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DECISION ANALYSIS APPLIED TO

INSPECTION INTERVAL DECISIONS

THESIS

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THESIS

Presented to the Faculty of the School of Engineering

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

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Master of Science in Operations Research

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Captain, USAF

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Preface

I am convinced that the Air Force can do a better job of scheduling aircraft subsystems for base-level inspections. The discussions I had on this subject with personnel at Headquarters Air Force Logistics Command and the Air Logistics Centers echoed this conclusion. Furthermore, the absence of any complete, systematic method of setting inspection intervals for base-level inspections confirmed in my mind the need for a decision-making aid in this area.

What I intended to do in this thesis was to draw attention to this deficiency and provide a strategy for correcting it. The general model I developed can serve as a starting point for System Program Managers and their staffs who are charged with making inspection interval decisions. It is designed to deal with the subjective factors (e.g. failure consequences, probabilities, opportunity costs) inherent in the aircraft maintenance world. The decision model I have proposed defines how these subjective factors affect inspection interval choice. I think this decision analysis approach is an improvement over the current "that looks about right" method. I hope those people in the Air Force who are responsible for making inspection interval decisions find my work useful.

Before I close, I want to thank my wife, [redacted] and son [redacted] for their patience and personal sacrifice during the research: it was a team effort. Also, I want to thank the Lord above, who was not only above me, but with me when I needed additional energy and creativity. Finally, I want to thank my faculty advisor, Captain Joe Tatman, for his reasoning, availability, and technical competence which motivated me and helped me draw upon my own potential in performing this research.

Kermit L. Stearns II

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Abstract

Using decision analysis techniques, a general model was developed for base-level aircraft inspection interval decisions. This model differs from current methods such as actuarial analysis and the Computer Monitored Inspection Program in that it is designed to define and measure the significance of the subjective uncertainties and risks inherent in inspection interval decisions. Failure data, cost data, expert opinion, and decision maker preferences are brought together in a single, unified decision-making framework. Decision alternatives are evaluated based on the entire "cost" picture (i.e. repair costs, opportunity costs, and inspection costs). The general model developed in this thesis can serve as a starting point for the analysis, but it must be tailored for the actual subsystems to which it is applied. Once the specific model for a given subsystem is built, it can be analyzed using existing software packages. An example of how the tailoring and analysis may be accomplished is provided in a detailed study of the B-1B Anti-Skid subsystem. The decision analysis approach will be most advantageous when used on subsystems which have potentially serious failure consequences or economical concerns.

DECISION ANALYSIS APPLIED TO INSPECTION INTERVAL DECISIONS

I. Introduction

Background

Scheduled inspections are a significant part of the United States Air Force's (USAF) preventive maintenance program. An effective, well-timed inspection program allows aircraft components to attain the inherent reliability designed into them. Conversely, an inspection interval with poor timing can lead to too many operational failures, high maintenance costs, loss of aircraft, and even loss of human life. In short, the effectiveness of a preventive maintenance inspection program is evaluated in terms of the failure consequences it prevents (9:36).

Understandably, choosing the best inspection interval for a given component is not an easy task. The decision must take into account the many uncertainties associated with modern aircraft hardware failures. What is the likelihood of failure? How does one catch a failure before it actually happens? What are the consequences when a given component fails? These are some of the questions that must be answered in order to make the best inspection interval decision. To compound the problem, some of the failure data collected as the system matures may be missing or inaccurate.

The USAF recognized the importance of effective preventive maintenance many years ago, but has been slow developing an effective decision process for the inspection interval part of preventive maintenance. In the early 1970s the USAF followed the lead of the commercial airlines and implemented a new maintenance program called

Reliability Centered Maintenance (RCM). A key part of the program was to adjust base-level inspection intervals for various aircraft components as operational failure data became available. According to AFLC/AFSC Regulation 66-35, Reliability Centered Maintenance Program, inspection intervals should be assessed every two years. This interval adjustment process is the responsibility of the System Program Managers (SPM) at Air Force Logistics Command (AFLC) Air Logistics Centers (ALC) (4:5,7).

Unfortunately, today there is still no standard USAF procedure for choosing inspection intervals. As a result, individual ALCs within AFLC have devised their own means of carrying out the inspection interval adjustment process. Few of these programs are documented and their success is ambiguous. Nozer Singpurwalla and Major Carlos Talbott assessed the benefits of the RCM program as a whole for one test case, the C-141, and found no clear improvements in logistics or operations measures (11:15).

Justification

AFLC is currently searching for a standardized procedure for determining optimal inspection intervals which could be organically (non-contractor) supported. AFLC/MMTQA recently proposed the problem to the AFIT Graduate Operations Research program as a student thesis.

Research Objectives

There are two objectives for this research project: 1) propose a general decision-making methodology which can be used by AFLC System Program Managers (SPMs) and their staffs to help in the selection of intervals for base-level inspections and, 2) demonstrate how this methodology can be applied to a specific aircraft subsystem, the B-1B

Anti-Skid subsystem. The end product of the research will be a decision-making framework, not a production software package or mathematical algorithm. The intent of this thesis research is concept exploration and development of a decision-making tool that AFLC SPMs can use to make inspection interval decisions.

Organization of the Thesis

This paper is organized to show a logical flow of ideas from establishing the need for an inspection interval methodology to demonstrating its use. The Introduction and Literature Review chapters help establish the need. The Model Development chapter explains how the general and specific decision models were built and defines the variables involved. The Model Analysis chapter identifies the best decision for the B-1B Anti-Skid subsystem's baseline model and presents sensitivity analyses, value of information calculations, and value of control calculations for selected variables. The Recommendations chapter addresses the insights, applicability, and limitations of the decision analysis approach.

II. Literature Review

Purpose

The purpose of this literature review is to summarize information pertaining to the following decision: how often should scheduled preventive maintenance inspections be performed on United States Air Force (USAF) aircraft subsystems? The review addresses the following subtopics: 1) the manner in which the USAF currently determines inspection interval length, and 2) the attributes of decision analysis which make it applicable to the inspection interval decision.

Scope of The Research Topic and Data Base Search

This review is intended to give the reader a general understanding of how the USAF currently determines base-level inspection intervals and how decision analysis could be used to improve the decision process. It is not a tutorial on the step-by-step analysis of each approach; rather, it focuses on the shortcomings of the current process and investigates how decision analysis may be able to cover them.

The on-line retrieval systems and manual indices available from the AFIT library provided information on relevant literature. Most of the literature on the current USAF approach to inspection interval analysis came from the DTIC and DIALOG on-line systems. The Operations Research/Management Science Service index provided sources of current decision analysis literature.

Method of Treatment and Organization

The following discussion of the literature is arranged by topic. The first section is a summary of the USAF's current decision

methodology. The second deals with the topic of decision analysis. At the end are concluding remarks which summarize the findings.

Discussion of the Literature

Current Approaches. The process of determining inspection interval length is not an established science in the USAF. Mathematical theory occupies part of the decision-making process, but it falls short when objectives are ill-defined and data is lacking. There are no regulations or standards that prescribe the process in its entirety. AFLC/AFSC Regulation 66-35, Reliability Centered Maintenance Program, directs AFLC System Program Managers (SPMs) to periodically (every two years) assess inspection intervals; however, it does not establish procedures for adjusting the intervals (4:5,7). It suggests two analytical tools that the SPM offices can take advantage of in the identification and justification of intervals; actuarial analysis and the Computer Monitored Inspection Program (CMIP).

Actuarial analysis is a broad term that refers to statistical analysis of failure data for the purpose of characterizing the reliability of aircraft components (9:453). There are many different statistical procedures available to inspection interval analysis. Nowlan and Heap documented a few of the most common in their RCM textbook (9:390-419). They all have the same limitations: 1) they must have detailed age-failure data (9:390) and 2) they present only reliability information to the decision maker and do not recommend a decision. Actuarial analysis is used extensively on aircraft engines to help determine when engine parts should be replaced (1:6). In Brill's thesis on preventive maintenance intervals for the F-100 engine, he stated that actuarial data is reviewed annually by an Engine Life Planning Board to

set maximum operating hours (MOH) limits for the engines (1:6-7). Then he stated that according to Air Force Manual 400-1, Selective Management of Propulsion Units, Volume I, Policy and Guidance, "MOH determination is based on judgment, considering safety, readiness, cost, inventory, and other logistics objectives" (1:7). This account illustrates a limitation of actuarial analysis. Actuarial analysis does not address the subjective information and values decision makers must consider while making decisions.

In contrast to actuarial analysis, CMIP is a specialized, well-documented, contractor-owned tool for setting inspection intervals. It is used at the Warner-Robins and San Antonio ALCs. The proprietor of CMIP, Dan Hall (Lockheed) stated that,

> CMIP was specifically designed to assist maintenance managers in evaluating the effectiveness of their scheduled maintenance program by identifying those inspection requirements which do not maintain the aircraft's inherent design levels of safety and reliability with a minimum expenditure of logistics resources. (3:1,2)

CMIP recommends an optimum inspection interval for functional components based on the goal of having no malfunctions between inspections (3:3,4). It does this by analyzing current maintenance data from the field and comparing it to the current inspection program. If the current program cannot provide at least a 70% confidence of no malfunctions in the interval between inspections, then CMIP recommends an alternative interval length (3:4).

The main limitation of CMIP is that it only addresses part of the inspection interval decision process. It identifies what intervals may need adjusting, but its recommended alternative is based on the goal of having no malfunctions. CMIP does not take into account situations where failures may be tolerated in the interest of cost effectiveness. As

noted in Nowlan and Heap's RCM textbook, if the cost of repairing failed units plus the costs of operational consequences is less than the costs of finding and correcting failures before they occur, then failures should not be avoided (9:52). Like actuarial analysis, CMIP supplies the decision maker with statistical analyses of existing maintenance data; however, for any other aspect of the decision, the decision maker must find other sources of information with which to make the decision.

Decision Analysis Approach. Decision analysis is a strategy for making decisions. It is a mix of systems analysis and statistical decision theory (6:21) that addresses all aspects of a decision problem: decision alternatives, outcomes of influential variables, probabilities of outcomes, and decision outcome values. Since the term "Decision Analysis" was first coined in 1966 by Ronald A. Howard, decision analysis theory and practice have been advanced by various members of the operations research community (6:vii). Unfortunately, the term decision analysis is now common enough that it has lost specific meaning, so Howard gives a more precise and descriptive definition:

> By decision analysis we mean a discipline comprising the philosophy, theory, methodology, and professional practice necessary to formalize the analysis of important decisions. Decision analysis includes procedures and methodology for assessing the real nature of a situation in which a decision might be made, for capturing the essence of that situation in a formal but transparent manner, for formally solving the decision problem, and for providing insight and motivation to the decision makers and implementers. (6:viii)

A decision analysis type approach seems necessary for today's "real world" problems. Any decision analysis must have the ability to deal with the subjective nature of uncertainties and values of outcomes which do not easily lend themselves to quantification. In a recent workshop on decision research directions sponsored by the National Science

Foundation, several experts in the decision analysis field agreed that "in the case of decision processes, what matters are human goals, perceptions, and emotions that do not lend themselves to quantitative analysis in the spirit of classical mathematics" (2:766).

The USAF problem of determining inspection intervals certainly fits into this category of "fuzzy" problems. Nowlan and Heap, United Airlines employees who write the RCM textbooks for the Air Force, addressed the problem of quantifying the real costs of failures by stating "we have no precise means of assessing either the inherent level of risk or the increased risks that do result from failures" (9:337). The consequences of component failures are further complicated by the human element. Nowlan and Heap stated, "results of the failures must be modified by the degree to which each function affects safety and by the ability of the pilot to compensate for many types of system failures" (9:337). A decision analysis approach could address these types of "fuzzy" consequences, risks, and probabilities inherent in the inspection interval decision process.

The strength of decision analysis lies in its ability to deal with probabilities and decision maker value preferences. Decision analysis treatment of probability is described by Howard below,

> Decision analysis treats probability as a state of mind rather than things [nature]. The operational justification for this interpretation can be as simple as noting the changing odds on a sporting contest posted by gamblers as information about the event changes. As new information arrives, a new probability assignment is made. (6:24,163)

Decision analysis does this by supplementing results from statistical analysis with other information available to the decision maker, such as expert judgment. Peter Morris introduced a new framework for use of

experts in decision making in his article "Decision Analysis Expert Use" (8:1233). In it he stated,

> The potential applications of a rich theory on expert use are many and varied.... In general the theory to be developed is especially pertinent to decisions affecting systems whose characteristics include significant uncertainty, complexity, or both -- precisely the practical domain of decision analysis. (8:1234)

The other area of the inspection interval problem where decision analysis may be helpful is in allowing the decision maker to clearly see the value (desirability) of each possible outcome of the decision. Computing the value for each possible outcome of each decision alternative is a major part of the decision analysis process.

For the inspection interval problem, the decision maker must place values on outcomes that affect human safety, aircraft availability, and maintenance costs. Decision analysis explicitly reveals to the decision-maker the preferences he/she is currently placing on these factors and allows re-evaluation of them if desired. Theodor Stewart described this step of the decision analysis process when he wrote, "the analyst interacts with the decision maker, and allows him/her to reveal preferences gradually by means of choices or value judgments expressed through comparison of actual decision alternatives" (12:1067).

An important part of this value modeling step is the sensitive subject of human life valuation. Aircraft are crewed by human beings who sometimes lose their lives in aircraft crashes caused by component failures. This is despite the fact that precaution is taken to design and maintain components with acceptably low safety risks. As Howard and others found in their study on nuclear reactor safety, setting an acceptably low probability for an outcome involving death implies that

the decision maker has made a value of life assessment (6:518). The same article by Howard and others proposes a value of life computation that could be used by USAF decision makers in cases where human life is involved (6:518).

