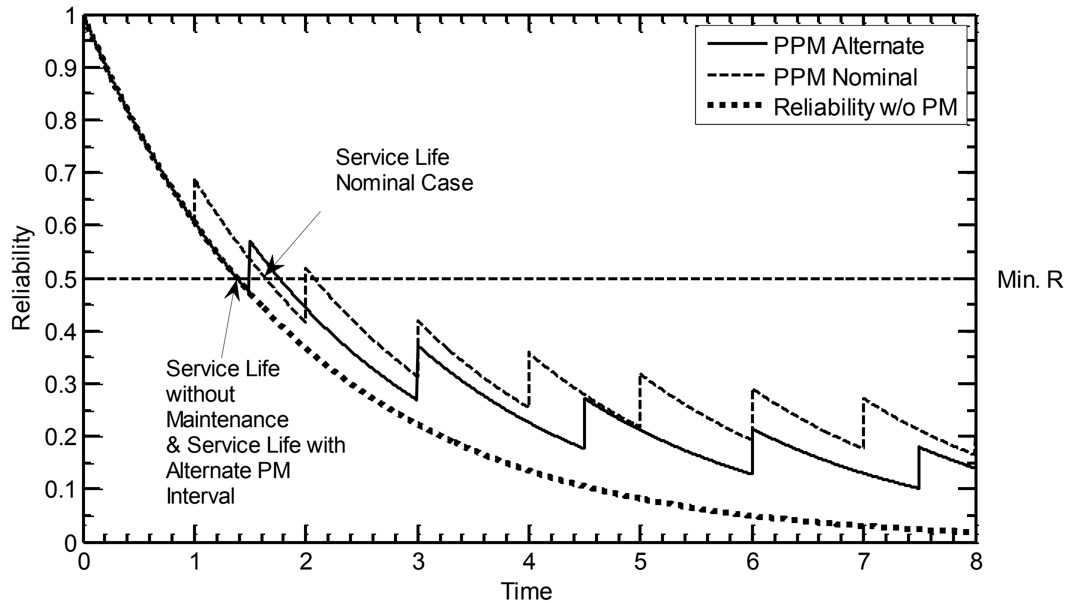

Figure 38. Type II PPM (Δt_{var} = 1.5)

In Figure 38, the maintenance interval is increased to 1.5 years. The service life decreases from 1.6 years to 1.4 years, because the system reaches minimum reliability before the first scheduled maintenance action can take place.

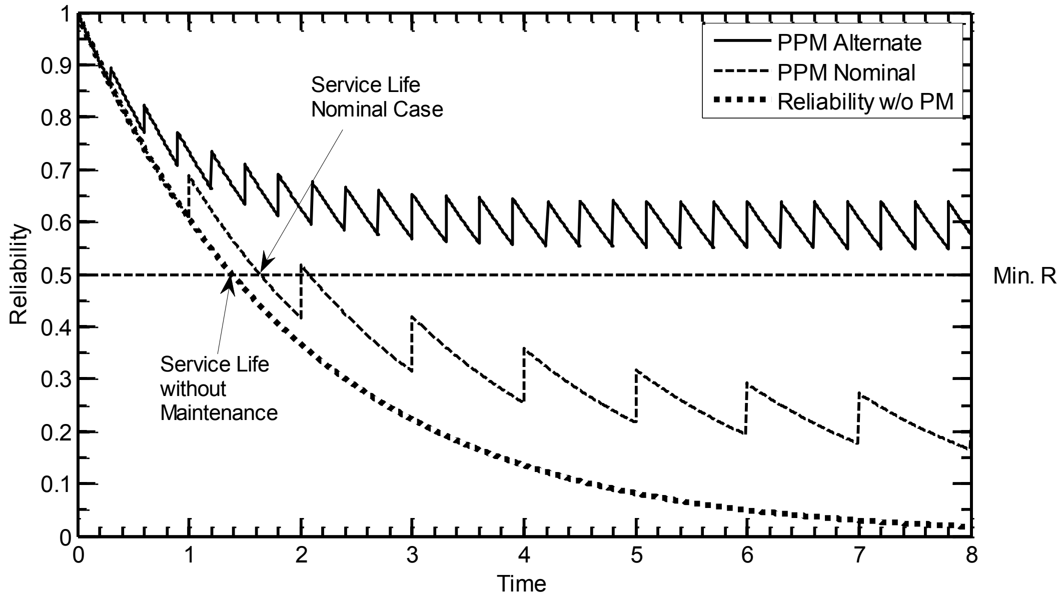

Figure 39. Type II PPM (Δt_{var} = 0.3)

In contrast, decreasing the maintenance interval increases service life. In Figure 39, decreasing Δt_{var} to 0.3 years results in what appears to be an infinite service life. Since the Type II model has the ability to undo all aging, with a very good maintenance policy, the reliability trajectory eventually settles, as seen in Figure 39. Since the reliability does not reach the minimum reliability level, the service life in this case is set to the maximum run time of the model (500 years) or as I will refer to it, the "service life ceiling." This result will be seen throughout the Type II analysis.

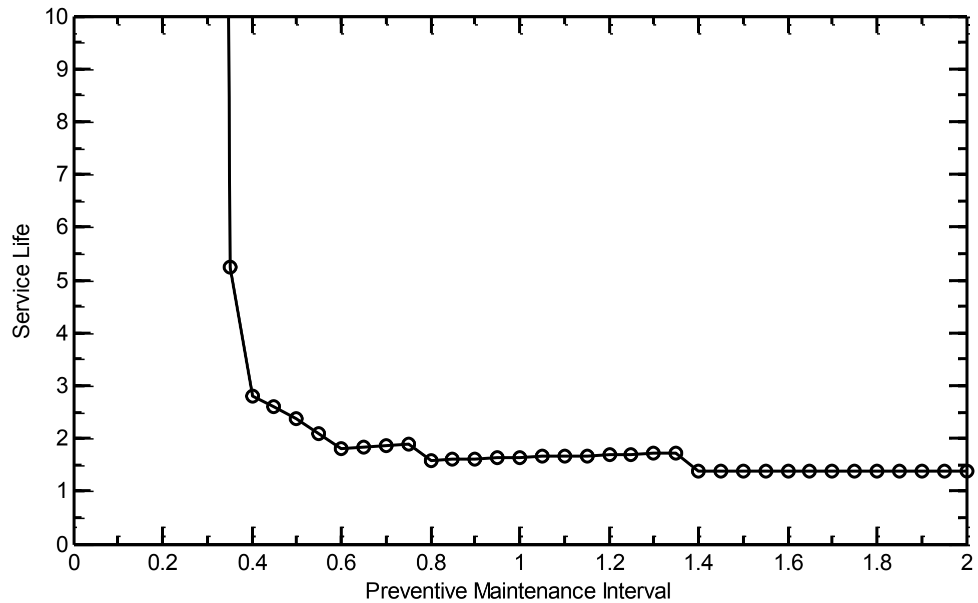

Figure 40. Service Life vs. Preventive Maintenance Interval, Type II

Figure 40 shows how the service life increases as the PM interval is decreased. Similar to the Type I case, a "stair step" trend is evident. Once the PM interval exceeds 1.4 years, the service life stops decreasing because the system reaches the minimum reliability level before the first PM action is performed.

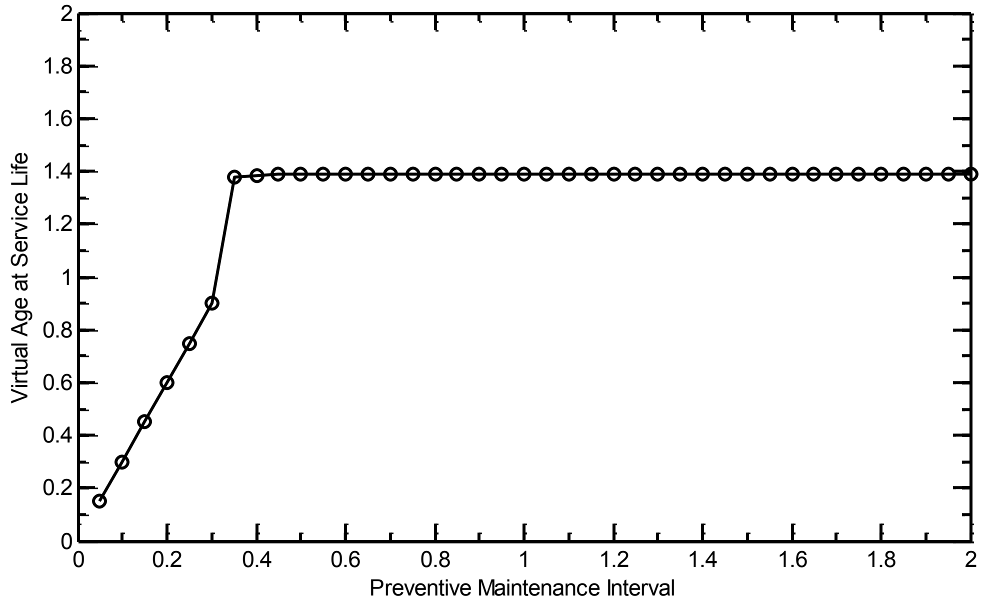

Figure 41. Virtual Age vs. Preventive Maintenance Interval, Type II

The virtual age at service life stays constant when the system's reliability trajectory reaches the minimum reliability level, as shown in Figure 41. Prior to a PM interval of 0.4, the system's reliability does not reach the minimum reliability; thus, the service life is set to the service life ceiling. Since we are looking at the virtual age at service life, the virtual age is based on the service life, the repair level, and the PM interval. With both the service life and repair level set to a constant, virtual age is only dependent on the PM interval; thus, the virtual age will vary for these PM intervals.

10.5.3 Repair Level—Type II

Figure 42 and Figure 43 show the effects of modifying the repair level, ϑ. In these trials, ϑ is varied while Δt and λ are kept at the nominal values.

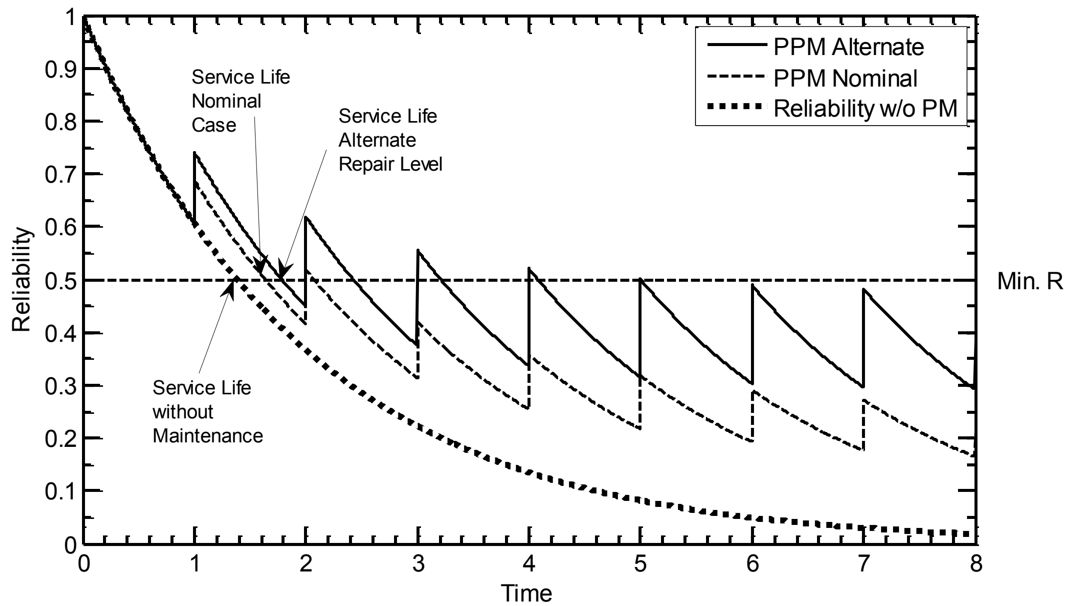

Figure 42. Type II PPM (ϑ_{var} = 0.6)

In Figure 42, increasing the maintenance effort (lower θ) minimally increases the expected service life from 1.6 to 1.77 years. In this case, the service life is extended by only 10.6%.

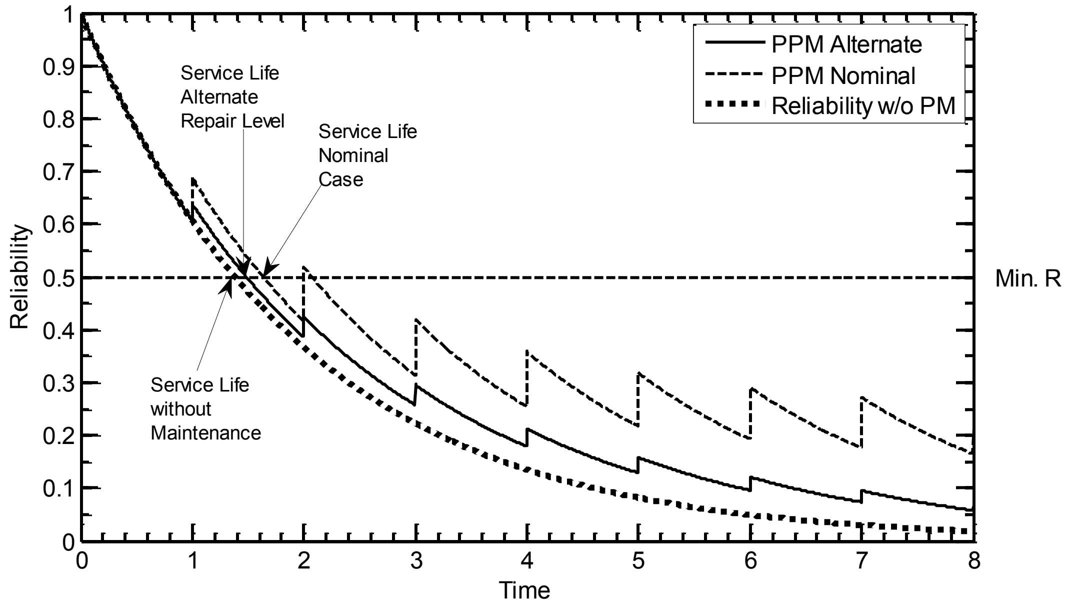

Figure 43. Type II PPM (ϑ_{var} =0.9)

Further decreasing the maintenance effort continues to decrease the service life (as shown in Figure 43). The ESL decreased from 1.6 to 1.49 years, a 6.9% decrease.

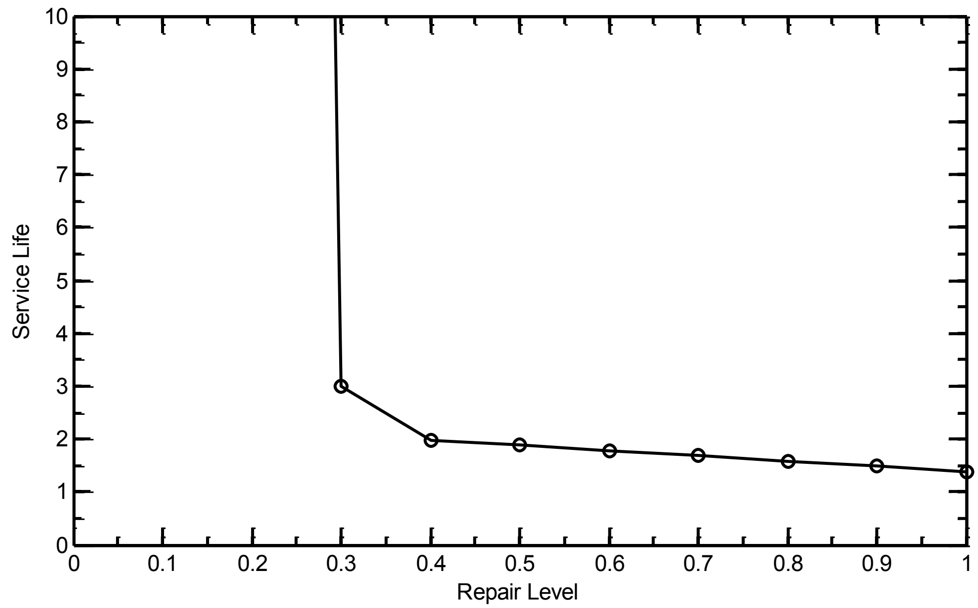

Figure 44. Service Life vs. Repair Level, Type II

Figure 44 shows how the service life varies with repair level. Performing better maintenance results in a longer service life. Using a lower repair level than 0.3 results in a service life equal to or greater than the ceiling value.

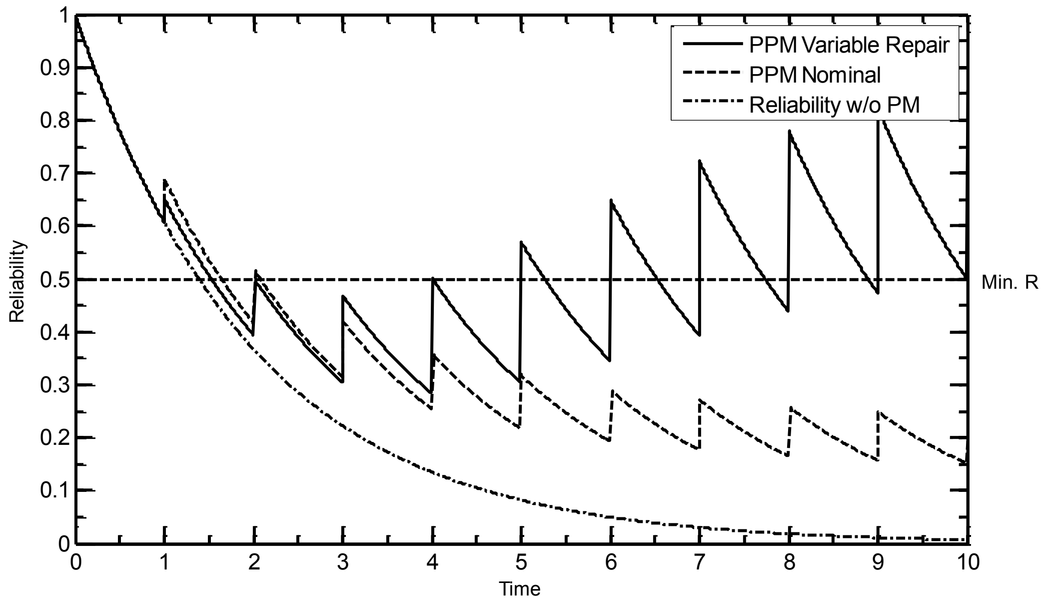

Figure 45. Reliability vs. Time for Variable Repair Level, Type II

Figure 45 shows the reliability over time when a variable repair level is applied to the Type II model. As the system ages, the variable repair level results in a higher reliability level than the nominal case. With the ability to undo all aging in the Type II model, the variable repair level causes the system's reliability to increase above the minimum reliability level.

10.5.4 Parametric Study—Type II

As in the Type I model, I conducted a parametric study using the Type II model parameters (Table 7).

Table 7. Type II Parameter Range

Parameter	Symbol	Value Range
Maintenance interval	Δt	0.05 – 5.0
Repair level	ϑ	0.05 – 0.95
System MTBF	λ	0.05 – 0.95

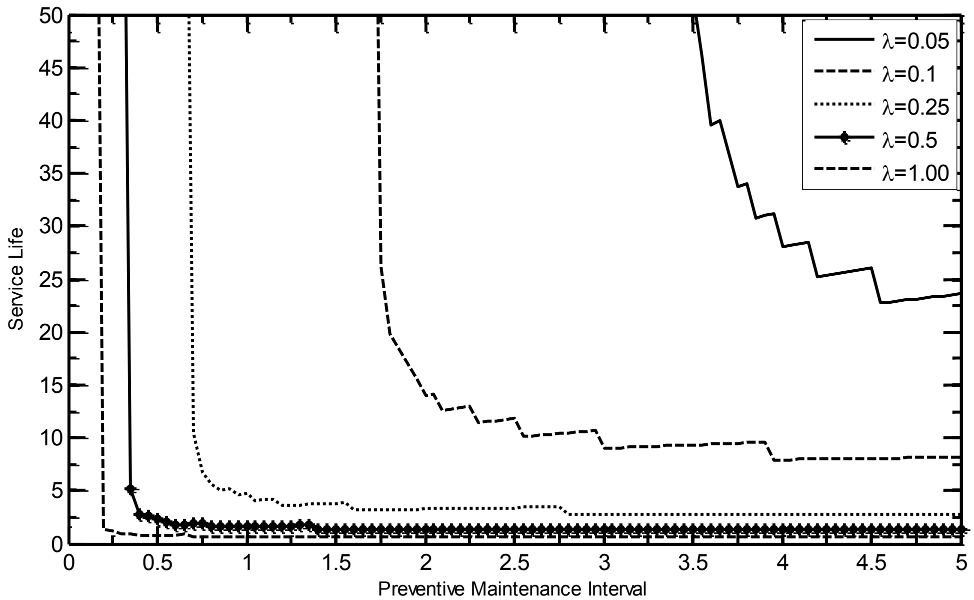

Figure 46. Service Life vs. PM Interval, ϑ = 0.75, Type II

Figure 46 shows how the service life varies with PM interval and system quality. As with the Type I model, better quality systems and more frequent maintenance results in longer service life. However, as shown earlier in Figure 39 with the Type II model, infinite service lives are possible with high quality systems and frequent maintenance. Service life decreases rapidly as the PM interval is increased. When the PM interval is high, even the higher (than Type I) absolute age reduction is not enough to counterbalance the aging between maintenance actions.

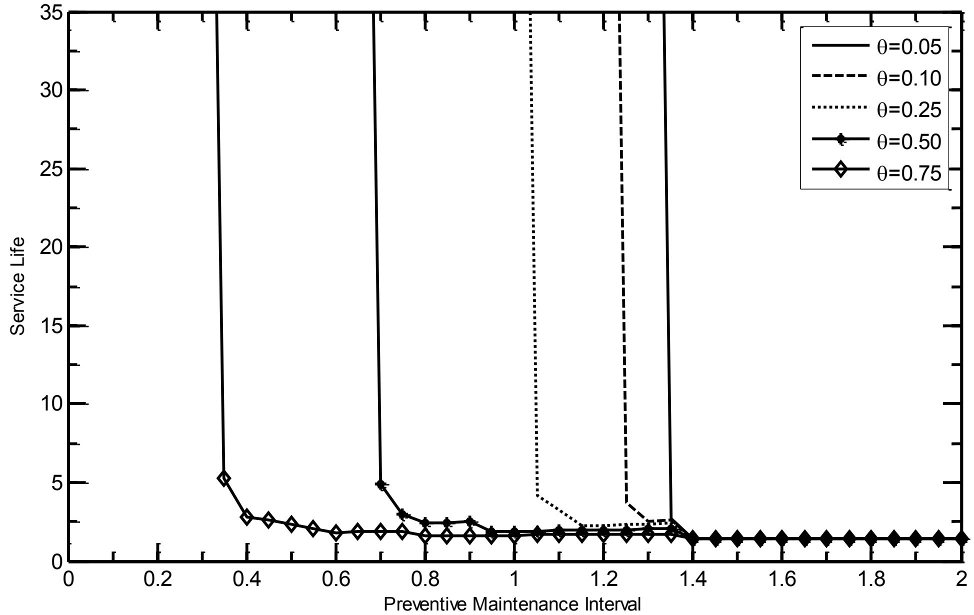

Figure 47. Service Life vs. PM Interval, λ = 0.5, Type II

Figure 47 shows the variation in service life with PM interval and repair level. Lower repair levels result in a higher gain in service life. When the PM interval exceeds 1.4, the minimum reliability is reached before the first maintenance action; thus, the service life is equal to the no-maintenance value of 1.4 years.