Conclusions

Inspection interval analysis is an important yet neglected part of the USAF's RCM program. There is no official procedure that precisely addresses the complete decision process. Actuarial analysis and the Computer Monitored Inspection Program are established tools used in the current decision process, but they are of limited value. The main drawback of both is that they do not address the subjective aspects of the decision-making process such as failure consequences, unreliable failure data, risk assessment, and value of decision outcomes.

Conversely, decision analysis is a *decision-making* strategy that is designed to treat the very aspects of decision-making the current approach fails to address. Decision analysis combines statistical analysis, expert opinion, and decision maker preferences in a single decision-making framework. The result is a complete decision-making aid that recommends an optimum decision alternative to the decision maker. Thus, decision analysis can be applied to the inspection interval decision process to help AFLC SPM organizations select effective inspection intervals.

III. Model Development

Introduction

Decision analysis as applied in this research is based on the methods described in The Principles and Applications of Decision Analysis by Ronald A. Howard (6) and as taught in the AFIT Graduate Operations Research Program. It is an iterative process which is repeated until the decision maker is comfortable enough with his/her understanding of the problem to make the decision. The initial part of the analysis requires that all variables thought to exert an influence on the decision be identified. The next step is to define the range of outcomes for each variable, how the variables mathematically affect each other, and what value the particular combinations of outcomes have to the decision maker. With this information, the first systematic screening of variables is done by performing deterministic sensitivity analysis. Once this is accomplished, stochastic (probabilistic) information is gathered on the remaining variables deemed significant to the decision. Then the expected value for each decision alternative is calculated and the alternative with the most attractive value (min in this case) is identified. Finally, various postsolution analyses are performed to reveal how sensitive the baseline solution is to changes in key variables.

For most real-world decisions like the inspection interval decision, there are a great number of variables influencing the decision. This number can be reduced initially with help from the decision maker and experts who are familiar with the problem. Normally, these key people can make an early screening of the variables based on significance to the decision. Later, the remaining variables may be screened further during

formal sensitivity analysis (e.g. deterministic sensitivity analysis). The criteria for this screening process is always whether or not the variable creates significant differences between decision alternatives. In this manner, the decision analysis moves from the general to the specific as information is screened and evaluated for significance.

At any given time in the analysis, all variables included in the model and their influence on each other and the decision are represented using an influence diagram (ID). An ID provides a graphical framework for both illustrating and solving a decision model (10).

The following sections present the general decision model first and then explain how it was tailored for the B-1B Anti-Skid subsystem inspection interval decision. The first section gives a general description of each variable in the general model. The second section explains in detail how the general model was simplified in building the Anti-Skid subsystem decision model. The last section in this chapter presents the deterministic sensitivity analysis performed on the variables in the model which remained after the initial screening.

The General Decision Model

The general ID developed to serve as a starting point for the analysis of any specific aircraft component is shown in Figure 1. Depending on the aircraft component being analyzed, certain variables can be simplified or deleted from this model if the analysis shows they are insignificant to the decision value.

The following paragraphs give a variable by variable description of the general model. Possible simplifications and sources of information for some variables are included.

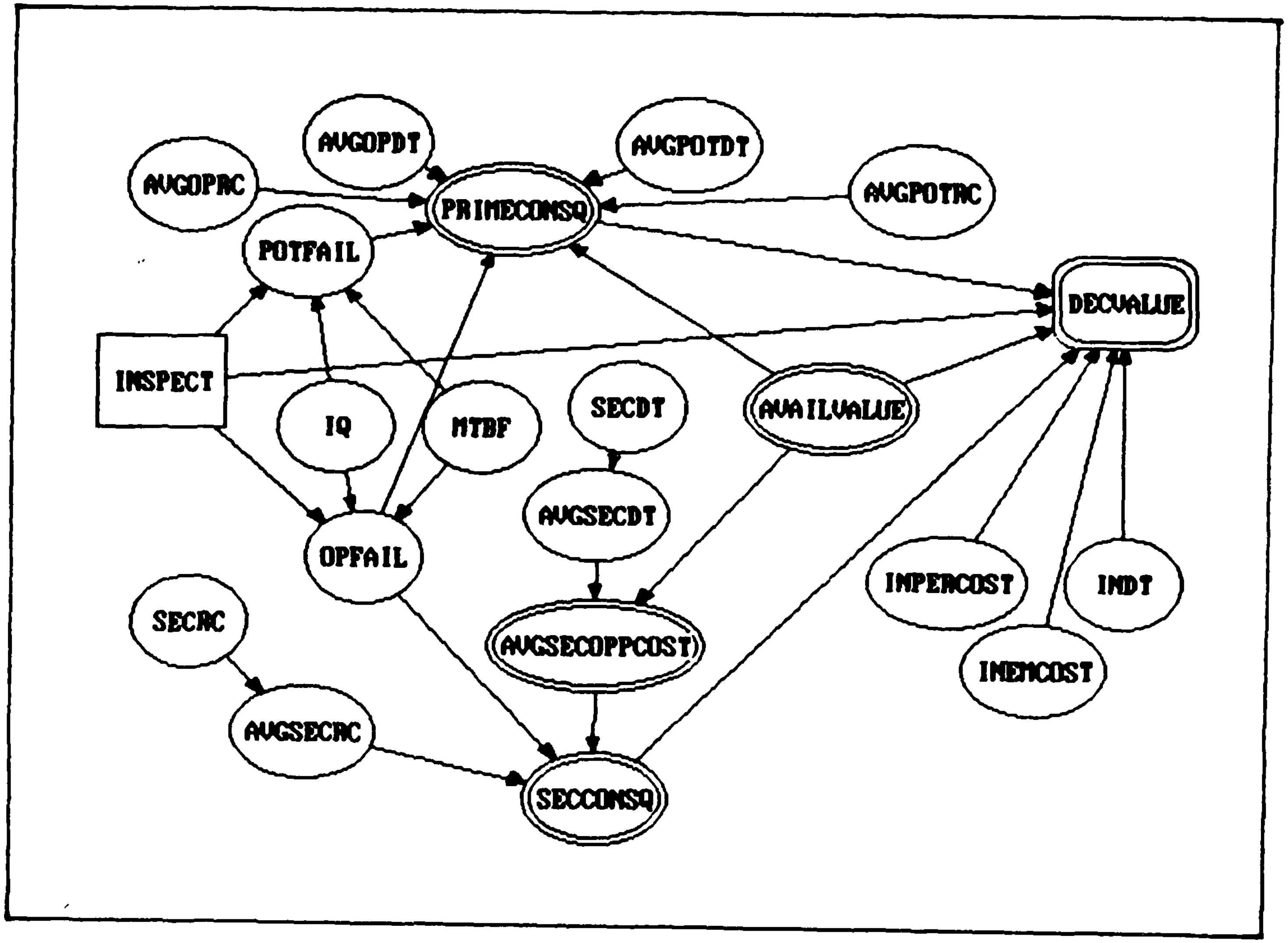


Figure 1. Influence Diagram for the General Model

INSPECT. INSPECT is the only decision variable in the model. The values it can take on are the alternative inspection intervals from which the decision maker must choose. The goal of the entire decision analysis is to indicate to the decision maker which alternative is the best. In the USAF, proposed alternative inspection intervals normally coincide with existing aircraft inspections. Inspections of individual subsystems are grouped or "packaged" with others so that the aircraft does not have to undergo thousands of minor inspections (9:109). For example, an aircraft may currently have inspection packages of every 50, 100, and 200 flying hours. If this was the case, an alternative different from these may not even be considered since no current maintenance "package" could incorporate it. An advantage of this limitation is that the new interval can be readily implemented by inspection personnel since it only requires moving a subsystem from one existing inspection package to another.

MTBF. MTBF is a continuous random variable which represents the mean time between failure for the aircraft subsystem being analyzed. Most other types of analyses dealing with reliability treat MTBF as a constant, ignoring the uncertainty surrounding its true value. In this model, treating it as a random variable allows consideration of a range of other possible values for MTBF. Actuarial analysis of historical failure data may provide a good estimate of the probability distribution for MTBF. Expert opinion could also be used to supplement actual data. This is especially advantageous if the decision maker questions the accuracy of the maintenance data.

IQ. IQ stands for Inspection Quality. This random variable measures, in time units (e.g. flying hours), the ability of inspectors to "capture" potential failures during inspections by detecting near-failure

or failure conditions. This variable is random in nature, but may be controlled somewhat by the inspection procedures developed for the component in question. For components with graceful degradation, IQ can be influenced according to how far the component is allowed to degrade before it is replaced. In a case where it was allowed to degrade within 20 hours of failure before correction, IQ would be equal to 20. However, for components which do not degrade gracefully (e.g. pure electronics), inspections are unable to catch failures before they happen during aircraft operation and IQ will be near zero. The front-end Reliability Centered Maintenance Analysis (RCMA) (4) performed by the aircraft manufacturer and delivered to the System Program Office is supposed to address the degradation of each aircraft component. The RCMA is the first clue as to what the IQ is for a given component.

<u>OPFAIL</u>. OPFAIL is a random variable representing the number of operational failures the subsystem experiences during the time frame the decision covers (referred to in this paper as "decision duration"). These are inherent or induced failures as defined in maintenance manuals and interpreted by the crew and maintenance personnel working with the aircraft. OPFAIL is a random variable with a wide range of discrete outcomes, but in the analysis its range can be truncated because after a certain point, further possible values will have extremely low chance of occurrence. The variables INSPECT, MTBF, and IQ influence the probability distribution for OPFAIL outcomes. If time between failures is assumed to be one of certain named distributions, such as the exponential, the different distributions OPFAIL takes on can be calculated analytically given values for INSPECT, MTBF, and IQ. This method is demonstrated in the B-1B Anti-Skid decision model.

POTFAIL. POTFAIL stands for potential failures. It is a random variable representing the number of times near-failure or failure conditions are found during inspections and subsequently corrected. Like OPFAIL, the variables INSPECT, MTBF, and IQ influence the probability distribution for POTFAIL, which may be derived analytically in a similar manner to OPFAIL.

SECDT. SECDT stands for Secondary Downtime. It is a random variable which, when given that a failure in the primary subsystem has occurred, represents the total time the aircraft is unavailable to the commander during correction of a failure in some other (secondary) subsystem whose failure was caused by the primary subsystem failure. Some aircraft subsystems have little or no potential for causing secondary downtime, while others, safety related items for example, may have great potential. SECDT is a continuous variable whose probability distribution must usually be derived from expert opinion. The rare event nature of this variable leaves little or no historical data from which to derive it. Information on this variable can be used to derive discrete values for AVGSECDT.

SECRC. SECRC stands for Secondary Repair Costs. It is a continuous random variable which, given that a failure in the primary subsystem has occurred, represents the total cost to the government for repairing other (secondary) aircraft subsystems whose failure was caused by the primary subsystem failure. Like SECDT, the potential here varies greatly from one subsystem to the next, but its actual occurrence may be relatively rare and historical data non-existent. Information on this variable can be used to derive discrete values for AVGSECRC.

AVGSECDT. AVGSECDT stands for Average Secondary Downtime. It is the average of SECDT over the decision duration time period. It is a continuous random variable which can be approximated using discrete values derived analytically from the SECDT probability distribution. An example of this derivation is described in the section on the Anti-Skid subsystem decision model.

AVGSECRC. AVGSECRC stands for Average Secondary Repair Costs. It is the average of SECRC over the decision duration time period. It is a continuous random variable which can be approximated using discrete values derived analytically from the SECRC probability distribution. An example of this derivation is described in the section on the Anti-Skid subsystem decision model.

AVAILVALUE. AVAILVALUE represents the dollar value the decision-maker places on a given time unit of aircraft availability. This variable should be set to a value which reflects the preferences of the decision maker. Ideally, this value should come directly from the decision maker since it is a subjective, indirect measure of the worth to national defense he/she places on the aircraft. Personnel at Oklahoma City ALC commented that one way to approximate this value is to divide aircraft flyaway cost by the life time of the aircraft.

AVGSECOPPCOST. AVGSECOPPCOST stands for Average Secondary Opportunity Cost. It is a deterministic variable made up of a function which multiplies AVAILVALUE by AVGSECDT. It is a measure of the opportunity or availability costs to the Air Force when secondary damage occurs.

AVGOPDT. AVGOPDT stands for Average Operational failure Downtime. AVGOPDT represents the average amount of downtime the aircraft

experiences while an operational failure of the primary subsystem is being corrected. It is a continuous random variable, but in specific analyses it may be set to a constant if it varies relatively little over time. Most subsystem failures on aircraft are resolved by a remove and replace procedure. For many components the time it takes to do this will be fairly standard. In addition, if this variable exhibits similar values to AVGPOTDT, both variables will be insignificant to the inspection interval decision. This relationship is explained in detail in the section on the Anti-Skid subsystem decision model.

AVGOPRC. AVGOPRC stands for Average Operational failure Repair Costs. AVGOPRC is the average total cost to the government the aircraft experiences when an operational failure of the primary subsystem is corrected. It is a continuous random variable, but in specific analyses may be set to a constant if it varies relatively little over time. As described in the section below on the Anti-Skid subsystem decision model, if this variable takes on similar values to AVGPOTRC, both variables will be insignificant to the decision.

AVGPOTDT. AVGPOTDT stands for Average Potential failure Downtime. It is similar to AVGOPDT, explained above, except that it only applies to primary subsystem potential failures, not operational failures.

AVGPOTRC. AVGPOTRC stands for Average Potential failure Repair Costs. It is similar to AVGOPRC, explained above, except that it only applies to primary system potential failures, not operational failures.