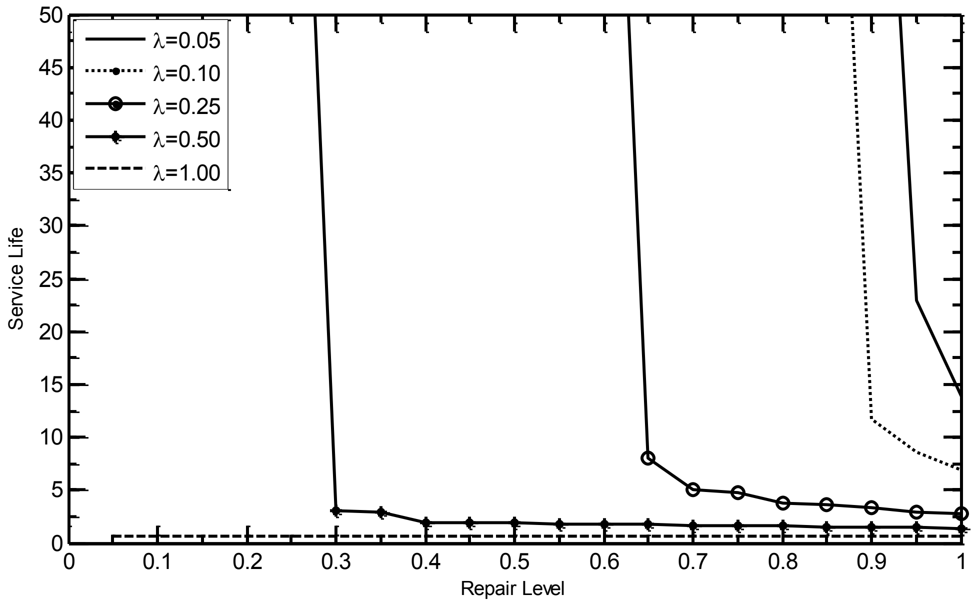

Figure 48. Service Life vs. Repair Level, PM Interval = 1, Type II

Figure 58 shows the variation in service life with repair level and system quality. With relatively frequent and adequate quality maintenance, infinite service lives are obtained in all cases. The highest quality systems can withstand poor maintenance, while the lower quality systems have short lives when the repair level is inadequate.

10.6 <u>Comparison of Type I and Type II Modeling Impacts</u>

To summarize, shortening the preventive maintenance interval increases service life and vice versa for both models. Generally, the Type II model results in higher service lives due to the ability to undo all damage. With small maintenance intervals, the Type II model can result in infinite service lives. In both models, performing better maintenance (lower repair levels) increases service life and vice versa. Because the Type II model can undo all aging, it is better able to withstand poor repair—in other words, the same repair level results in higher service lives in Type II than in Type I.

Performing extensive, frequent maintenance can extend service life significantly if the Type II assumption holds. We do observe such types of behavior in commercial aircraft, for example, which are usually retired, not due to reliability concerns, but rather because more operationally cost-effective aircraft have become available. However, at some point, even these aircraft must be retired as their structures age beyond financially feasible repair. In other words, the Type II assumption may hold for a number of years, and then become invalid as new modes of aging appear.

Thus far I have considered the effect of the modeling parameters on service life, and implicitly assumed that longer service lives are better. In the next chapter, I explicitly trade service life vs. operating, maintenance, and acquisition costs, using a value formulation.

CHAPTER 11. MAINTENANCE OPTIMIZATION OPTIONS

When optimizing maintenance, it is common to optimize either the reliability or the maintenance cost. For example, a minimum acceptable reliability is set, and the minimum cost to achieve this reliability is found. Or, the maximum cost is set, and the resulting maximum possible reliability is found. Such approaches can lead to policies that do not maximize the net present value of the system. Sometimes, more maintenance results in a greater marginal return in revenue [Marais, 2013]. Here, therefore, I use an approach based on maximizing the net present value of the system.

11.1 Value-Based Optimization

This section introduces the value-based formulation. The next two sections discuss how the parameters in the formulation are obtained.

The overall value of a system is given by the total benefits less costs over the lifetime of the system. The net present value (NPV) of a flow of service can be calculated as the discounted sum of the revenue and cost flows:

$$Value = \sum_{t=0}^{T} \frac{Revenue(t)}{(1+r)^t} - \sum_{t=1}^{T} \frac{Cost(t)}{(1+r)^t} \tag{8}$$

where T is the obtained service lifetime (see Section 4.2) and i is the discount rate indexed to the time step t.

In this case, it is useful to separate the costs out as follows:

$$Value = -Cost_{acq} + \sum_{t=0}^{T} \frac{Revenue(t,r)}{(1+i)^t} - \sum_{t=1}^{T} \frac{Cost_{op}(t) + Cost_m(t, repair)}{(1+i)^t} \tag{9}$$

Where $Cost_{acq}$ is the acquisition cost and is assumed to be realized as a lump sum at the onset of operation, $Cost_{op}$ is the operating cost, and $Cost_m$ is the maintenance cost. Both operating costs and revenues may vary with time and with system reliability, r. As discussed next, the maintenance cost may vary with time and with repair level, ϑ.

An extensive discussion on acquisition cost is beyond the scope of this thesis, but in general I will assume that cost is related to performance and quality, with better performing or higher quality systems being more costly. Similarly, I will assume that operating cost increases, and revenue decreases, as reliability decreases.

Finally, modeling maintenance cost is difficult. Several approaches have been suggested. The simplest approach is to assume that preventive maintenance actions are identical in cost with the cost being a function of pre-determined cost parameters. This assumption reflects, for example, the case of a simple oil change. Regardless of the age of the vehicle, the oil change costs the same. Another approach is to assume that the maintenance cost is a function of the repair level (see Equation 6) with higher repair levels associated with higher costs. Under this assumption, a given maintenance action costs the same regardless of the virtual age improvement gained, which would imply that greater age gains do not require greater effort. For example, based on the degree of corrosion, the cost of a part will be dependent on only the level of repair, not accounting for the system's virtual age before the repair. Unlike the simple approach where the repair of the part would cost the same regardless of the degree of corrosion, this approach takes into account the extent of the repair as part of the cost. Another approach is to assume that the maintenance cost is proportional to the virtual age gained. Thus greater age reductions cost more with cost depending on the age before maintenance. For example, overhauling an engine at a virtual age of 10 years will cost more than overhauling the engine at a virtual age of 3 years.

In this thesis, I assume that for a particular system the cost of a maintenance action is a function of the repair level. This approach considers that “better” maintenance actions cost more, but that the same level of maintenance costs the same regardless of the system age. Thus, an oil change would always cost some nominal amount, but if we wanted to do an oil change and replace the brake fluid, it would be more costly. In a Type I model, the age reduction of each maintenance action is constant, thus under this assumption the cost is constant with both repair level and age reduction. In a Type II model, the absolute age reduction increases with age, thus this assumption may underestimate the cost of maintenance for Type II models.

CHAPTER 12. IMPACT OF MODELING DECISIONS ON OPTIMAL POLICIES

In this chapter I apply the value formulation to derive optimal maintenance policies for Type I and Type II models. Then, I consider what happens to the optimal value if the modeling decisions are incorrect. In particular, I consider the impact of modeling Type I systems as Type II, and vice versa, and the impact of incorrect values for the maintenance and system quality parameters.

12.1 Assumptions

In developing my value model of maintenance, I make a number of simplifying assumptions to keep the focus on the main argument of this work. These assumptions affect the particular mechanics of the calculations but bear no impact on the main results, as will be shown shortly. My assumptions are the following [cf. Marais and Saleh, 2009]:

(i) I consider only the impact of maintenance on revenue- generating capability.

(ii) I consider only single-unit systems.

(iii) The systems in the model have no salvage value at replacement or end of life.

(iv) Finally, for simulation purposes, I consider discrete-time steps, and assume that the duration of maintenance activities is negligible compared with the size of these time steps.

12.2 Nominal Parameters—Type I and Type II

I use the net present value formulation presented in Section 11.1 to calculate the NPV under different maintenance strategies. The acquisition cost varies with the system quality parameter, λ, as follows:

$$Acquisition\ Cost = \frac{Cost_{base}}{\lambda} \tag{10}$$

Where the base cost is set at $5000.

The revenue varies with reliability according to:

$$Revenue = D - \ E * e^{-F*Reliability} \tag{11}$$

where D= 5, E = 3, F = 3.

The operating cost varies linearly with reliability, with less reliable systems being more expensive to operate:

$$Operating\ Cost = -A * Base\ Cost * Reliability + B * Base\ Cost \tag{12}$$

where the base cost = $600 is the minimum operating cost (i.e. fuel, crew, consumables), and A = 3 and B = 5 are multipliers. I assume that any cost variation solely as a function of time is negligible.

The maintenance varies with repair level as follows:

$$PM\ Cost = Cost_{m,base}\ * \theta \tag{13}$$

Where the base maintenance cost $Cost_{m,\ base}$ is $1000.

Table 8 summarizes the relations and nominal values.

Table 8. Nominal Values for Value-Based Optimization Parameters

Parameter	Nominal Value
***Cost**$_{base}$*	$5000
Revenue (D, E, F)	D = 5 E = 3 F = 3
Base Operating Cost	$600
Operating Cost (A, B)	A = 3 B = 5
PM Cost	$1000
Discount rate, *i*	0.1

12.3 Example Optimal Maintenance Strategies: Type I Model

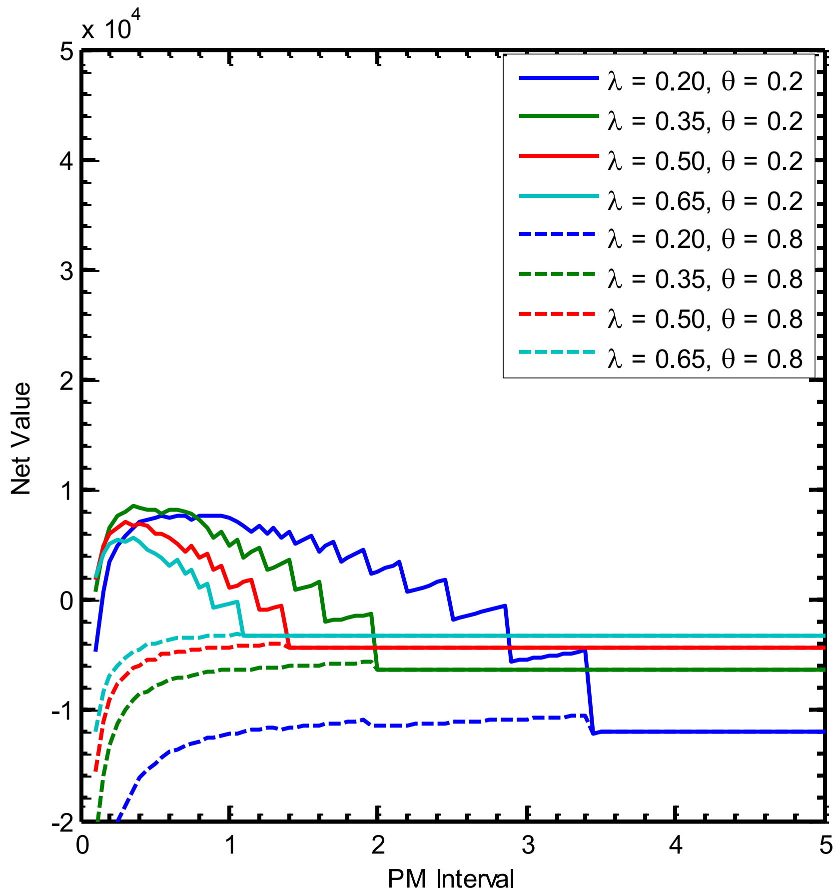

Figure 49. Net Value for Constant Operating Cost, Repair Level, & Revenue for R_{min} = 0.5, Type I

Figure 49 shows the net value for various levels of λ and two levels of repair (ϑ). At the better repair level (ϑ = 0.2), the net value is higher over a longer range of PM intervals than the worse repair level. The highest net values are obtained with small PM intervals. In all cases, performing maintenance too frequently decreases the net value because the maintenance cost becomes too high. Note that the cost of too frequent maintenance is underestimated here because I assume maintenance occurs instantaneously. At the worse repair level, there is not a maintenance policy that results in a positive net value.