PRIMECONSQ. PRIMECONSQ stands for Primary Consequences. It is a deterministic variable made up of a function which sums up all repair and opportunity costs (as a result of downtime) associated with both

operational and potential failures of the primary subsystem. It is computed by the equation

$$\text{PRIMECONSQ} = \text{OPFAIL}\ (\text{AVGOPRC} + (\text{AVGOPDT} \times \text{AVAILVALUE})) + \text{POTFAIL}\ (\text{AVGPOTRC} + (\text{AVGPOTDT} \times \text{AVAILVALUE})) \quad (1)$$

SECCONSQ. SECCONSQ stands for Secondary Consequences. It is a deterministic variable made up of a function which sums up all opportunity costs (as a result of downtime) and repair costs associated with operational failure secondary consequences. It is computed by the equation

$$\text{SECCONSQ} = \text{OPFAIL}\ (\text{AVGSECOPPCOST} + \text{AVGSECRC}) \quad (2)$$

INPERCOST. INPERCOST stands for Inspection Personnel Cost. It is a random variable made up of a function which multiplies the average number of manhours it takes to perform an inspection by a standard wage rate for Air Force personnel. For most subsystems this variable may be treated deterministically by using a single nominal value. Maintenance manuals normally indicate the number of persons required to perform an inspection for a given subsystem. Maintenance personnel can provide expert opinion on how long the inspection normally takes to perform. Air Force Regulation 173-13 can be used to obtain Air Force personnel wage rates.

INDT. INDT represents the average amount of downtime the aircraft experiences while undergoing a single inspection of the subsystem. If this time varies little, it may be set to a nominal value. Maintenance personnel can normally provide information on this variable.

INEMCOST. INEMCOST stands for Inspection Equipment and Material Costs. It represents the average cost the Air Force incurs while performing a single inspection in terms of expendable materials and test equipment. Maintenance personnel can normally provide information on this variable.

DECVALUE. DECVALUE stands for Decision Value. It is a deterministic variable made up of a function which measures the value (costs) to the decision maker of each possible decision outcome (all possible combinations of outcomes of the other variables in the model). It reflects all inspection consequences and operational consequences which differentiate one decision alternative from the another. Its value is computed by the equation

$$\text{DECVALUE} = [(\text{Decision duration/INSPECT})\ (\text{INPERCOST} + (\text{INDT} \times \text{AVAILVALUE}) + \text{INEMCOST})] + \text{PRIMECONSQ} + \text{SECCONSQ} \quad (3)$$

The decision alternative with the lowest expected value (cost) is the optimal inspection interval. A simplifying assumption made here is that the decision maker chooses based on expected value. This means, for example, that to the decision maker costs of $100,000 are twice as bad as costs of $50,000. If the decision maker does not exhibit this type of behavior, a unique utility function must be derived which transforms the dollar value of each decision outcome into utility (6:627). In this case the decision would be based on lowest expected utility instead of lowest expected value.

The Anti-Skid Subsystem Decision Model

The B-1B Anti-Skid subsystem is made up of five subcomponents: control box, speed sensor, manifold, control valves, and filter element. A rough schematic of the system breakdown/function description is shown in Appendix A. Currently, this subsystem is inspected only on an exception basis: it has no scheduled inspections. It is only inspected in the case of brake overheating, hard landings, suspected failure, etc. It was chosen as the test case for this thesis because it is a relatively simple subsystem, degradation is detectable, and its operational failure

has the potential for causing serious damage to other subsystems on the aircraft.

The ID model developed specifically for the Anti-Skid subsystem is shown in Figure 2. As a result of initial screening, many of the random variables in the general model were modified in this model. The reasons for these modifications are discussed below.

IQ was set equal to a constant in the model because it is so heavily influenced by how rigorous the inspections are performed. Captain Scott Dayton, ASD/B-1BEF, provided approximate maximum values for the individual components comprising the Anti-Skid subsystem. The average of these values was 5 flying hours, with a low of 0 and a high of 20. Consequently, in the baseline model, IQ was set equal to 5. The extreme values in the range were investigated during sensitivity analysis to allow the decision maker to see how inspection quality affects the inspection interval decision.

The variables AVGOPDT, AVGOPRC, AVGPOTDT, and AVGPOTRC were set equal to constants after discussions with Capt Dayton confirmed the author's own opinion that the decision choice would be insensitive to these variables. Nominal values for these variables were 4 hours, $500, 4 hours, and $500 respectively. These values reflect the assumption that average repair costs and average downtime for the Anti-Skid subsystem components will be the same for both operational failures and potential failures. That is, it will take about as long and cost about as much to correct a near-failure during an inspection as it will to correct an operational failure of the B-1B Anti-Skid subsystem.

The inspection cost variables INPERCOST, INDT, and INEMCOST were set equal to constants because of their relatively small magnitudes compared

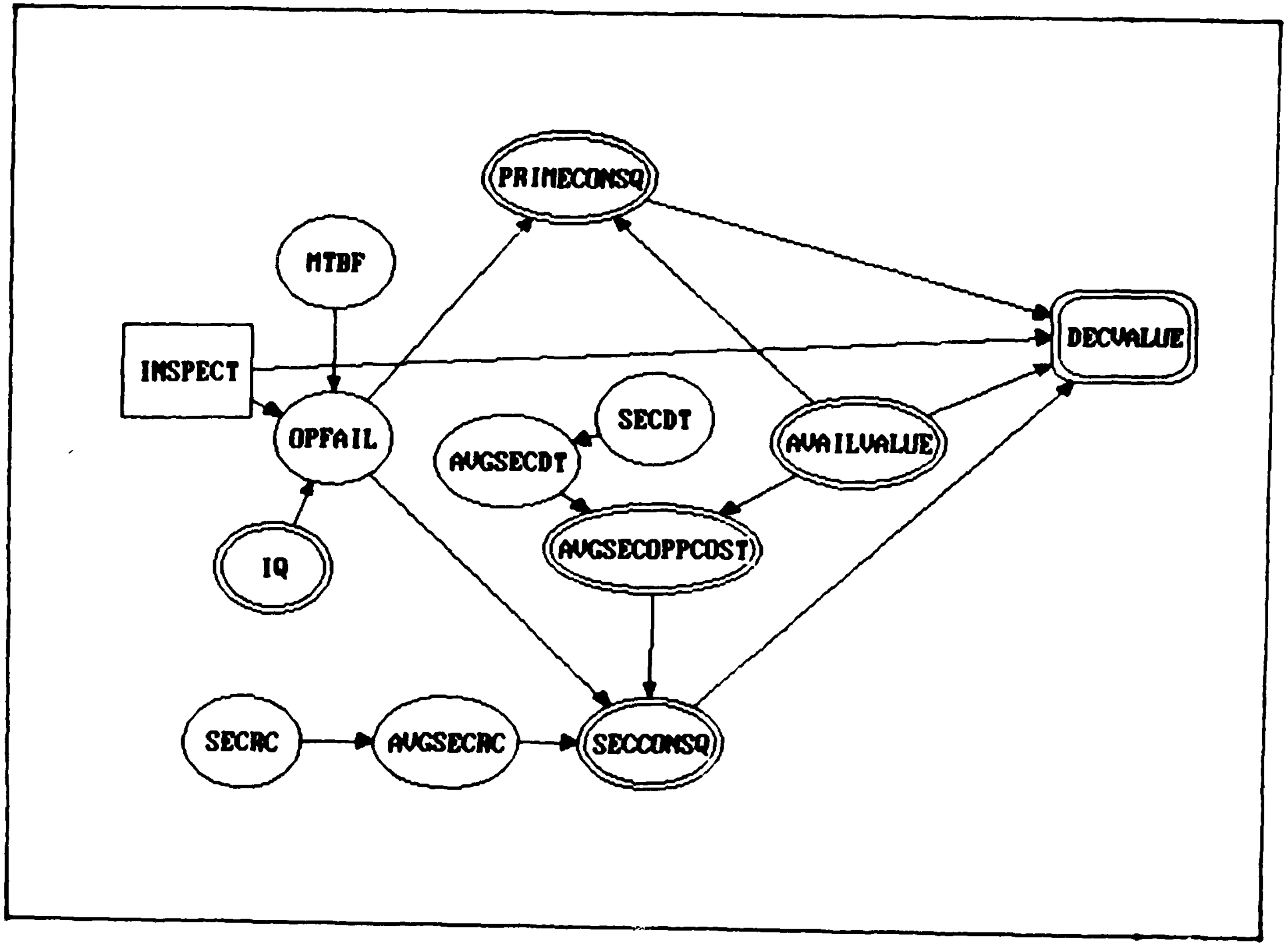


Figure 2. Influence Diagram for the B-1B Anti-Skid Subsystem Model

to the decision value (DECVALUE) and because their invariance over time would not significantly affect the decision. Examination of maintenance manuals revealed that inspections of the Anti-Skid subsystem can be performed relatively quickly (within one hour) by two Airmen with no need for special equipment or materials. The resulting inspection costs were small compared to the overall decision value (DECVALUE) which measured in the hundreds of thousands of dollars. INPERCOST, INDT and INEMCOST were set to nominal values of $30, 1 hour, and $0 respectively. INPERCOST was calculated using a $15 per manhour composite wage rate from AFR 173-13, Table 3-4, Change 1, 15 May 1987.

POTFAIL was deleted from the Anti-Skid subsystem decision model because of its relatively small effect on the decision value (DECVALUE). In the general model, the impact of potential failures is wholly contained in the primary consequences (PRIMECONSQ) part of the DECVALUE function Eq (3). In the PRIMECONSQ function Eq (1), the number of potential failures (POTFAIL) is multiplied by the average repair costs (AVGPOTRC) and average opportunity costs per potential failure (AVGPOTDT * AVAILVALUE). As discussed above, these repair cost and downtime factors were set to the constants $500 and 4 hours respectively. AVAILVALUE was set to a constant of $1182. Now, for the worst MTBF of 285 flying hours, the expected number of total failures (i.e. all failures, no matter when discovered) is 2 over the two-year period. Therefore, the expected number of potential failures could be no greater than 2 and the greatest contribution to PRIMECONSQ would be 2(500 + (4 X 1182)) = $10,456. This means that the largest expected difference POTFAIL could cause between two alternatives is $10,456. This is insignificant compared to the impact operational failures (OPFAIL) had on

DECVALUE and therefore POTFAIL was not included in the final model for the Anti-Skid subsystem. In addition, since the variables AVGPOTRC, and AVGPOTDT only play a role when POTFAIL is non-zero, these two variables were also deleted from the PRIMECONSQ function and the model.

The following paragraphs explain how decision alternatives, random variable probabilities, availability value, and primary consequences were determined for the corresponding variables remaining in the model.

INSPECT. The decision duration in this model was a two-year time period since this is the Air Force goal for the time between reassessment of inspection intervals (4:5). In this model, three alternative intervals were considered for the decision variable INSPECT: 5, 100, or 600 flying hours. The 5 hour alternative equates to inspecting every sortie. (Operations historical data obtained from the AFOTEC Test Team at Dyess Air Force Base indicated that the average sortie was 4.5 hours long.) The 100 hour alternative correlates to an already existing inspection interval for the aircraft. The 600 hour alternative equates to not inspecting the Anti-Skid subsystem at all during the decision duration (two years). According to AFR 173-13, Change 2, 9 March 1988, a B-1B would average about 600 flying hours over a two-year time period.

MTBF. The probability distribution for MTBF was constructed based on failure data and expert opinion obtained from the AFOTEC Follow-On Test and Evaluation Team at Dyess AFB, Texas. An inherent assumption here was that B-1B operations at Dyess were representative of the B-1B fleet as a whole. Discussions with individuals in the B-1B SPM organization at Oklahoma City ALC and the AFOTEC Test Team revealed that there was a lack of confidence in the failure data reported by AFLC's Maintenance and Operational Data Access System (MODAS). The AFOTEC team

uses an in-house system, called OMNIVORE, to report failure data. This data base was used instead of MODAS because the SPM organization had more confidence in it than they did in MODAS data. The AFOTEC reports on the Anti-Skid subsystem indicated a MTBF of 437 flying hours (based on counting inherent and induced failures over a three year period). This point estimate was incorporated into a probability distribution derived by combining the point estimate and expert opinion. AFOTEC Test Team engineer, Captain John Wilder, was interviewed and he provided information on the likelihood that the true MTBF would take on a range of values around the 437 hour point estimate. Probability wheel and interval techniques (6:614-624) were used for this interview. Raw data from this interview is included in Appendix F. A manually fitted probability distribution curve for MTBF is shown in Figure 3.

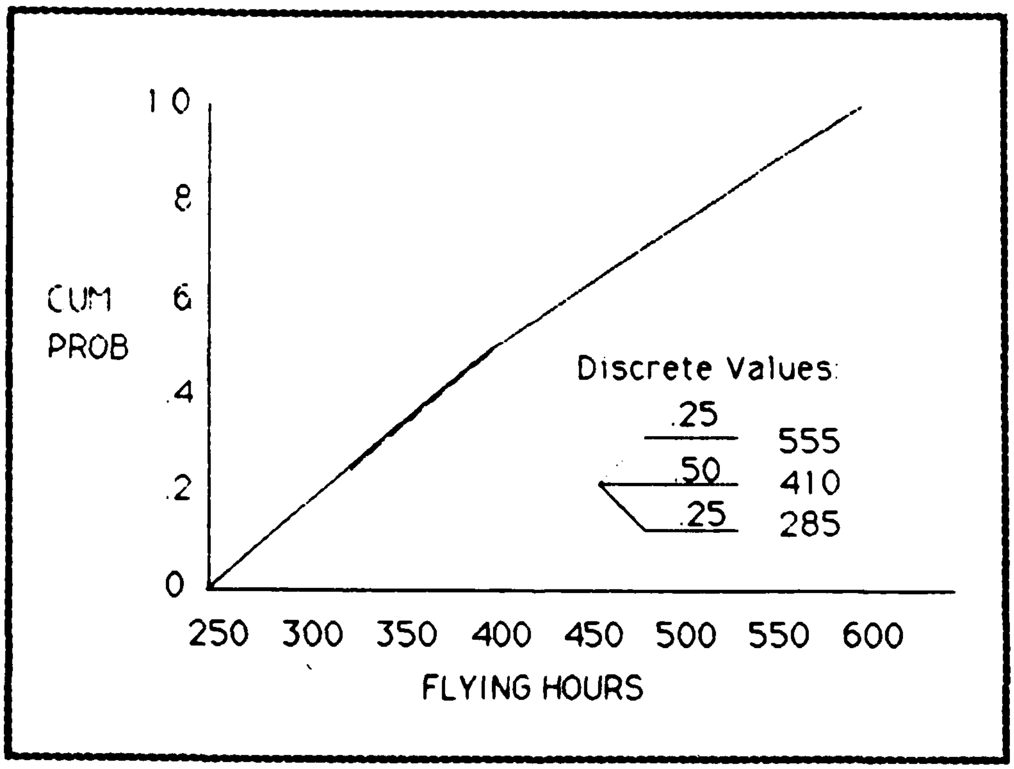


Figure 3. MTBF Probability Distribution

In order for the ID model to be solvable, MTBF (and all other continuous random variables) had to be reduced to a certain number of discrete outcome values. For simplification, the probability distribution was sectioned graphically (13) into three discrete values: 285, 410 and 555. These values represent the 1/4, 1/2, and 3/4 fractiles for this distribution and as such have probabilities of .25, .50, and .25 respectively. Appendix B shows how the MTBF distribution was sectioned. The distributions for SECDT and SECRC were sectioned in a similar manner.