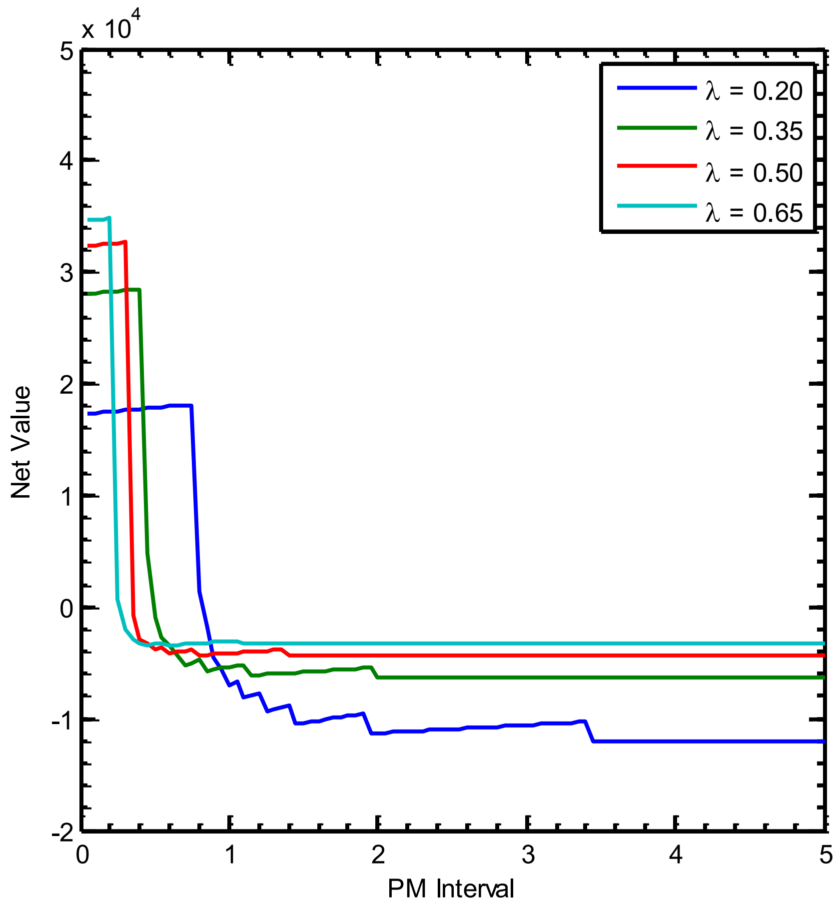

Figure 50. Net Value for Constant Operating Cost & Revenue, Variable Repair Level, Type I

Performing better repairs as the system ages results in a higher net value, as shown in Figure 50. Here, the repair level varies according to Equation 6. In contrast to the constant repair level case, varying the repair level makes a lower quality system (λ =

0.65) the best choice. This result occurs because the better repair as the system ages counteracts the acquisition cost of better system.

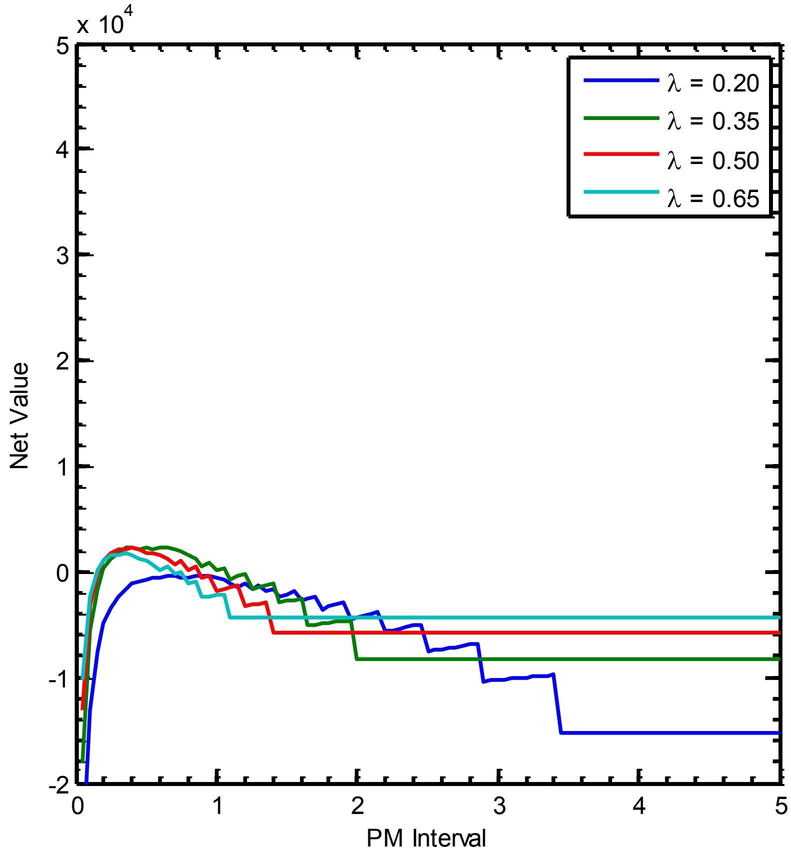

Figure 51. Net Value for Variable Operating Cost, Constant Repair Level & Revenue, Type I

If the operating cost increases as reliability decreases (according to equation 12), the shape of the curve is similar to the constant operating cost case, as shown in Figure 51. However, the maximum net values decrease, and better quality systems as well as more frequent maintenance are required to obtain a positive net value. This increase in operating cost as the virtual age increases is likely a more accurate representation of actual system behavior.

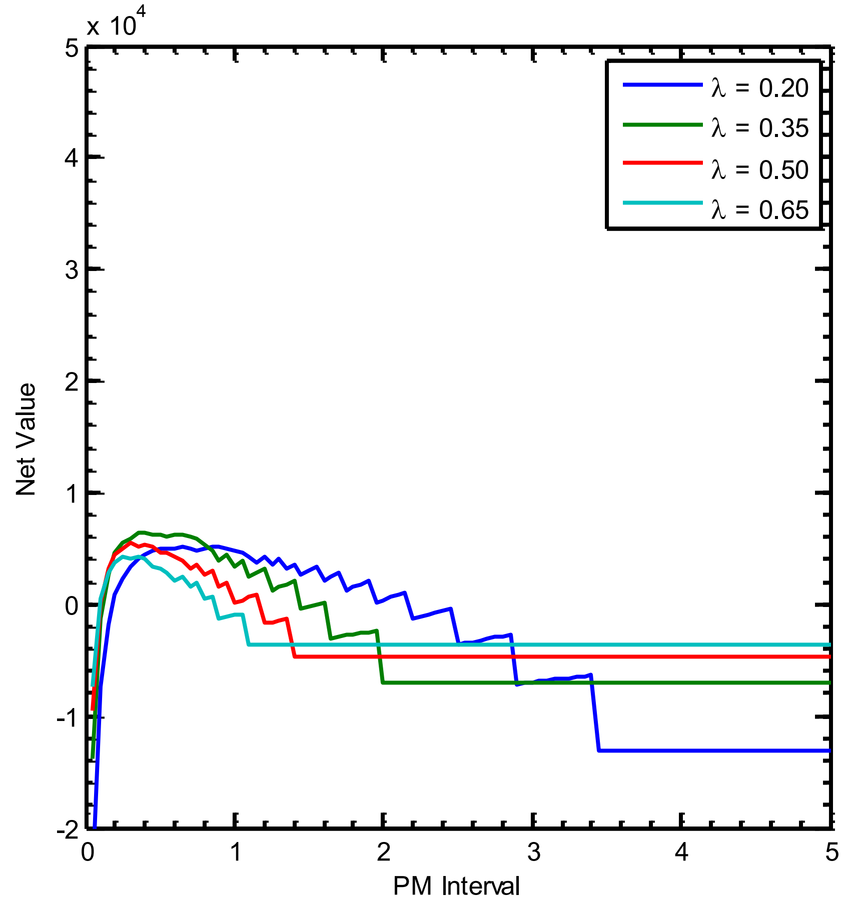

Figure 52. Net Value for Variable Revenue, Constant Operating Cost /Repair Level, Type I

When revenue decreases with reliability, we see similar behavior to the increasing operating cost case, as shown in Figure 52.

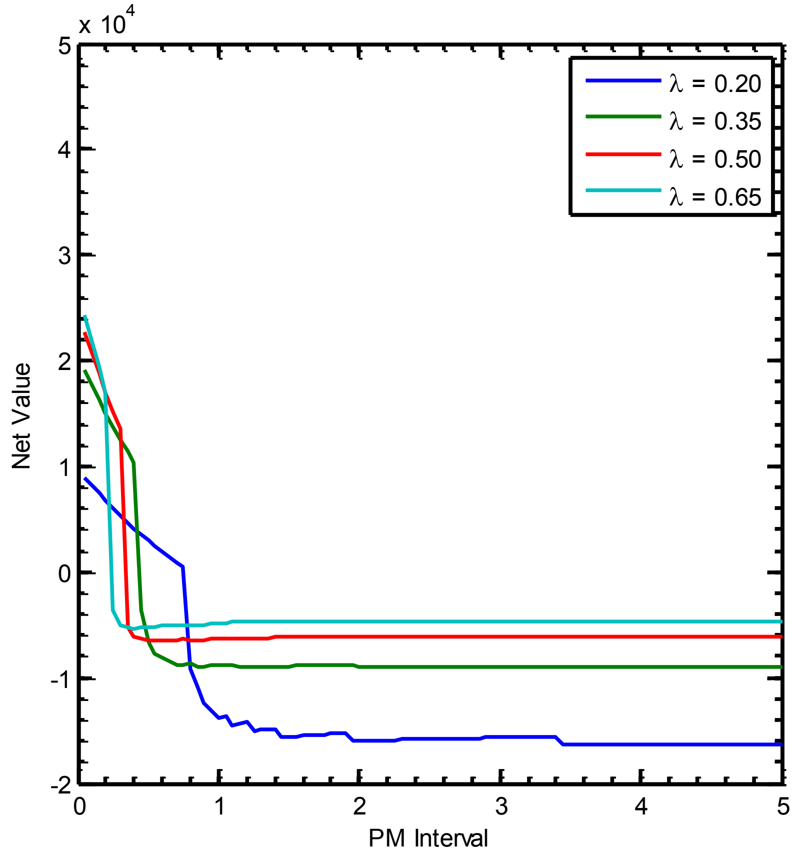

Figure 53. Net Value for Variable Operating Cost, Repair Level, and Revenue, Type I

Finally, Figure 51 shows the net value when operating cost, repair level, and revenue vary. Qualitatively, the variable repair level has the most impact. Varying the repair level has a dramatic impact on system value, and also allows upfront investment in a lower quality system.

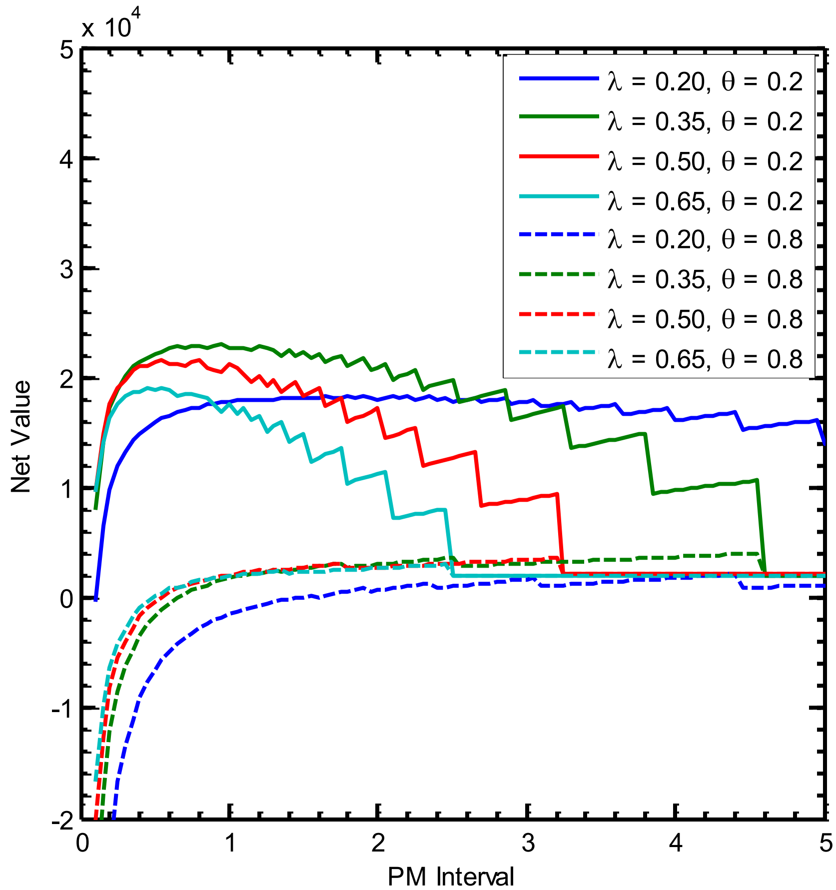

Figure 54. Net Value for Constant Operating Cost, Repair Level, and Revenue for R_{min} = 0.2, Type I

Thus far I have assumed that the system reaches its end of life when the reliability goes below 0.5. As shown in Figure 54, the net system value increases if the minimum reliability is increased. Allowing the system to deteriorate to a lower level of reliability, increases the service life and thus, the revenue.

12.4 Example Optimal Maintenance Strategies: Type II Model

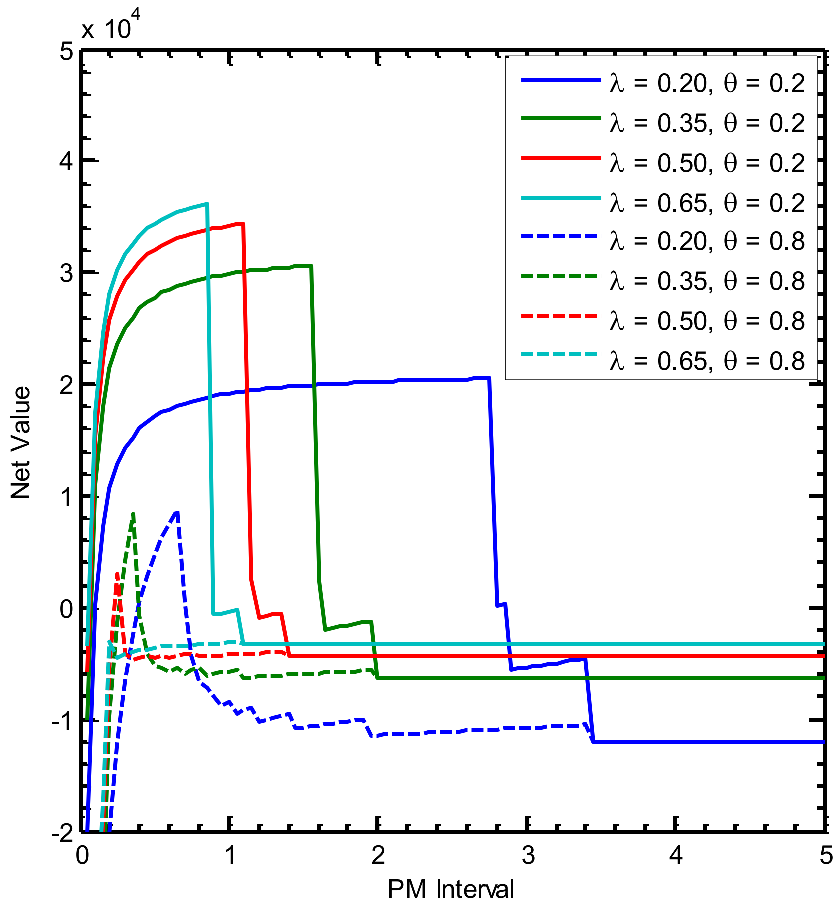

Figure 55. Net Value for Constant Operating Cost, Repair Level, and Revenue for R_{min} = 0.5, Type II

Figure 55 shows the net value for various levels of λ and two levels of repair (ϑ). In the Type II case, the highest value is obtained with a lower quality system (λ = 0.65) that is maintained frequently (PM interval = 0.85). In contrast, the Type I model suggested that a better quality system (λ = 0.35), coupled with more frequent maintenance (PM interval = 0.35) was the best option. Note also that the net values obtained under the Type II assumption are much higher.

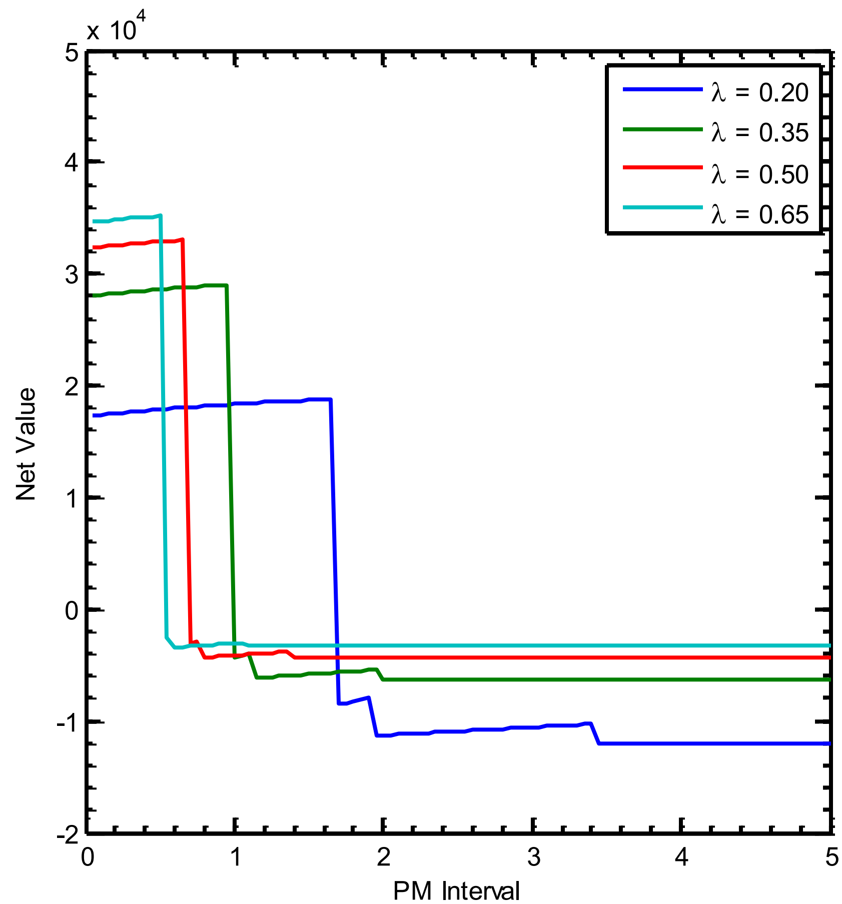

Figure 56. Net Value for Constant Operating Cost/Revenue and Variable Repair Level, Type II

Similar to the Type I model, performing better repairs as the system ages results in a higher net value, as shown in Figure 56. Again, the repair level varies according to Equation 6. In contrast to Type I, the variable repair level does not affect the best system quality choice. In the Type II model, repair level is less important because it is applied to all aging.

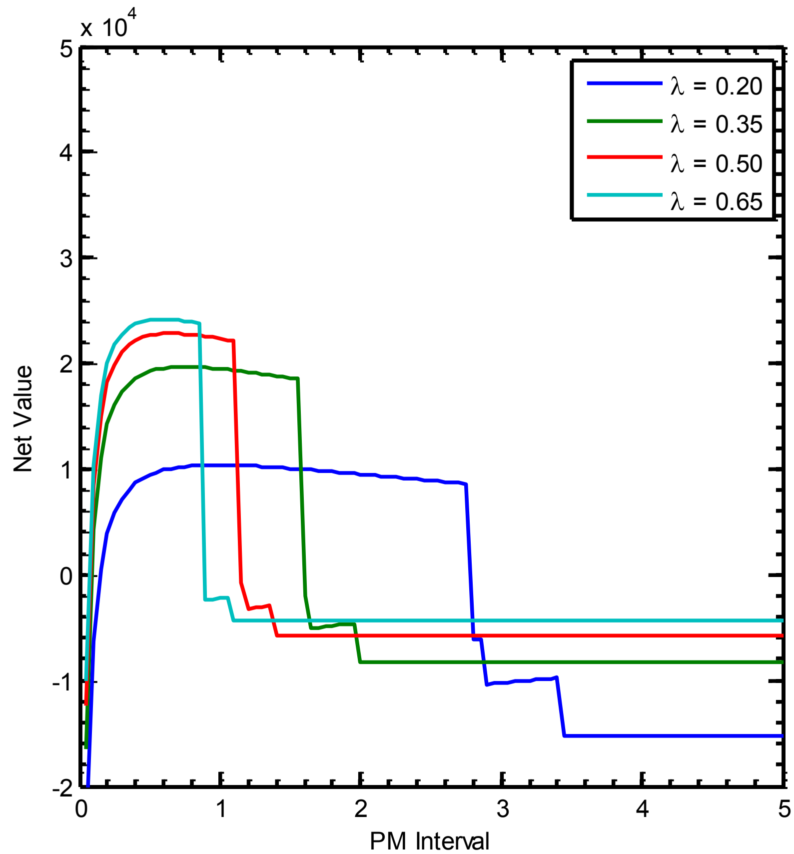

Figure 57. Net Value for Variable Operating Cost and Constant Repair Level/Revenue, Type II

Figure 57 shows a similar trend as seen in the constant operating cost, repair level, and revenue case. A system quality design of 0.65 is still preferred but in this case, results in a lower maximum net value than in the constant operating cost/repair level/revenue case.

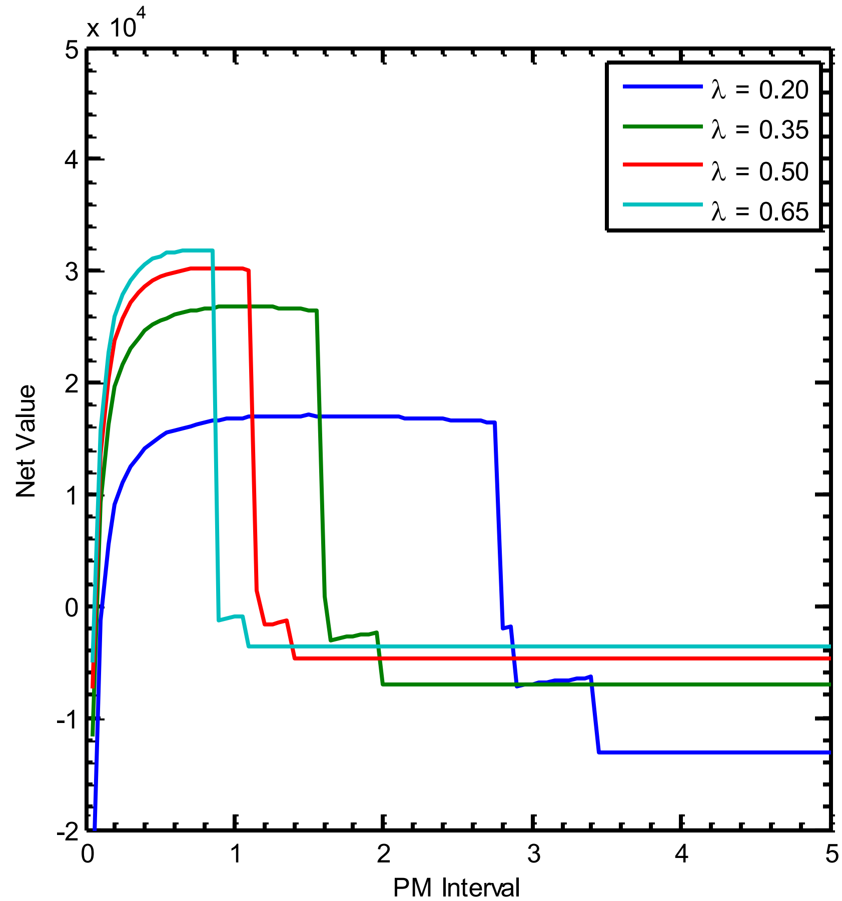

Figure 58. Net Value for Variable Revenue, and Constant Repair Level/Operating Cost, Type II

Figure 58 shows the net value when the revenue decreases with reliability according to Equation 11. The net value decreases, but again, the medium quality system (λ = 0.65) is preferred, because reliability decreases more slowly over time than in the Type I case.