<u>OPFAIL</u>. The probability distribution for OPFAIL was analytically derived based on the assumption that the time between failures for the Anti-Skid subsystem is distributed exponentially. This assumption was made because the exponential distribution is commonly used to model time between failure for electronic components (7:147) and OMNIVORE data revealed that the bulk of Anti-Skid failures are attributed to its electronic components. Also, this assumption is made in an existing interval analysis model, CMIP (3:3), used at the Warner-Robins and San Antonio ALC's.

If the time between failures is distributed exponentially with a mean of $1/\lambda$, then the failures themselves are distributed as Poisson with mean λ (5:536). In general, the Poisson Probability function is

$$p(X=x_o) = [\, e^{-\lambda t} (\lambda t)^{x_o}]/x_o! \qquad (4)$$

where x_o = a given outcome for the random variable X
λ = the mean value (rate) of X over time t
t = the total time period of interest

Since failures are assumed to occur by Poisson, this equation can be used to calculate the different probability distributions for OPFAIL given parameters INSPECT, MTBF, and IQ. For our particular case, λt is computed by multiplying 1/MTBF by the sum of all time between inspections

not covered by IQ,

$$\lambda t = (1/MTBF)\ [(\text{decision duration}/INSPECT)\ (INSPECT - IQ)] \qquad (5)$$

IQ time is not included since operational failures cannot occur during that time period.

The probability distributions for OPFAIL were computed on a LOTUS spreadsheet and are shown in Appendix C. The range of possible outcomes for OPFAIL is 0 through 5, 5 being the maximum number because probabilities beyond 5 are infinitesimal for any of the λt values.

SECDT. The probability distribution for SECDT was constructed from an interview with Capt Dayton, ASD/B-1BEF. Capt Dayton is the B-1B SPO's expert on landing gear systems. The entire distribution was derived from his expert opinion, since no such historical data on the B-1B exists. Probability wheel and interval techniques (6:614-624) were used to obtain Capt Dayton's best engineering judgment about the likelihood of secondary downtime given that an operational failure in the Anti-Skid subsystem had occurred. Raw data from this interview is included in Appendix F. A manually fitted probability distribution curve is shown in Figure 4.

In order to obtain a set of discrete outcomes for this variable, the distribution was graphically sectioned (13) into three discrete values: 8, 100, and 325. Probabilities for these values are .25, .50, and .25 respectively. The sectioning of the MTBF distribution shown in Appendix B serves as an example of how it was done for SECDT.

AVGSECDT. Three discrete values for AVGSECDT were derived analytically from the SECDT probability distribution using a series of standard statistical calculations. These calculations are presented in detail in Appendix D. The three discrete values produced from the calculations were 5.954, 133.25, and 260.546 with probabilities of .25,

.50, and .25 respectively.

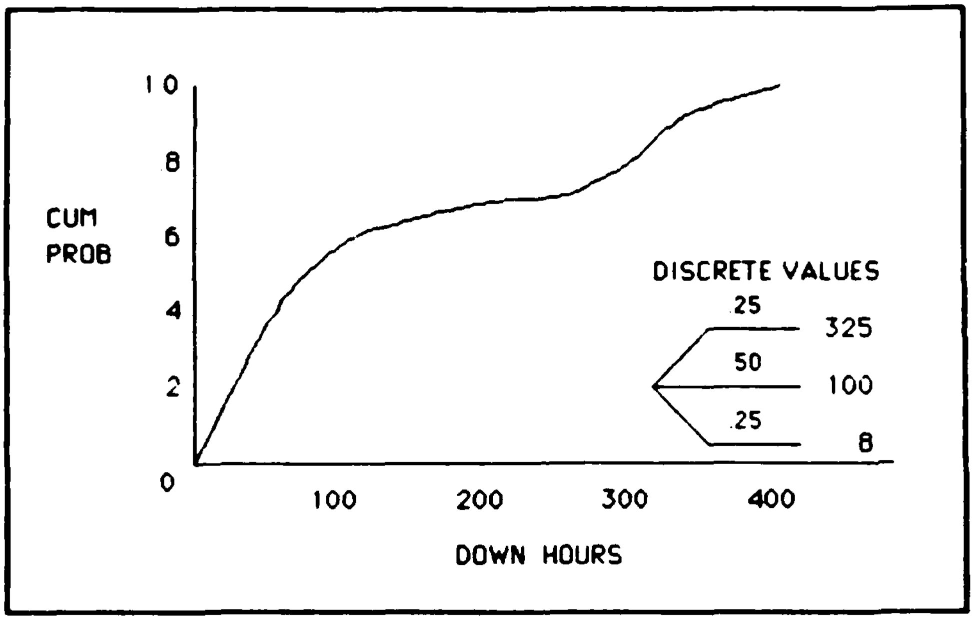


Figure 4. SECDT Probability Distribution

SECRC. The probability distribution for SECRC was constructed from an interview with Mr. Floyd Minnich, 4950th Test Wing, Wright-Patterson AFB, Ohio. Although not specifically assigned to the B-1B, Mr. Minnich is an expert on heavy aircraft landing gear and their failure consequences. He is a retired Air Force member with over 20 years experience in the heavy aircraft maintenance world. The probability distribution was derived from his expert opinion. Probability wheel and interval techniques (6:614-624) were used to obtain his best judgment about the likelihood of secondary repair costs given that an operational failure in the Anti-Skid subsystem had occurred. Raw data from this

interview is included in Appendix F. A manually fitted probability distribution curve is shown in Figure 5.

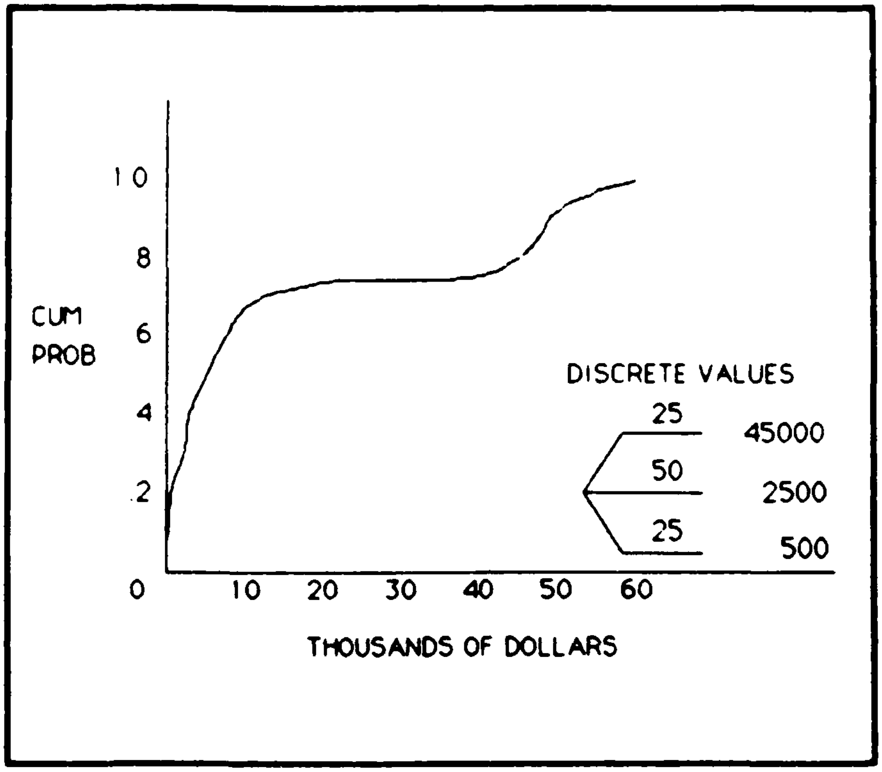


Figure 5. SECRC Probability Distribution

The probability distribution for SECRC was graphically sectioned (13) in the same manner as were MTBF and SECDT. The sectioning of the MTBF distribution shown in Appendix B serves as an example of how it was done for SECRC. The three discrete values for SECRC are 500, 2500, and 45000 with probabilities of .25, .50, and .25 respectively.

AVGSECRC. Three discrete values for AVGSECRC were derived analytically from the SECRC probability distribution in the same manner AVGSECDT was derived from SECDT. (Appendix D presents the calculations

that were performed for AVGSECDT which serve as an example.) The three values calculated for AVGSECRC were $0, $12625, and $32998 with probabilities of .25, .50, and .25 respectively.

AVAILVALUE. AVAILVALUE was set equal to $1182 in the baseline model. Ideally, this value should come directly from the decision maker, but in this study the value was approximated by dividing aircraft flyaway costs ($207 Million) by a 20 year lifetime. The flyaway cost was taken from AFR 173-13, Table 2-6, Change 2, 9 March 1988. The 20 year lifetime was used since it is commonly used for bomber aircraft Operating and Support cost estimates at ASD. The impact on the decision of setting this variable to different values was explored during preference sensitivity analysis.

PRIMECONSQ. The Anti-Skid subsystem model's equation for PRIMECONSQ is the same as for the general model except that the influence of POTFAIL was removed since, as explained earlier, that variable was not significant to the decision value. The new equation for PRIMECONSQ is

$$PRIMECONSQ = OPFAIL\ (AVGOPRC + (AVGOPDT \times AVAILVALUE)) \quad (6)$$

Deterministic Sensitivity Analysis

The purpose of deterministic sensitivity analysis is to identify which variables are deterministically significant to the decision. It is the first systematic screening of the variables in the model. It is performed in the model development phase of the decision analysis so that the analyst's time and energy can be efficiently focused on the key variables during the rest of the analysis. One excursion taken in this phase of the research was to explore two different ways of performing the deterministic sensitivity analysis: the common method and the response

surface method. Both methods are introduced here briefly then discussed in detail later.

The common method performs deterministic sensitivity analysis on a variable by setting all other variables to their nominal values and then observing the deterministic change in the decision value (DECVALUE) as the variable being studied is set in turn to the high and low values in its range. One major weakness of this approach is that it only measures the "main effect" of each variable. It does not systematically measure the effect on DECVALUE of two or more variables interacting together simultaneously (an "interaction effect"). In instances where a variable had no significant main effect of its own, but had a significant interaction effect with some other variable, the common method would overlook the interaction effect, screen out the variable, and an error may be introduced into the decision analysis at that point. Another weakness is that since it only measures the magnitude of change in DECVALUE, it is left up to the ad hoc judgment of the analyst to determine if the magnitude is significant. It does not systematically "draw the line" between significance and insignificance.

The response surface method overcomes the weaknesses of the common method by considering all possible interaction effects as well as main effects and ranking them according to statistical significance. The response surface method performs the analysis by making experimental runs using a factorial design matrix of the high and low settings of all variables. Each run corresponds to a unique combination of the high and low settings. The value for DECVALUE is then recorded for each run. Next, using all main effects and possible interaction effects as the independent variables and the DECVALUE response as the dependent

variable, a polynomial approximation is derived using multiple regression ("PROC REG" on SAS, for example). Standard analysis-of-variance (ANOVA) t-statistics provide a measure of the significance for each term in the polynomial, and thus a measure of each effect's significance to the decision value.

Common Method Analysis. The variables chosen for analysis by the common method were those variables remaining from the initial screening of the model which have a deterministic path to DECVALUE in the influence diagram: INSPECT, OPFAIL, AVGSECRC, and AVGSECDT. Each variable was analyzed separately by setting it to its high and low values in turn while the other values were temporarily set to their nominal (middle) values. The case of all variables equal to their nominal values was used as a reference line ($533,000). The graph in Figure 6 shows the relative deterministic effect of each variable on DECVALUE. From this analysis, it is clear that OPFAIL and AVGSECDT are significant to the decision value. INSPECT, the decision variable, looks only marginally significant. However, this analysis only reflects the deterministic effect of INSPECT on DECVALUE. INSPECT also has a stochastic effect on DECVALUE since it influences the OPFAIL probability distribution. Therefore, the significance of INSPECT cannot be judged solely on the results of this deterministic sensitivity analysis alone. On the other hand, AVGSECRC seems insignificant compared to the other variables. Based on this method of evaluation, it could probably be set to a constant nominal value for the rest of the decision analysis.