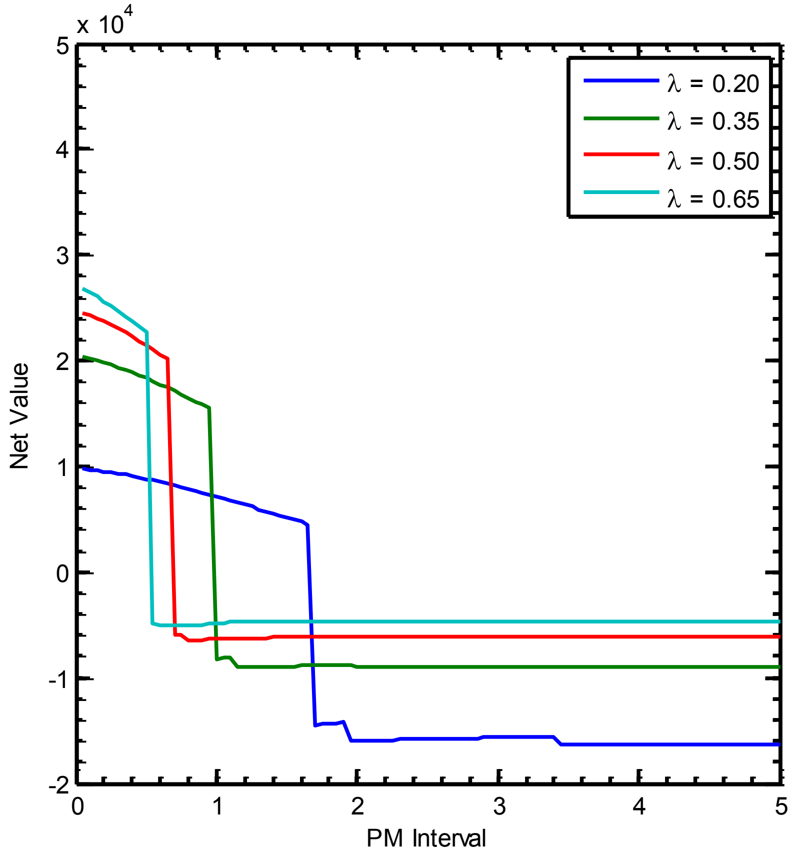

Figure 59. Net Value for Variable Operating Cost, Repair Level, and Revenue, Type II

Figure 59 shows that, as in Type I, the repair level has the most impact on net value. However, the impact is smaller, and varying the parameters does not affect the choice of best parameters.

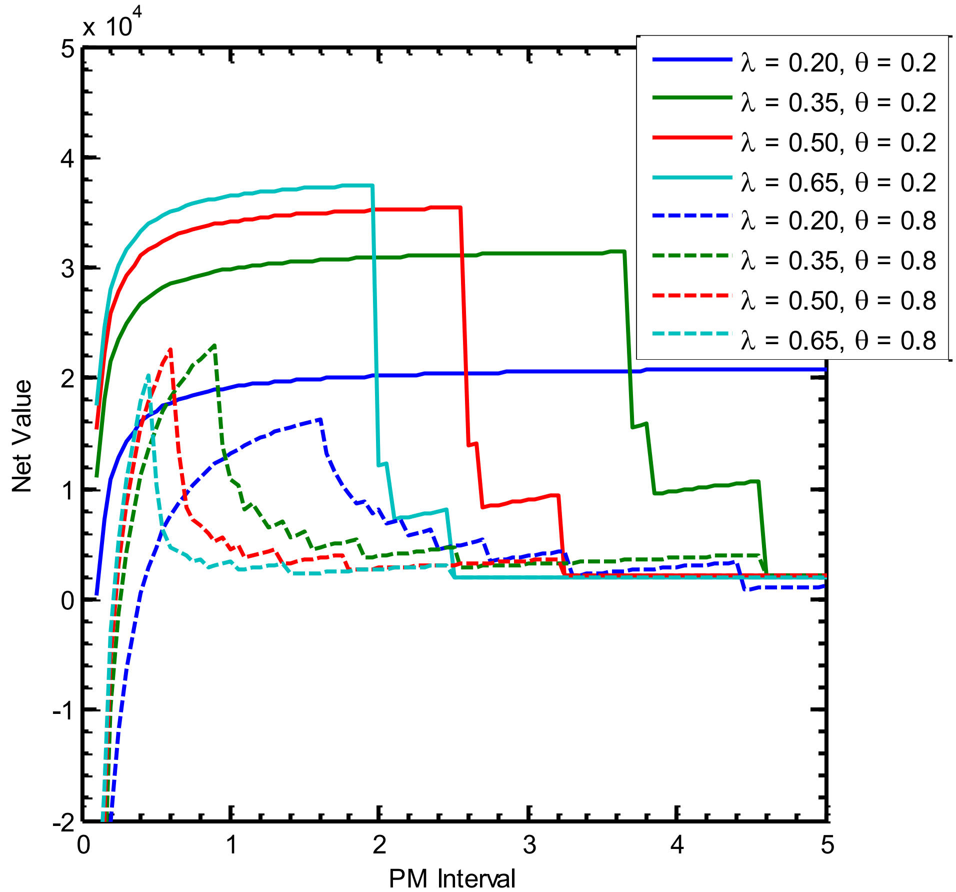

Figure 60. Net Value for Constant Operating Cost, Repair Level, and Revenue for R_{min} = 0.2, Type II

Finally, as for Type I, decreasing the minimum acceptable reliability increases the system value, as shown in Figure 60. However, the marginal gain is smaller than for Type I, because reliability decreases more slowly and many cases reach infinite reliability.

Lowering the minimum reliability level, results in positive net value for the worse repair level over a range of PM intervals but this value is dwarfed by the net value that can be

Table 9. Model Comparison of Best Options for Net Value Cases

	Type I		**Type II**	
	Constant	Varying	Constant	Varying
PM Interval [years]	0.35	0.05	0.85	0.05
Repair Level	0.2	Varying	0.2	Varying
System Quality	0.35	0.65	0.65	0.65
Net Value [dollars]	8487	24380	36097	26770
Service Life [years]	8.70	>500	>500	>500

Table 9 shows the best maintenance policy for each of the preceding scenarios. The Type I model with constant operating cost, repair level, and revenue results in the lowest maximum net value. Conversely, for the constant case, the Type II model results in a much larger net value, accompanied by a long service life (> 500 years). This result occurs because (1) the Type II model allows all aging to be undone, and (2) my maintenance cost model (cost proportional to repair level, see Equation 13) likely underestimates cost in the Type II model.

Similarly, the Type II model again results in maximum net value when cost, repair level, and revenue vary. However, the maximum net value is lower than in the constant case, because I account for the effect of aging on cost and revenue. The varying case is likely a more accurate reflection of system behavior.

12.5 Impact of Modeling Assumptions and Decisions on Net Value Obtained

So far, I have analyzed how the design parameters affect the resulting maintenance policies. In addition, I have looked at quantifying the service life and maintenance and operating costs in order to determine the best set of design parameters that will result in the best maintenance policy. Using the net value function, the case of variable operating cost/constant repair level proves to result in minimizing the maintenance costs while sustaining a high net value. Now, using these cases, I will compare the Type I and Type II models and discuss what happens when incorrect assumptions are made.

As an aside, this work is related to robust optimization. The focus of robust optimization is to minimize the impact of uncertainty on the solution [for a review, see Gabrel et al., 2013]. Considered an alternative to stochastic linear programming, there are many existing approaches to robust optimization. One of the more common approaches is the 2-stage stochastic optimization model. The first stage minimizes the sum of costs of the parameters that are decided before the optimization process (i.e. design parameters) while the second stage optimizes the control variables. Mulvey et al. (1995) describes a decision being robust if the actual cost of the realized scenario remains close to the optimal expected cost for all scenarios. No matter the approach taken, much of the work stated focuses on infrastructure and process planning.

Here, in contrast to robust optimization, my focus is on explicitly assessing the impact of data uncertainty and modeling decisions. First I consider the impact of incorrect assumptions about the deterioration rate, the maintenance level. I begin by identifying the optimal combination of design and maintenance level to derive a maintenance policy (i.e., determine the PM interval). Next, I determine the net value of the system under that policy, but for different values of λ, ϑ, or PM interval. Note that both λ and ϑ follow the same convention in that smaller values of λ mean better system quality and smaller values of ϑ mean better repairs.

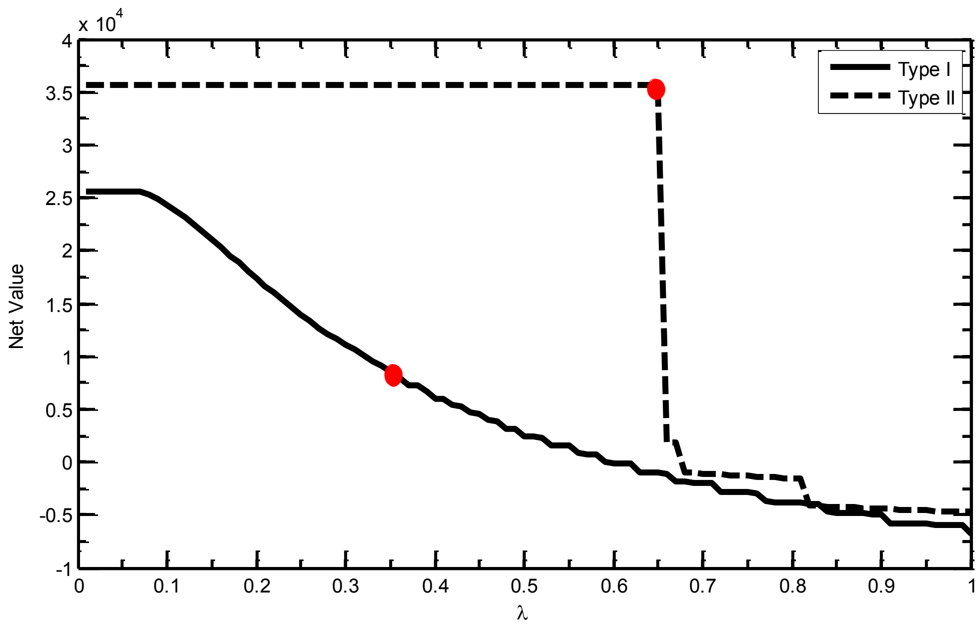

Figure 61. Net Value vs. λ, Constant Operating Cost, Repair Level, and Revenue

Figure 61 shows the net value as λ varies for the best maintenance strategy when the operating cost, repair level, and revenue are constant (see Table 9). For Type I models, the net value increases when the system is better than assumed—in other words, if we get a better system than we paid for, the net value increases. Conversely, if we get a worse system than we paid for, the net value decreases. In both cases the change in value is significant but not rapid. In contrast, for the Type II model, the value declines rapidly when the system is worse than paid for. In the Type II optimal maintenance policy case, the service lifetime is infinite, hence the net value does not increase for better than assumed systems (revenue does not depend on reliability in this case).