Response Surface Method Analysis. In order to obtain a comparison between methods, the same variables analyzed by the common method were analyzed by the response surface method. (A major limitation of the

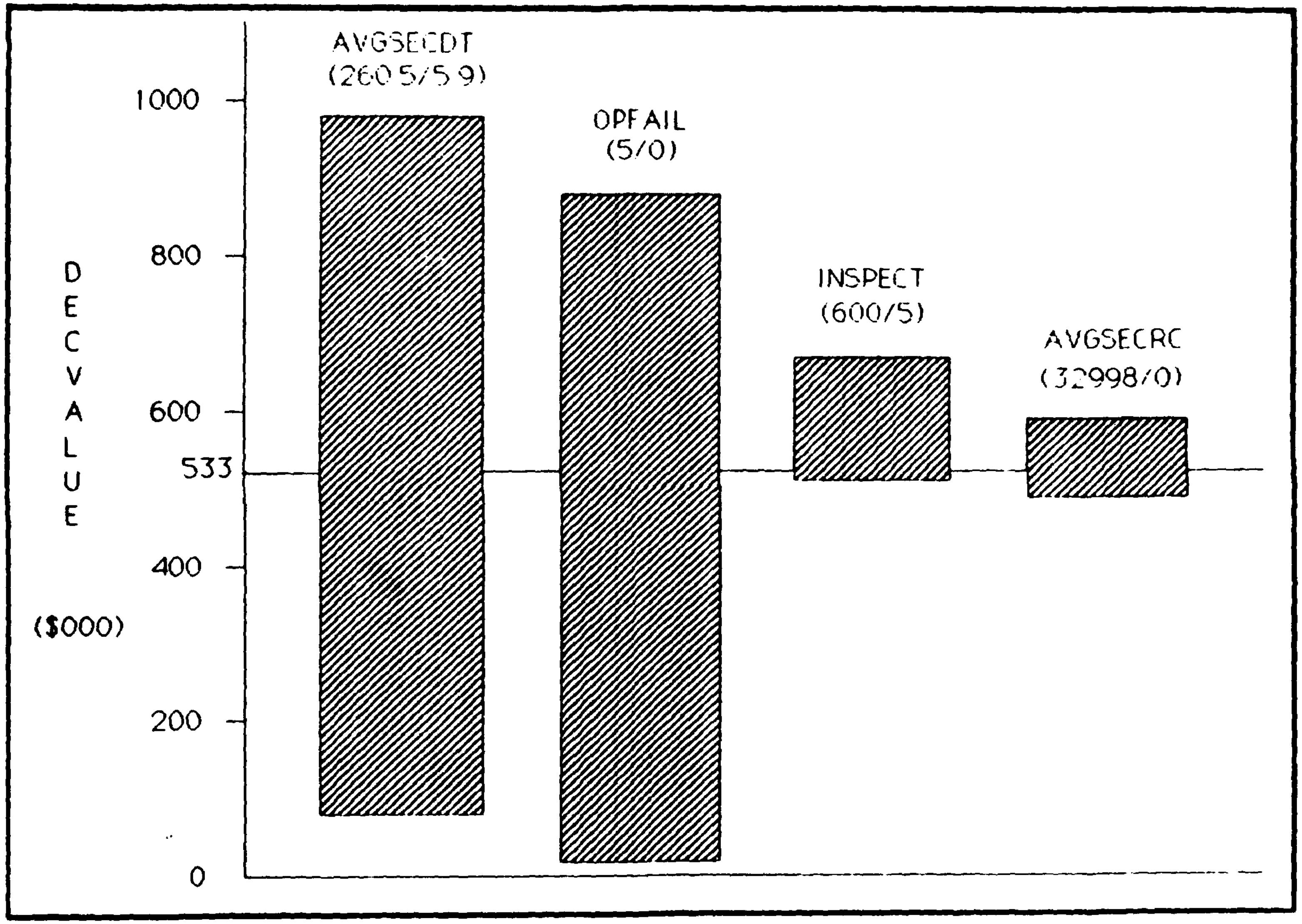


Figure 6. Results of Common Method Deterministic Sensitivity Analysis

response surface method is that the variables analyzed must be independent of each other, which is true for the deterministic effects of these four variables.) The full 2^4 factorial design matrix used is shown in Appendix E. For simplification, only two-way interaction effects were considered. SAS was used to perform the regression on the data. PROC REG was used first to fit a regression model and then PROC STEPWISE was used as a follow-up to reveal the order in which the independent variables entered the regression model. The SAS Program File used to accomplish this is shown in Appendix E.

The t-statistics for each effect are the key statistics of interest here. The F and R^2 statistics for the model are very high, as expected, since the only error in the model is lack of fit, not random error. A standard ANOVA t-test was performed by SAS on each effect, testing the null hypothesis that the effect had a coefficient of zero (i.e. the effect was insignificant). In the t-test, a critical value of t, with some chosen confidence level, is taken from a table for the t distribution and compared to a calculated value of t from the data. If $|t|_{data} < t_{critical}$ the null hypothesis cannot be rejected, the coefficient of the effect will be assumed to equal zero, and the effect will be considered insignificant. However, if the probability of $|t|_{data} < t_{crit}$ is small, then the effect will be assumed to have a non-zero coefficient and the effect will be considered significant. Table 1 lists for each effect the probability that $|t|_{data}$ is less than t_{crit} based on a confidence level of 90%.

Table 1. Response Surface Method t-Statistics for Effects

Effect	Probability |t| data < t crit
INSPECT	.0001
OPFAIL	.0001
AVGSECRC	.0001
AVGSECDT	.0001
OPFAIL*AVGSECRC	.0001
OPFAIL*AVGSECDT	.0001
INSPECT*OPFAIL	.3079
INSPECT*AVGSECRC	.3079
INSPECT*AVGSECDT	.3079
AVGSECRC*AVGSECDT	.3079

Based on these statistics, all four main effects are significant as well as OPFAIL's interaction with AVGSECRC and AVGSECDT.

The summary of the stepwise regression procedure is shown in the table below.

Table 2. Response Surface Method Stepwise Regression Summary

Step	Effect
1	OPFAIL
2	AVGSECDT
3	OPFAIL*AVGSECDT
4	INSPECT
5	AVGSECRC
6	OPFAIL*AVGSECRC

(Effects not shown in the summary were not significant enough at the .10 level for entry into the regression model.) This stepwise regression

summary indicates the relative rank of the effects in terms of statistical significance on the decision value. Notice that an interaction effect, OPFAIL*AVGSECDT is more significant than the main effects for INSPECT and AVGSECRC.

Comparing Results. For this decision model, the two different methods of performing deterministic sensitivity analysis yielded slightly different indications of what variables were significant to the decision value. The common method showed the following ranking based on magnitude of DECVALUE change:

1) AVGSECDT
2) OPFAIL
3) INSPECT
4) AVGSECRC

It also indicated that AVGSECRC may be relatively insignificant because of its small effect compared to the other variables. Conversely, the response surface method yielded the following ranking based on ANOVA statistics:

1) OPFAIL
2) AVGSECDT
3) INSPECT
4) AVGSECRC

Using the common method, the analyst may choose to simplify the AVGSECRC variable by setting it to a constant nominal value. In contrast, using the response surface method, the analyst would probably keep all four variables intact since they all have statistically significant effects on DECVALUE by that method of evaluation.

The differences between these two methods would be even more dramatic if a decision model was evaluated in which the response surface method brought a two-way interaction effect into the regression model before it brought in one or both of the component main effects. If this was the case, the common method would screen out a component main effect because of its stand-alone insignificance. In contrast, the response surface method would indicate to the analyst that the component variable should be left intact because of its significant interaction effect.

Summary of Assumptions

The previous section explained how the Anti-Skid subsystem model was developed. In the process, several important assumptions were made. These assumptions are summarized below:

1) The decision maker chooses the best alternative based on expected value.

2) The interval chosen will remain in effect for two years (i.e. decision duration equals 2 years)

3) Operational activity for aircraft in the B-1B fleet evens out from aircraft to aircraft over a two-year time period.

4) Operational B-1B aircraft activity at Dyess AFB is representative of the other B-1B bases.

5) Time between failures of the Anti-Skid subsystem can be modeled as an exponential distribution.

6) Repair costs and downtime resulting from failures of Anti-Skid subsystem components are the same for operational and potential failures.

7) Anytime an inspection is performed, all potential failures will be correctly identified within the inspection quality (IQ) limits.

8) Once identified, all potential failures will be fixed correctly.

9) Inspections will not induce failures.

10) Loss of human life is not a possible consequence of a B-1B Anti-Skid subsystem failure.

IV. Model Analysis

Introduction

This chapter presents the solution and follow on sensitivity analyses for the B-1B Anti-Skid subsystem decision model, all of which is intended to serve as an example for analyses of other aircraft subsystems. The follow-on analyses performed were stochastic sensitivity analysis, preference sensitivity analysis, expected value of perfect information, and expected value of control. These analyses are an important, integral part of the overall decision analysis process because they systematically measure the importance of key variables in the decision. Also, they can provide answers to "what if" questions on the initial solution which will inevitably occur in the mind of the decision maker.

Stochastic sensitivity analysis is different from the deterministic sensitivity analysis performed in the model development phase of the decision analysis in that instead of merely measuring the change in decision value (DECVALUE) when other variables change, it measures the change in the expected value of the optimal decision alternative (called the "certain equivalent") as the variable under study changes from high to low. Also, the other random variables in the model are not temporarily set at nominal values, but are allowed to vary stochastically through their ranges. Preference sensitivity analysis is similar to stochastic sensitivity analysis except that it examines changes in the certain equivalent caused by changes in constants which the decision maker will set (i.e. they are subject to his preference).

The first section in this chapter identifies the best decision alternative for the baseline model. (The baseline model is the decision

model for the Anti-Skid subsystem in which the variables have been set as explained in the Model Development chapter.) Once the baseline solution is established, the various analyses are presented in the order in which they were performed.

Solution for the Baseline Model

The influence diagram for the B-1B Anti-Skid subsystem was solved using the microcomputer-based INDIA software package. With INDIA, once the influence diagram is input, the "Analyze" command solves for the decision alternative having the minimum expected value (cost). Of the three alternative inspection intervals (5, 100, and 600), 5 had the lowest expected value, equal to a certain equivalent of $144,240. (In the current B-1B flying program, 5 flying hours roughly equates to one sortie.) A comparison of the expected value for each of the three decision alternatives is shown in Figure 7.

An interesting attribute of this alternative is that, since in the baseline model inspection quality (IQ) also equals 5 flying hours, no operational failures will be experienced. In other words, the best decision is to perform inspections every 5 flying hours so that operational failures can be avoided between inspections. The reason this alternative has the lowest expected value (costs) is because without operational failures occurring, there is no risk of incurring any costly secondary consequences. The relationship here between the inspection interval and IQ is similar to what exists for items placed on preflight inspection checklists. The consequences of failures for these items are serious enough that inspections are done every flight with the assumption that operational failures will be avoided. The inspection quality is assumed to be at least as long as the average sortie, so that failures

which would otherwise occur between inspections are detected during the inspections.

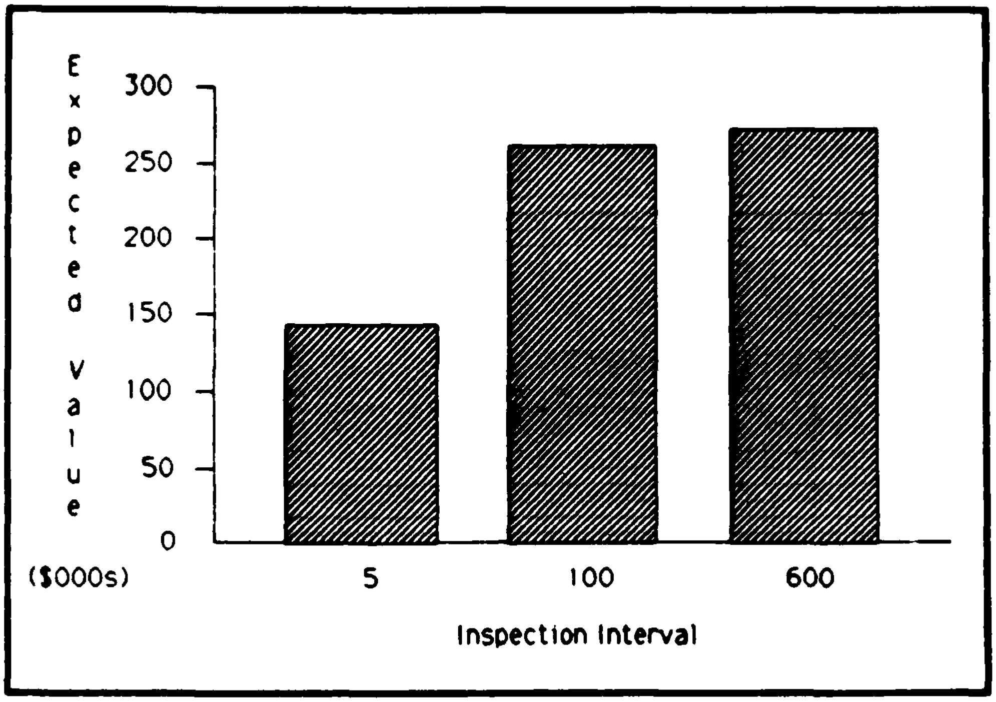


Figure 7. Comparison of Expected Value for Decision Alternatives

How does this solution change with changes in IQ, MTBF, etc? Answering this question is the objective of the following sections.

Stochastic Sensitivity Analysis

The variables normally included in a stochastic sensitivity analysis are the decision variable and all random variables in the model. For the B-1B Anti-Skid subsystem influence diagram these variables are the decision alternatives (INSPECT), MTBF, number of operational failures (OPFAIL), average secondary repair costs (AVGSECRC), and average secondary downtime (AVGSECDT). As an exception, this analysis also

investigated the model's stochastic sensitivity to different values of IQ even though it is treated as a constant in the model.

The graph shown in Figure 8 shows the relative stochastic sensitivity of the model's certain equivalent to each variable. Judging by magnitude of change, all variables except MTBF and AVGSECRC have significant stochastic effects on the certain equivalent. The nil effects of these two variables mean that no matter what outcome in their ranges these two variables take on, the certain equivalent of the decision will not change from the optimal value of $144,240, nor will the optimal decision alternative of inspecting every 5 flying hours change. The reason MTBF has no effect on the baseline solution is that no matter what MTBF is, the decision to inspect every 5 flying hours will avoid all operational failures and the costly secondary consequences. The reason AVGSECRC has no effect is that even at its low value, the model will still want to avoid secondary consequences because AVGSECDT is so substantial. If AVGSECRC is at its high value, secondary consequences are even more costly, and the model will certainly stay with the decision to avoid all operational failures.