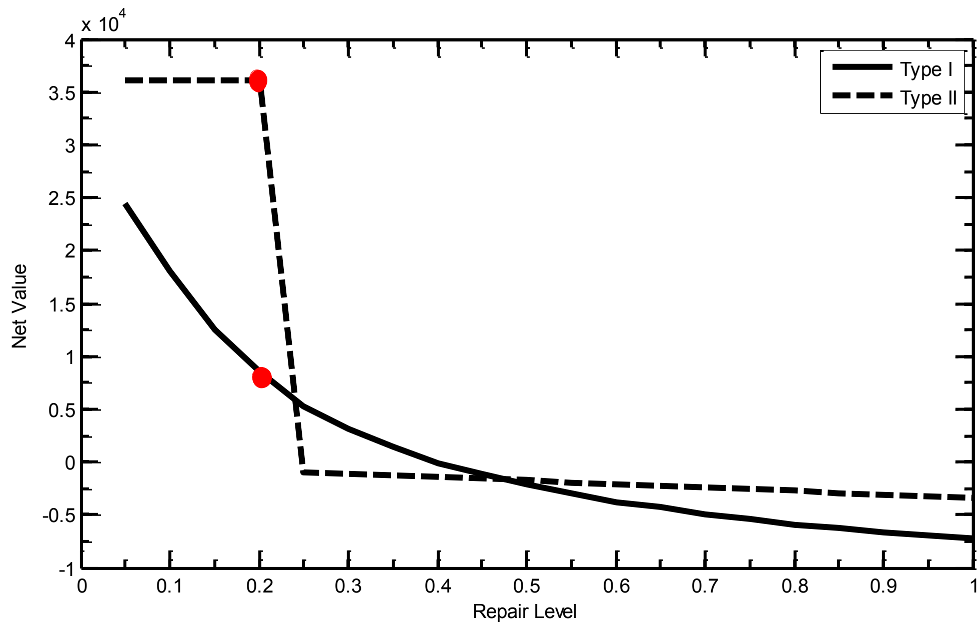

Figure 62. Net Value vs. Repair Level, Constant Operating Cost, Repair Level, and Revenue

Figure 62 shows the impact of performing better or worse repair than assumed. In this case I set the maintenance cost to correspond to the assumed repair level. The Type II model is much more sensitive to variations in repair level than the Type I model. Between the repair level of 0.20 and 0.25, the Type II net value dramatically decreases due to the large decrease in service life. Using a better repair level than 0.2 results in a constant net value for Type II because service life is >500 years. In contrast, the net value for the Type I model gradually decreases as the service life gradually decreases and thus, overestimating the level of repair does not have as big of a consequence.

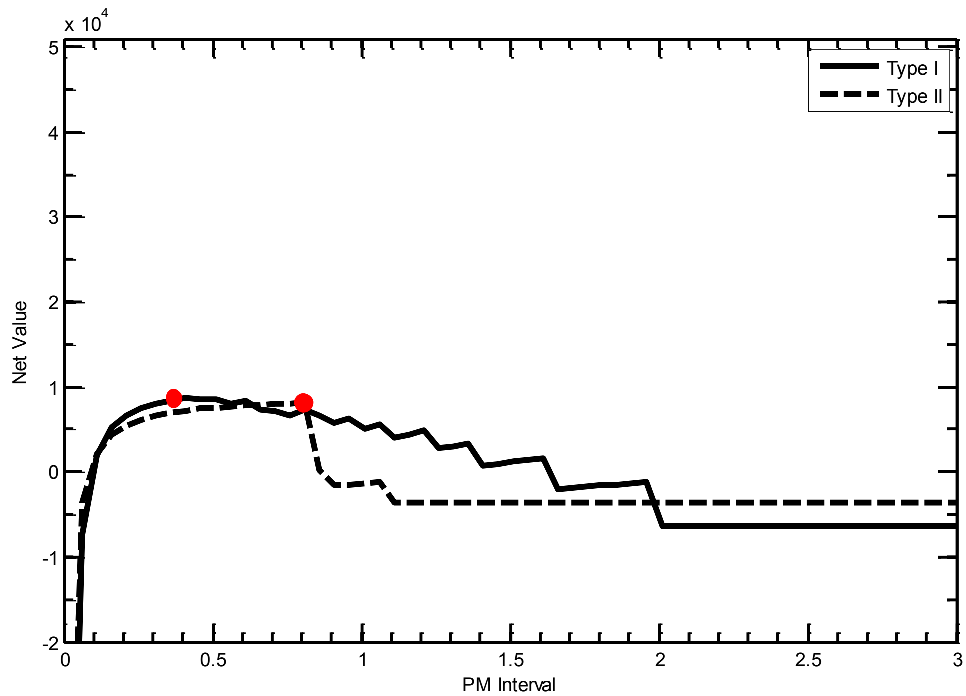

Figure 63. Net Value vs PM Interval, Constant Operating Cost, Repair Level, and Revenue

Finally, consider how the net value varies when maintenance is performed more or less often than planned, as shown in Figure 63. If the preventive maintenance interval is shorter than the optimal PM interval, the net value decreases for both models. The benefit of more frequent maintenance does not offset the increase in maintenance cost. In both cases the net value also decreases if maintenance is performed less often than planned, but, the Type II model is much more sensitive to deferred maintenance. As shown in Table 9, for the Type II model the maximum value is obtained with a relatively good repair level of 0.2 and a medium quality system. Thus the system is allowed to deteriorate quite significantly between maintenance actions, knowing that the good repair will restore the system. Deferring this maintenance results in rapid aging and a short service life.

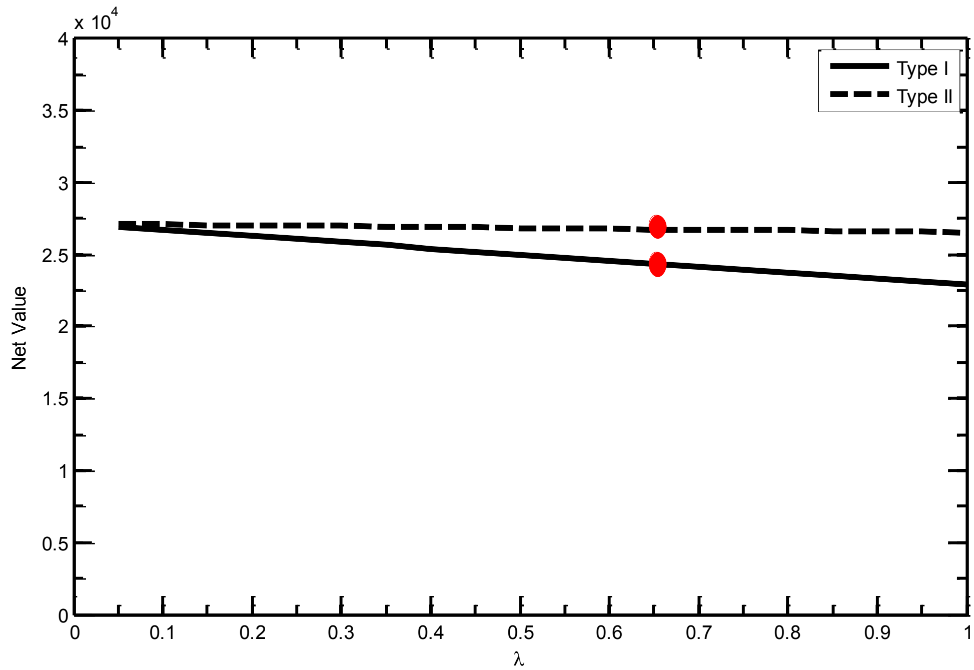

Figure 64. Net Value vs. λ, Type I and II models, Varying Operating Cost, Repair Level, and Revenue

Figure 64 shows the net value as the system quality (λ) deviates from the optimal value (see Table 9). The reliability cut-off is at the nominal level of 0.5. In the Type II case, errors in assumed quality have little effect on net value. This somewhat counterintuitive result occurs because, as system quality decreases ($\lambda > 0.65$), there is little increase in net value (see Figure 59). The optimal PM interval of 0.05 years always results in an infinite service life for Type II. Therefore, better-than-paid-for systems do not offer additional service life, but, the “free quality” improves the net value to that of the medium quality system.

For the best strategy, the PM interval is the smallest interval of 0.05 for both models. At this frequency of preventive maintenance, a mid-range system quality value results in the highest net value if the Type II assumption holds. The ability to undo all damage combined with a small PM interval, means that the service life is very high even with the worst design level. For both models, overestimating or underestimating λ does leads to a gradual loss of net value.

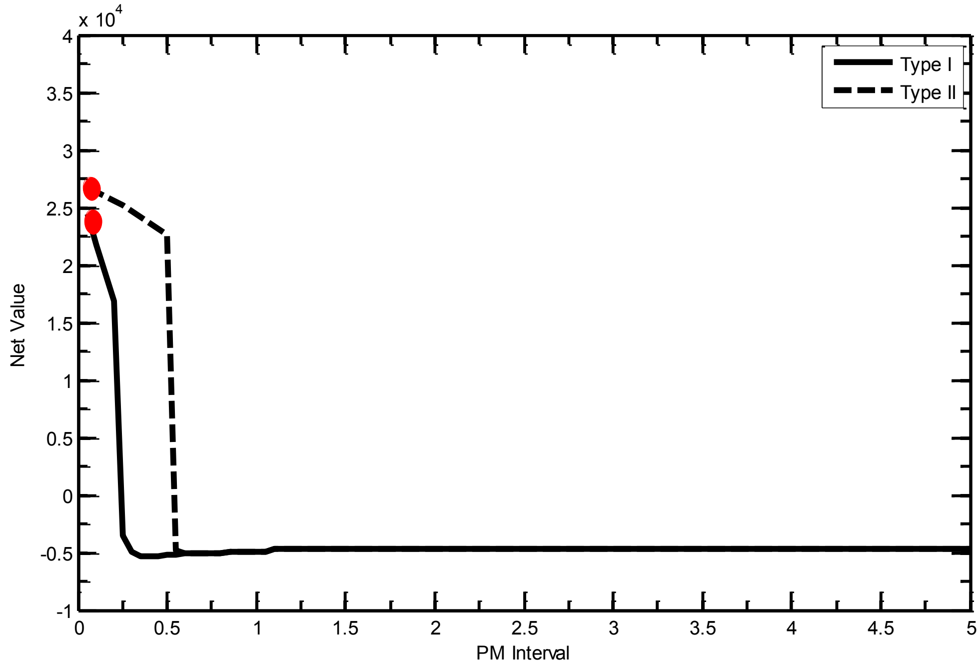

Figure 65. Net Value vs. PM Interval, Type I and II models, Varying Operating Cost, Repair Level, and Revenue

As shown in Figure 65, performing maintenance less often than required results in a precipitous drop in value. If there is a likelihood that maintenance will not be performed as scheduled, it may be better to select a slight off-optimal plan that is more forgiving of late maintenance.

Finally, consider the impact of using the wrong type of model, e.g, assuming that maintenance has a Type II impact (can undo all ageing), while in reality the system responds more like Type I (can only undo recent ageing). In this case, the reliability "recovery" will be overestimated.