All the foregoing results apply to the baseline model which has IQ = 5. Next, a separate analysis was performed on IQ to investigate how the decision might change with IQ set at other values in its range. The results of this analysis are shown in Figure 8 with the original sensitivity analysis on the other variables.

The analysis on IQ reveals that the certain equivalent and decision do change when IQ moves from 5 hours to an extreme value of 1 hour. However, when IQ is set to the other extreme of 20 hours, the certain equivalent and decision are unchanged. Consequently, an additional

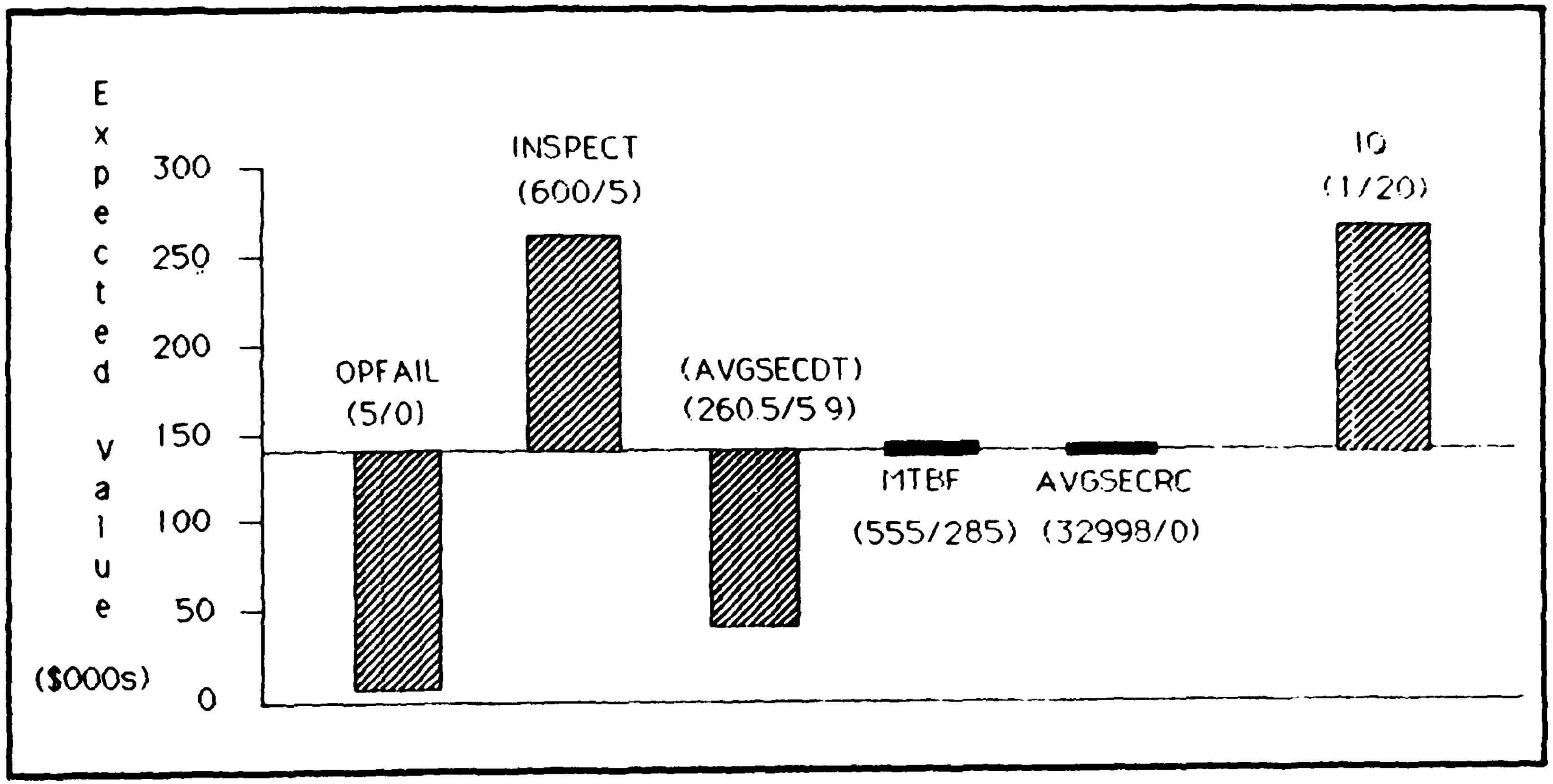


Figure 8. Results of Stochastic Sensitivity Analysis on Baseline Model

stochastic sensitivity analysis was performed with IQ set equal to 1 hour to see if MTBF would become a significant factor in the decision. The only random variable included was MTBF because its nil effect in the baseline model was caused by the INSPECT = 5, IQ = 5 combination.

The graph in Figure 9 shows the stochastic sensitivity analysis performed with IQ = 1.

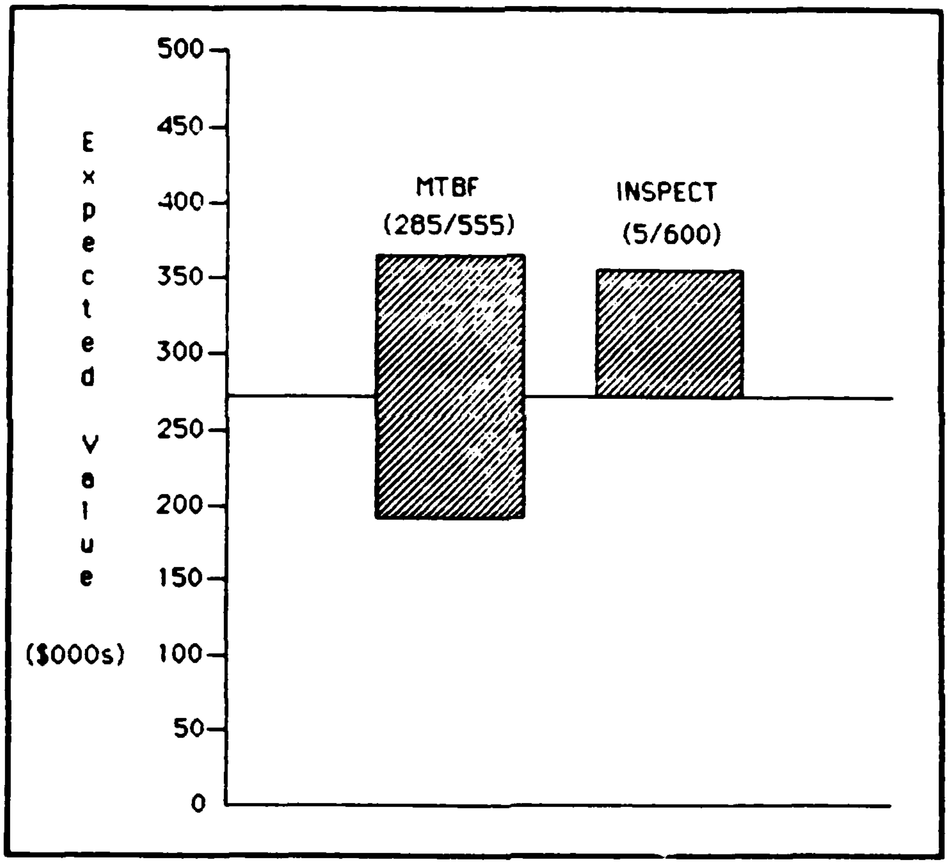


Figure 9. Results of Stochastic Sensitivity Analysis with IQ = 1

In this second analysis, the certain equivalent is now $270,020 and the optimal decision is to inspect every 600 flying hours. Now, the certain equivalent is sensitive to a change in MTBF, but the optimal

decision is not. With IQ = 1, no matter what value MTBF takes on in its defined range, the optimal decision will be to inspect every 600 flying hours. The reason for this is because with IQ = 1, inspections are ineffective; they have little chance of preventing operational failures, so inspections might as well not be performed during the two-year time period.

Since stochastic sensitivity analysis revealed that the best decision alternative changes from 5 to 600 when IQ changes from 5 to 1, this range of IQ was investigated further. The impact of changes in IQ on the expected value of each alternative is shown in Figure 10. This analysis reveals that the optimal decision alternative changes from 5 to 100 hours when IQ drops below 3 hours and then it quickly changes to 600 hours.

Also, as a general result, this analysis verifies intuition by showing that having inspection quality (IQ) greater than the inspection interval (INSPECT) is overkill. Notice how the expected value for INSPECT = 5 levels off past IQ = 5. Improving IQ past 5 adds no benefit to the 5 hour inspection interval, but it does lower the costs of the other alternative intervals. Clearly, if the curves of INSPECT equal to 100 and 600 were projected further for very high values of IQ, they would eventually drop below the curve for INSPECT = 5 and become better alternatives. They also would level off when IQ equaled 100 and 600 respectively.

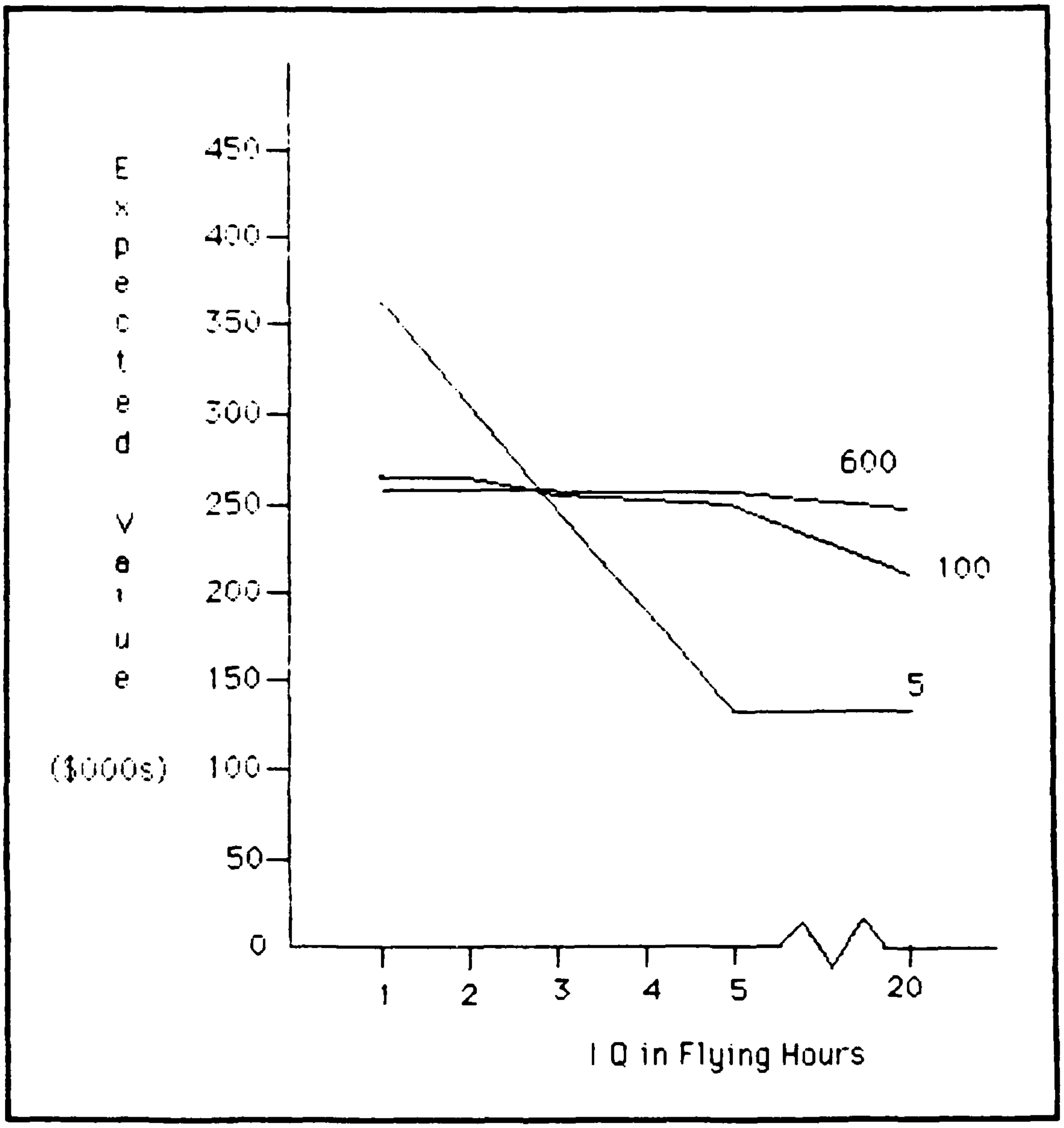


Figure 10. Expected Value of Decision Alternatives for Various IQ Values

Preference Sensitivity Analysis

The purpose of preference sensitivity analysis is to investigate other values or ranges of values which key "controllable" variables may take on. The only variable included in this analysis was the value of one hour of aircraft availability (AVAILVALUE).

AVAILVALUE represents the deterministic value which the decision maker places on an hour of aircraft availability. It is a measure of the subjective value he/she places on the B-1B's contribution to national defense. The value used in this decision model was $1182, an approximation derived from acquisition costs. The decision maker may want to adjust this value. How would the certain equivalent and decision change from the baseline solution if AVAILVALUE was changed? Figure 11 shows how the expected value of each alternative changes with + and - 100% changes in AVAILVALUE. This graph shows that with all other variables set as determined for the baseline case, changes in AVAILVALUE do not change the optimal decision. For any value of AVAILVALUE, the best decision is still to inspect every 5 flying hours. (Actually, this conclusion is probably not valid for large changes in AVAILVALUE, since variables simplified or deleted in the model, such as POTFAIL, may suddenly become significant when AVAILVALUE is small. A reappraisal of the model should be undertaken if AVAILVALUE is set significantly lower than $1182.) The reason for this insensitivity is that inspecting every 5 flying hours avoids all operational failures, thus avoiding costly secondary consequences. A small value would have to be placed on availability before avoiding operational failures would no longer be an attractive alternative.