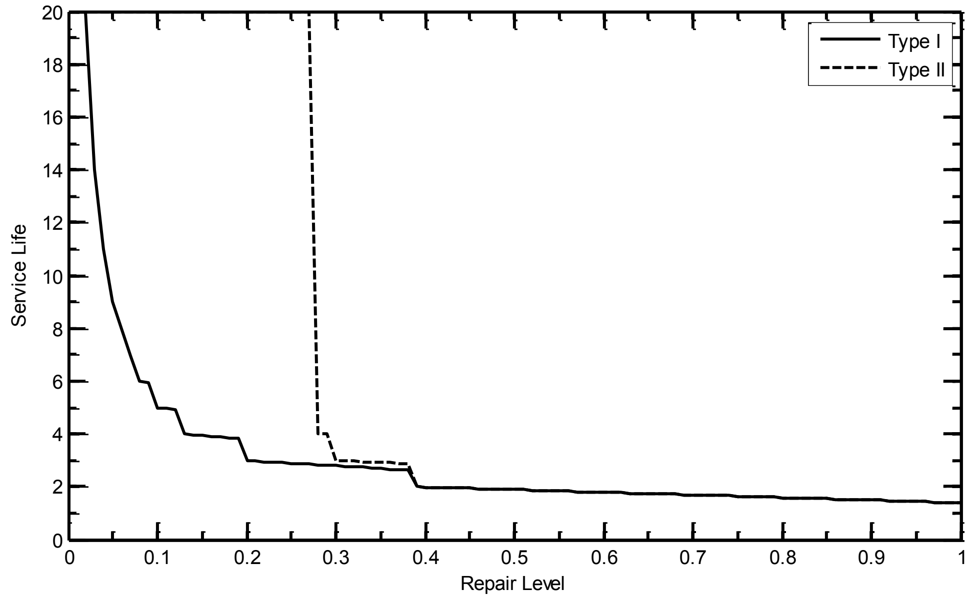

Figure 66. Service Life vs. Repair Level, ϑ

Figure 66 shows how the service life varies as a function of repair level for both the Type I and Type II models. When the repair is poor (high ϑ), the service life obtained is low, because poor repairs in both models cannot overcome the initial rapid drop in reliability. When the repair level is good (low ϑ), the Type II model results in higher service lifetime, because it can undo all aging. Thus assuming that a system is Type II when it is in fact Type I, can result in significant overestimates of service life.

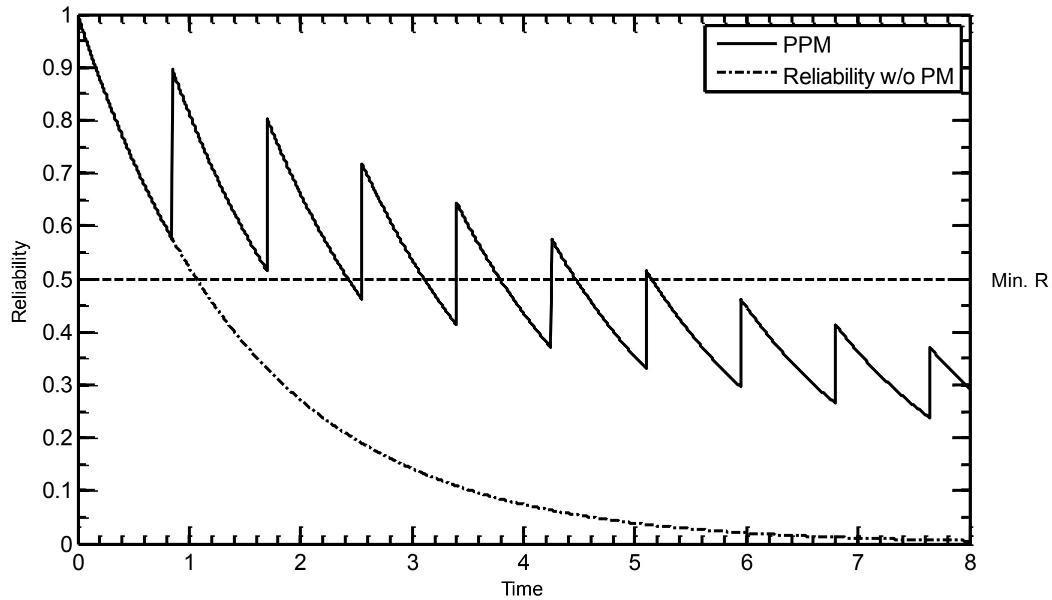

Figure 67. Type I Model with Type II Maintenance Policy

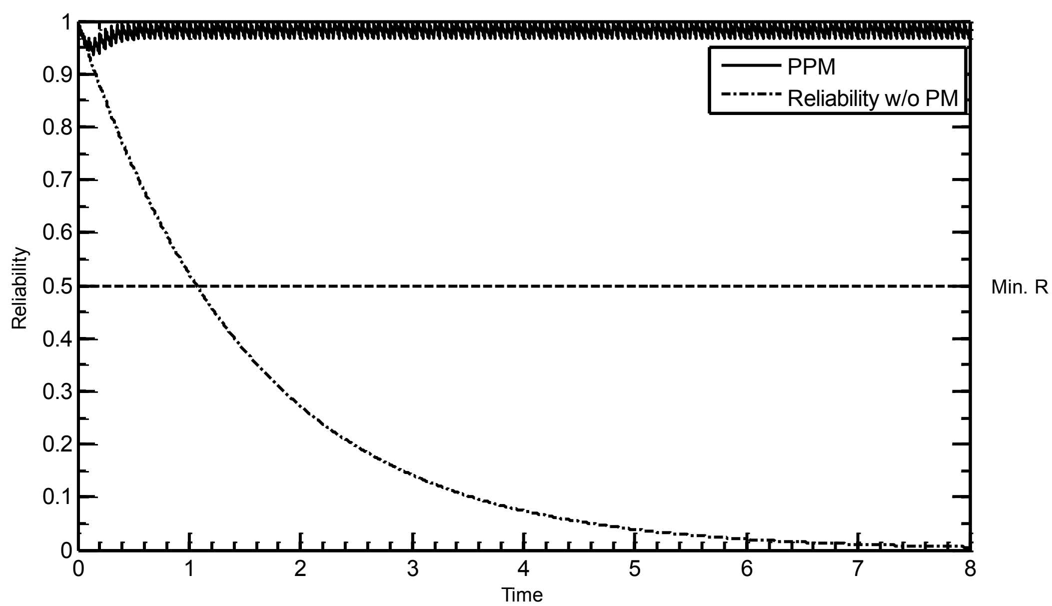

Figure 68. Type II Model with Type I Maintenance Policy

Figure 67 and Figure 68 show the effect of applying the best maintenance policy (see Table 9) to the opposite model. The optimal Type II policy which considers the repair level, operating cost, and revenue constant, results in an infinite service life. Applying this policy to a system that responds in a Type I manner, results in a service life of 2.43 years. Conversely, applying the optimal Type I policy of varying only the repair level (service life >500 years) to a system that responds in a Type II manner, results in a service life > 500 years. When repair is improved as the system ages, the Type I model behaves much like the Type II model; therefore, there is relatively little effect on the net value and service life.

Table 10 shows the model results when the best maintenance policy of the opposite model is applied.

Table 10. Model Results

	Service Life	**Net Value**	**PM Interval**	**Repair Level**	**System Quality**
Type I (with applied Type II Policy)	2.43	1490	0.85	0.2	0.65
Type II (with applied Type I Policy)	500	35021	0.05	Varying	0.65

My analysis shows that very different results are obtained using Type I and Type II assumptions. These assumptions correspond to different models of the impact of maintenance, and to different ways of performing maintenance. For example, Type II maintenance could correspond to a complete engine overhaul, while Type I maintenance could correspond to replacing the engine oil. Thus, in reality, most systems will be subjected to a combination of Type I and Type II maintenance; nevertheless, most research on maintenance optimization is done under the Type I assumption, with Type II perpetually left for future work. I have also identified some ways in which the models fail to capture reality. As mentioned above, Type I or Type II maintenance may not be applicable to all systems. With multi-unit systems, better results can likely be obtained by using a combination of Type I and Type II models.

CHAPTER 13. PART II CONCLUSION

In Part II of this thesis I have investigated the effect of modeling decisions on assumed system behavior over time, and on net system value. I showed that repair level has the most significant effect on reliability over time, service life, and system value. Performing maintenance less often than planned results in dramatic loss of value—thus it may be better to create a slightly off-optimal maintenance schedule that is not so sensitive to deferred maintenance. Finally, the Type II maintenance model is more optimistic about the effect of maintenance and results in longer service lives and higher net values. If this assumption is incorrectly made about a Type I system, the effect on achieved service lives and net value can be severe. If there is uncertainty about whether a system responds as Type I or Type II, it is safer to assume it is Type I.

CHAPTER 14. CONCLUSION

This thesis has presented an explicit consideration of the impacts of modeling decisions on the resulting maintenance planning. Incomplete data is common in maintenance planning, but is rarely considered explicitly. Robust optimization aims to minimize the impact of uncertainty—here, in contrast, I showed how its impact can be explicitly quantified. Doing so allows decision makers to determine whether it is worthwhile to invest in reducing uncertainty, and where.

In Part I, I reviewed limitations of incomplete data using the available data from the DDG-51 case study. Next, I attempted to construct a reliability model of the ship class. Analysis of maintenance effort and cost against time suggests that significant effort is expended on numerous small unscheduled maintenance tasks. I surmised that some of these corrective tasks are the result of deferring maintenance and therefore decreasing the ship reliability. Then, I used a series of graphical tests to identify the underlying failure characteristics of the ship class. The tests suggest that the class follows a renewal process, though there appear to be several outlier ships, suggesting that some ships may not be maintained to the same level as the class in general.

In Part II, I reviewed the literature on multi-unit maintenance and provided a conceptual discussion of the impact of deferred maintenance on single and multi-unit systems. I showed that the single-unit assumption can be used without significant loss of accuracy when modeling preventive maintenance decisions, but leads to underestimating reliability and hence ultimately performance impacts in multi-unit systems. Using a design-of-experiments, I have shown how the maintenance parameters affect the estimated system's lifetime and cost of maintenance. From this, I looked at providing a way to quantify the value obtained from service life versus the costs associated with operation and maintenance of the system. Using this formulation, I showed the interplay between the costs and design parameters. Thus, the trade-off between having a good system with high levels of maintenance effort can be compared to the 'bad' system with same levels of effort. In addition, this study provides a comparison between the models so that a decision can be made on the proper ratio of use for both models if one wanted to use a combination of both models for one system. Finally, the differences seen between the Type I and Type II models means that if the wrong model is chosen, the decision can be an expensive mistake.

As stated earlier, a combination of both models would be more helpful to determine the optimal maintenance plan for a multi-unit system. By studying these combinations, a decision maker can help determine the best trade-off between the service life of the system and the cost to maintain the system. Overall, I have highlighted both advantages and disadvantages to using either model and the assumptions that can be made for these maintenance models.

Future work should further investigate the impact of the type of value function on the resulting maintenance policy. A sensitivity analysis on the function type for both the operating cost and variable repair level should be done. Only one type of function was used for the current analysis; so it would be interesting to see, for example, what happens when the operating cost is not defined by a linear function. In addition, the effects on the optimization of the maintenance policy if the total change in reliability were used to estimate the maintenance costs instead of the repair level should be investigated. Finally, the impact of uncertainty on the resulting maintenance policy should be analyzed and quantified.

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APPENDIX

APPENDIX NAMING CONVENTION FOR THE ARLEIGH BURKE CLASS

Each ship in the Arleigh Burke class is given a name and a hull identifier. The name of a ship is determined by a committee who generally choose to name the ship after a notable person. The hull identifier (xxx-xxxx) specifies the ship class code and the hull number. The hull number is given in a chronological order so the hull number given to a ship is determined by how many ships of the same type precede that ship and the number given to the first built ship of that class. For the Arleigh Burke class, the class code is 'DDG' and the hull numbers currently range from 0051 to 0116. As an example, the first built ship is named the USS Arleigh Burke (named after a former Chief of Naval Operations, Admiral Arleigh A. Burke) and has a hull identifier of DDG-0051. The Curtis Wilbur was the fourth ship constructed; thus, its hull identifier is DDG-0054.