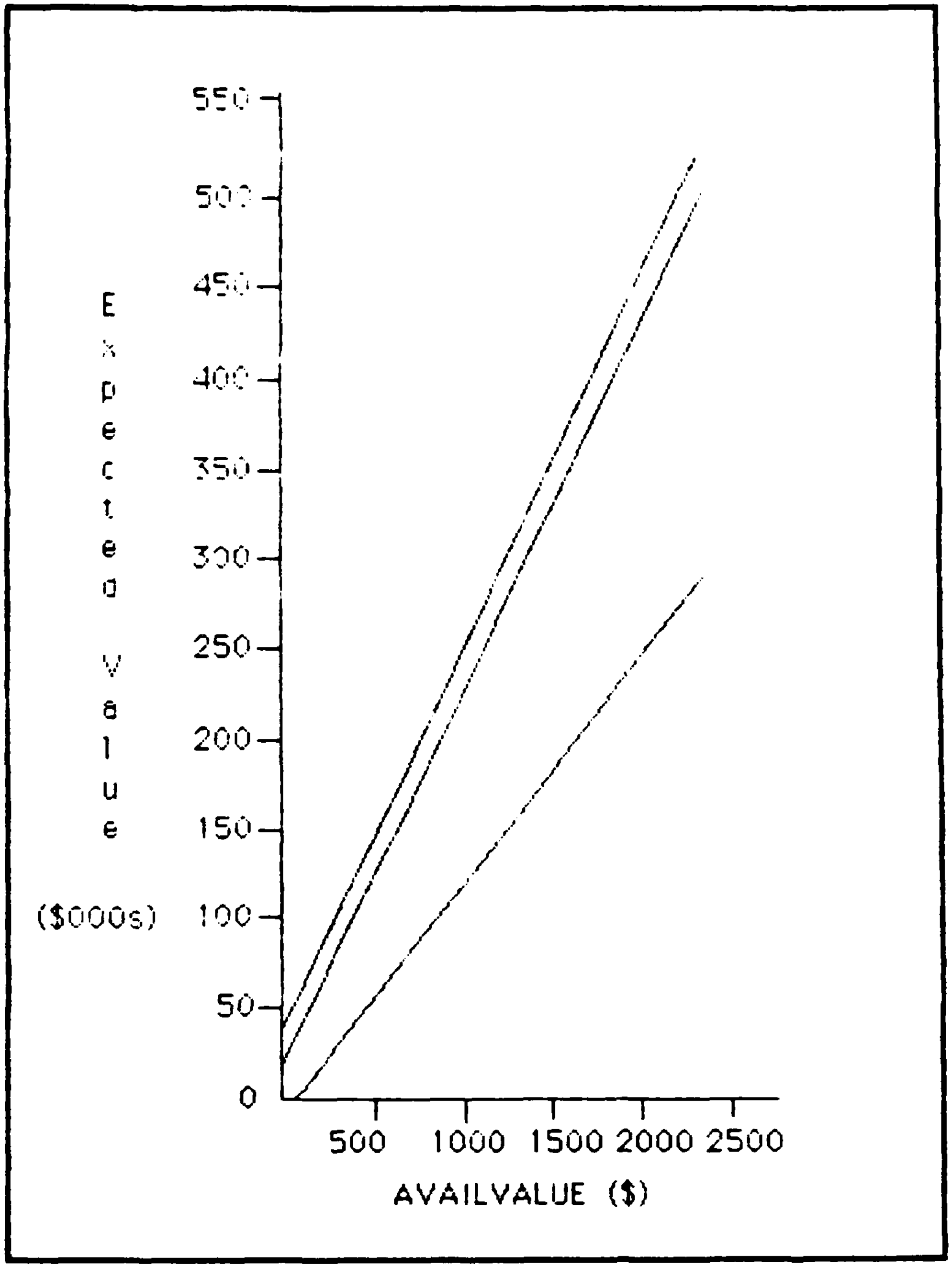


Figure 11. Preference Sensitivity Analysis on AVAILVALUE

Expected Value of Perfect Information (EVPI)

EVPI provides an upper limit for the value of additional information on a given random variable in the model. For example, suppose a contractor offered to do an actuarial analysis on MTBF (at 95% confidence level) for $25,000 in order to help the decision maker decide on the best inspection interval. By computing the value of knowing MTBF perfectly (100% confidence level), an EVPI analysis would indicate whether this offer was reasonable or not.

EVPI is obtained by first measuring the certain equivalent of the model when the decision maker is assumed to know (i.e. have perfect information on) the value of the random variable being analyzed. This expected value with perfect information is then compared to the original certain equivalent of the decision. The absolute difference between the two is the EVPI for the given variable. In the influence diagram, this is performed by adding an arc from the random variable to the INSPECT node. This symbolizes that information about the random variable is known before the inspection interval decision is made.

EVPI calculations were performed on the baseline model (IQ = 5) and for an additional situation where IQ = 1. For the baseline model, the variables analyzed were the random variables MTBF, AVGSECRC, and AVGSECDT. For the IQ = 1 case, only MTBF was analyzed.

The EVPI calculations for the baseline model are shown in Table 3.

Table 3. EVPI, Baseline Model

Variable	EVPI Calculation		EVPI
MTBF	| $144,240 - 144,240 |	=	$0
AVGSECRC	| $144,240 - 144,240 |	=	$0
AVGSECDT	| $118,570 - 144,240 |	=	$25,670

The fact that EVPI for MTBF and AVGSECRC equals $0 is not surprising since the stochastic sensitivity analysis on the baseline model revealed that the certain equivalent and optimal decision were not sensitive to changes in these variables. These calculations confirm the common sense notion that the decision maker would not want to pay any money for information on variables that had no effect on his decision. Conversely, EVPI for AVGSECDT has value to the decision maker, and such information would change the certain equivalent to a lower value (cost). However, $25,670 is the most the decision maker would want to invest to gain more information about AVGSECDT.

The EVPI calculation for MTBF in the case of IQ = 1 is shown below:

$$\text{EVPI for MTBF} = |\ 270{,}020 - 270{,}020\ | = \$0 \tag{7}$$

The reason why EVPI for MTBF is $0 in this case is because <u>knowing</u> the value of MTBF ahead of time does not allow the decision maker to avoid any costs and the optimal decision would stay the same (as shown in the stochastic sensitivity analysis, Figure 9.) However, as described next, <u>controlling</u> MTBF would have value.

Expected Value of Control (EVC)

The EVC represents the value to the decision maker of being able to control, by design, the outcome of MTBF. The calculation for EVC in the case of IQ=1 is shown below:

$$\text{EVC} = |\ 192{,}145 - 270{,}020\ | = \$77{,}875 \tag{8}$$

This means that $77,875 would be saved if the decision maker could set MTBF to the best value in its range (555). If this was possible, the best decision would be to not inspect during the two-year time period.

V. Recommendations

The general model presented in this thesis is a meaningful representation of the base-level inspection interval decision. Using this model can help the SPM and his staff breakdown this inherently complex and subjective decision into the individual issues that must be quantified. Through the decision analysis process, a qualified analyst must modify the general model into a model tailored for the particular subsystem being studied. The specific model developed in this thesis for the B-1B Anti-Skid subsystem serves as an example of how this process could be carried out.

However, performing a decision analysis of this caliber is no small task, and the analyst doing it must have formal training in decision analysis techniques. This training is necessary to develop expertise at conducting expert opinion interviews, statistical analysis, etc. More often than not, statistical data for the random variables will be non-existent or highly suspect. Consequently, considerable expertise is required to obtain the necessary information. Also, as is true for any evaluation, it is preferable that the analyst have first-hand exposure to the aircraft subsystem being evaluated. This knowledge is especially helpful in modifying the general decision model to represent the decision for a specific aircraft subsystem.

Due to the considerable investment of time and energy required to perform a thorough decision analysis, not every aircraft subsystems should be analyzed in this manner. The best candidates for a decision analysis are those subsystems on the aircraft which are considered either costly to inspect or costly to not inspect (in terms of possible operational consequences.) The type of decision analysis presented here

would provide a thorough treatment of these "strategic" decisions, but it is too pain-staking for subsystems of lesser consequences.

Since the general model is intended to serve as a shell to be uniquely modified for specific subsystems, specific recommendations about which variables to modify are not appropriate. However, the function of one important variable, inspection quality (IQ), could be modified and investigated in a follow-on decision analysis thesis.

Currently, IQ is treated as a random variable in the general model, but it may be possible to model it as a decision variable. As was explained earlier, this variable is influenced by how rigorous of an inspection the SPM wants his/her maintenance personnel to perform. Therefore, it is arguable that IQ could be modeled as a decision variable, like INSPECT, rather than a random variable. In this case the model would be representing two decisions: how often to inspect and how thorough to inspect.

Another area that may prove fertile for further research is deterministic sensitivity analysis. Of the two methods compared in this thesis, the response surface method seemed superior. It allowed for a more systematic screening of variables for significance because it formally considered interaction (multi-variable) effects as well as main (single variable) effects and judged significance on proven statistical tests. The comparison between the two methods should be carried further by applying them to other decision analysis problems.

Even though it is primarily intended to serve as an example, the decision model presented here specifically for the B-1B Anti-Skid subsystem should prove very useful to the B-1B SPM and his staff. It identifies the issues they should consider when making the inspection

interval decision for the Anti-Skid subsystem. Clearly, the range of outcomes, probability distributions, and value functions for these variables should be completely reviewed and verified by the SPM staff before the decision recommended in this thesis is adopted. Stochastic sensitivity analysis has shown that those variables deserving special attention during verification are number of operational failures (OPFAIL), secondary downtime (SECDT), average secondary downtime (AVGSECDT), and inspection quality (IQ).

Interestingly, MTBF was not a significant variable in the B-1B Anti-Skid subsystem analysis. The analysis showed that for a MTBF varying stochastically over a range of 285 to 555 flying hours, the effect on the decision was minimal. However, if the MTBF could be designed with no uncertainty to a value of 555 flying hours, the decision would change and inspections during the two-year time period would not be necessary.

If inspection quality (IQ) is found to actually be greater than 5 for the Anti-Skid subsystem, another decision alternative, equal to the actual IQ should be considered. In the model presented here, IQ was equal to 5 flying hours which allowed the 5 hour inspection interval to result in preventing all operational failures. However, if IQ is greater than 5, 10 for example, then an inspection interval of 10 hours would become the best interval. It would result in less inspection costs because of fewer inspections and yet still prevent all operational failures. It is important to keep in mind that the alternatives considered should be ones which could be practically implemented by base-level maintenance. Nò alternative should be considered which the SPM or base-level maintenance personnel would not consider implementing.

Another value which must be coordinated with the SPM is the value of availability (AVAILVALUE). The research presented here used an approximation for AVAILVALUE that may not be acceptable to the current SPM. Although this analysis revealed that for the B-1B Anti-Skid subsystem AVAILVALUE did not impact the decision, in general it is a significant factor and with stochastic sensitivity analysis the decision maker can easily explore other ranges of value.

The SPM may also want to relax some of the assumptions made in this thesis. In particular, the SPM may not be an expected value decision-maker. If this is the case, a unique utility function must be derived and applied to DECVALUE, transforming DECVALUE (dollars) into utility (unitless). This would more accurately model the decision maker's attitude toward the true value of the decision outcomes. Another assumption which may need to be relaxed is the homogeneous fleet assumption. In many cases, the flying activity varies greatly from base to base even for the same aircraft type. In these cases, a specific model would have to be built for each base if the SPM wanted to treat each base independently because of the different flying programs.

Lastly, although loss of human life was not included as a possible consequence in either of the models in this thesis, it is a possibility for some aircraft subsystems and should not be ignored in the analysis. In these cases the loss of human life should be addressed in a value of life variable and an average number of lives lost variable. Then these two variables could be multiplied together and added into the secondary consequences function (SECCONSQ). As with the value of availability, through sensitivity analysis the decision maker could vary the value he/she places on life and see the impact on the optimal alternative.

VI. Conclusion

Inspection interval decisions often must take into account complex operational failure consequences which can only be measured subjectively. Current methods of analysis, CMIP for example, ignore subjective aspects of the decision such as risks of failure consequences, value preferences of availability and decision outcomes, and the reliability of failure data. These types of issues are the realm of decision analysis.

The decision analysis presented in this thesis identified the most important issues bearing on the decision and modeled them in an influence diagram. The diagram can be solved by existing software packages which identify the best decision alternative for a given state of information. These programs also can assist in performing the different types of postsolution analyses which reveal to the decision maker the key variables and the degree to which they affect the decision.

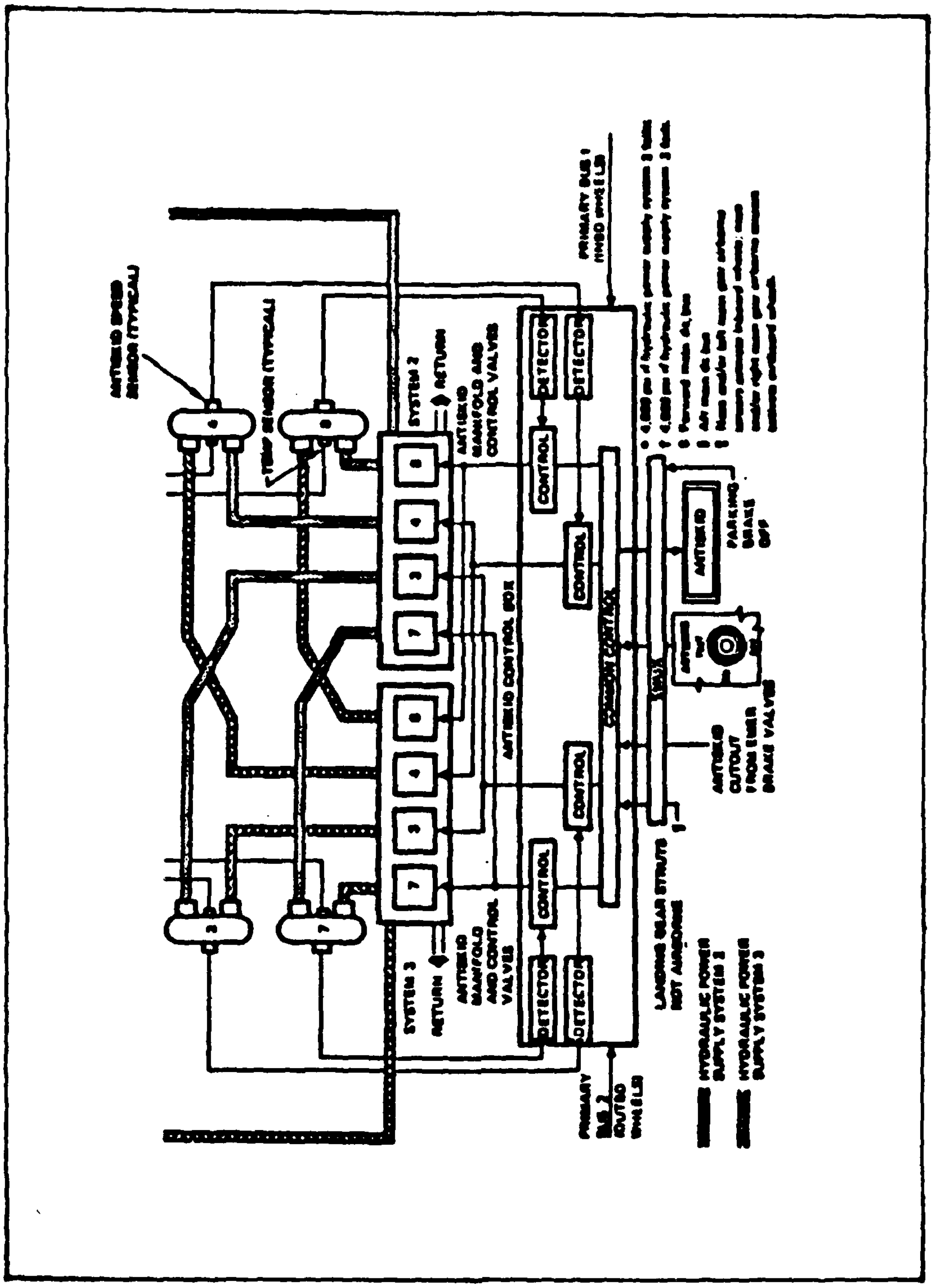
Two influence diagram models were created for use by AFLC SPM organizations. First, a general decision model was constructed that is able to accommodate the decision structure for most aircraft subsystem inspections. In most cases, modification of the general model's structure will be both necessary and prudent when applying it to a specific subsystem.

An example of how a decision analysis would be performed for a specific subsystem decision was accomplished using the B-1B Anti-Skid subsystem. This relatively simple subsystem was analyzed in order to serve as a learning tool for USAF analysts wishing to learn about and adopt the decision analysis approach to inspection interval analysis.

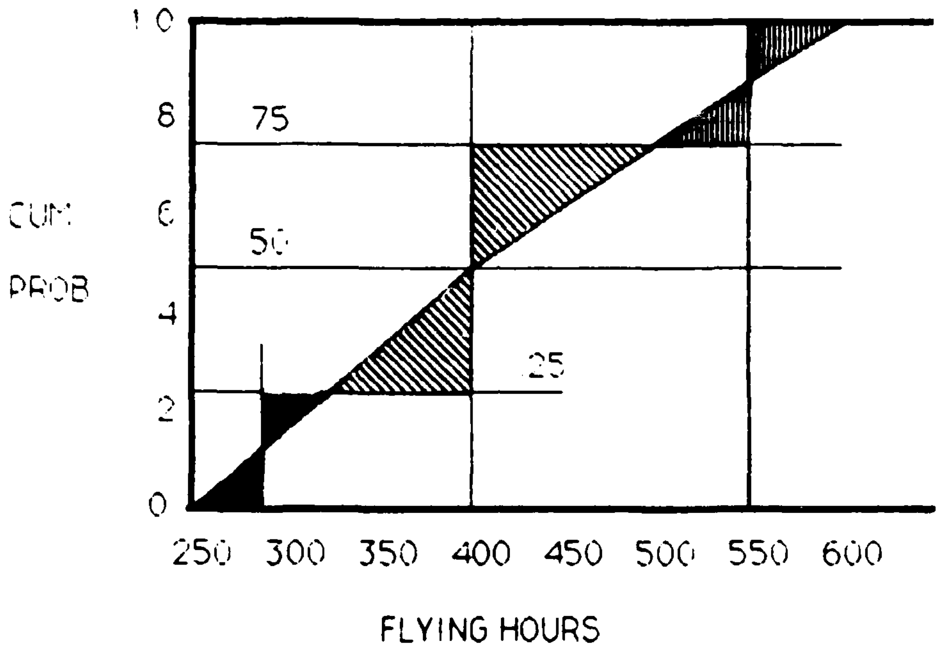
Finally, many important recommendations were given, emphasizing the limitations and applicability of the decision analysis approach. It is

self-evident that decision analysis is not simple enough to be used on every aircraft subsystem requiring periodic inspection. However, it is a thorough way to decide how often to inspect subsystems where the risks, costs, and other consequences of operational failures are high and difficult to quantify.

Appendix A: <u>B-1B Anti-Skid Subsystem Breakdown/Function Description</u>



Appendix B: <u>Graphical Sectioning of the MTBF Probability Distribution</u>



Explanation: The vertical lines were drawn at the points corresponding to 555, 410, and 285 because at these points the areas of like shading are equal to each other. These values can be used as approximations for the 75th, 50th, and 25th fractiles.

Appendix C: OPFAIL Probability Distributions (Baseline Model)

		Number of OPFAIL					
INSP	MTBF	0	1	2	3	4	5
5	285	1	0	0	0	0	0
100	285	0.135335	0.270670	0.270670	0.180447	0.090223	0.052653
600	285	0.123969	0.258813	0.270165	0.188009	0.098127	0.060914
5	410	1	0	0	0	0	0
100	410	0.249014	0.346190	0.240644	0.111518	0.038759	0.013871
600	410	0.234284	0.339998	0.246705	0.119341	0.043297	0.016372
5	555	1	0	0	0	0	0
100	555	0.358069	0.367747	0.188843	0.064649	0.016599	0.004091
600	555	0.342298	0.366968	0.196708	0.070295	0.018840	0.004888

Appendix D: Derivation of Discrete Values for AVGSECDT from SECDT

1. Assume AVGSECDT probabilities are distributed as a Normal probability distribution.

2. $E(SECDT) = 325(.25) + 100(.50) + 8(.25) = 133.25$

3. $VAR(SECDT) = E(SECDT^2) - [E(SECDT)]^2$

$$= 31422.25 - (133.25)^2$$
$$= 13666.69$$

4. Use E(OPFAIL) for n:
With MTBF = 410, INSPECT = 100, and IQ = 5, E(OPFAIL) = 1.37

5. $E(AVGSECDT) = \sum_{i=1}^{n} 1/n \; E(SECDT)$

$$= n(1/n)\;(133.25)$$
$$= \underline{133.25}$$

6. $VAR(AVGSECDT) = \sum_{i=1}^{n} (1/n)^2 \; VAR(SECDT)$

$$= (1/n)^2 \sum_{i=1}^{n} VAR(SECDT)$$
$$= (1/n)^2 \;(n)\; VAR(SECDT)$$
$$= VAR(SECDT)/n = 13666.69/1.37 = 9975.69$$

7. $Std\ Dev(AVGSECDT) = [VAR(AVGSECDT)]^{1/2} = 99.84$

8. For a Standard Normal probability distribution:

$Z = (X - mean)/std\ dev$

For the 75th fractile (x), Z = 1.275 so,

$$1.275 = (x - mean)/std\ dev$$
$$x = mean + 1.275(std\ dev)$$
$$= 133.25 + 1.275(99.84)$$
$$= \underline{260.546}$$

For the 25th fractile (y), Z = -1.275 so,

$$-1.275 = (y - mean)/std\ dev$$
$$y = mean - 1.275(std\ dev)$$
$$= 133.25 - 1.275(99.84)$$
$$= \underline{5.954}$$

Appendix E: SAS Input Matrix and Program File

2^4 Design Input Matrix

OBS	INT	OPF	ASRC	ASDT	IO	IARC	IADT	OARC	OADT	ARCDT	CVAL
1	-1	-1	-1	-1	1	1	1	1	1	1	144240
2	1	-1	-1	-1	-1	-1	-1	1	1	1	1202
3	-1	1	-1	-1	-1	1	1	-1	-1	1	205568
4	1	1	-1	-1	1	-1	-1	-1	-1	1	62530
5	-1	-1	1	-1	1	-1	1	-1	1	-1	144240
6	1	-1	1	-1	-1	1	-1	-1	1	-1	1202
7	-1	1	1	-1	-1	-1	1	1	-1	-1	370558
8	1	1	1	-1	1	1	-1	1	-1	-1	227520
9	-1	-1	-1	1	1	1	-1	1	-1	-1	144240
10	1	-1	-1	1	-1	-1	1	1	-1	-1	1202
11	-1	1	-1	1	-1	1	-1	-1	1	-1	1710206
12	1	1	-1	1	1	-1	1	-1	1	-1	1567168
13	-1	-1	1	1	1	-1	-1	-1	-1	1	144240
14	1	-1	1	1	-1	1	1	-1	-1	1	1202
15	-1	1	1	1	-1	-1	-1	1	1	1	1475196
16	1	1	1	1	1	1	1	1	1	1	1732158

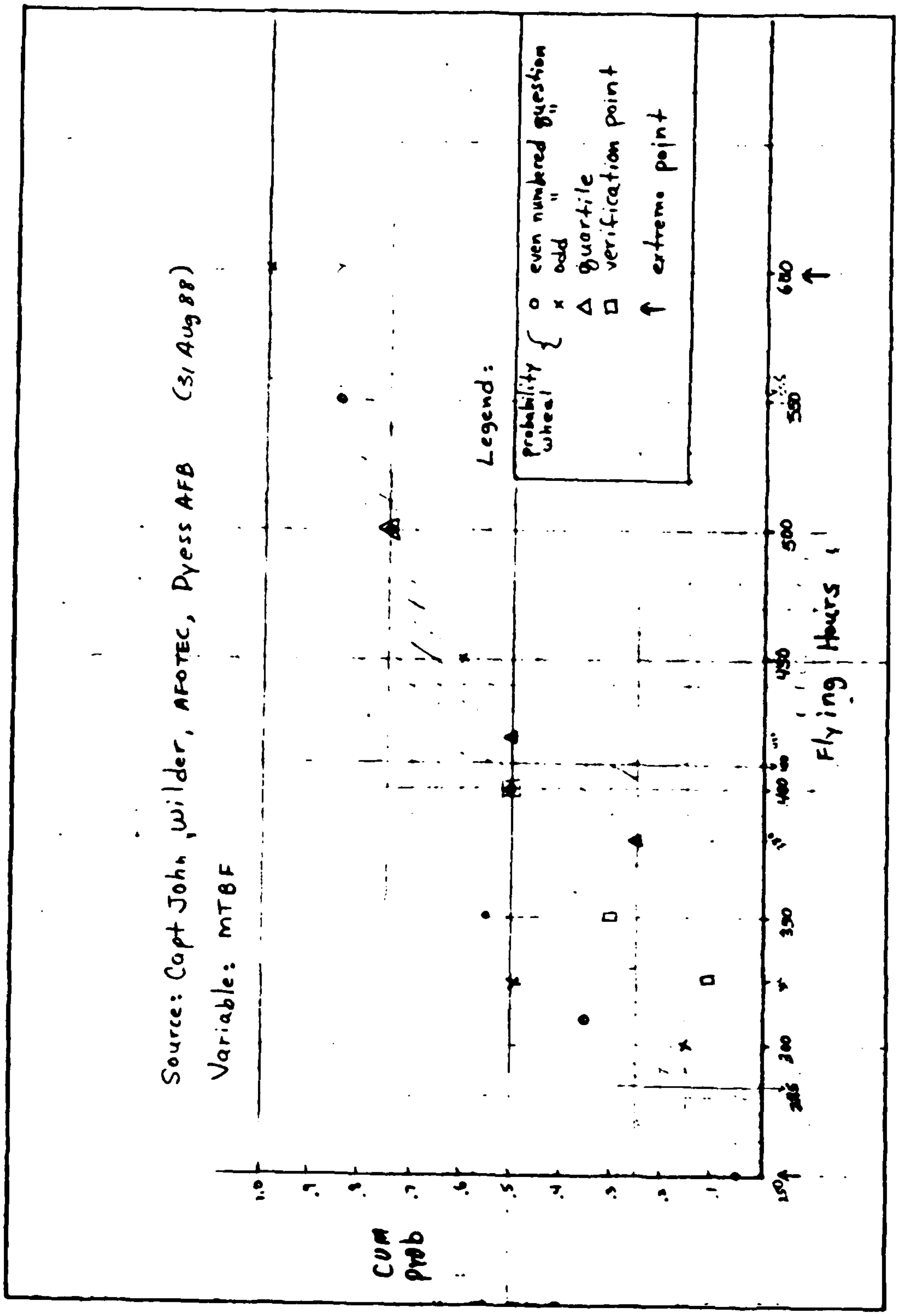
Program File

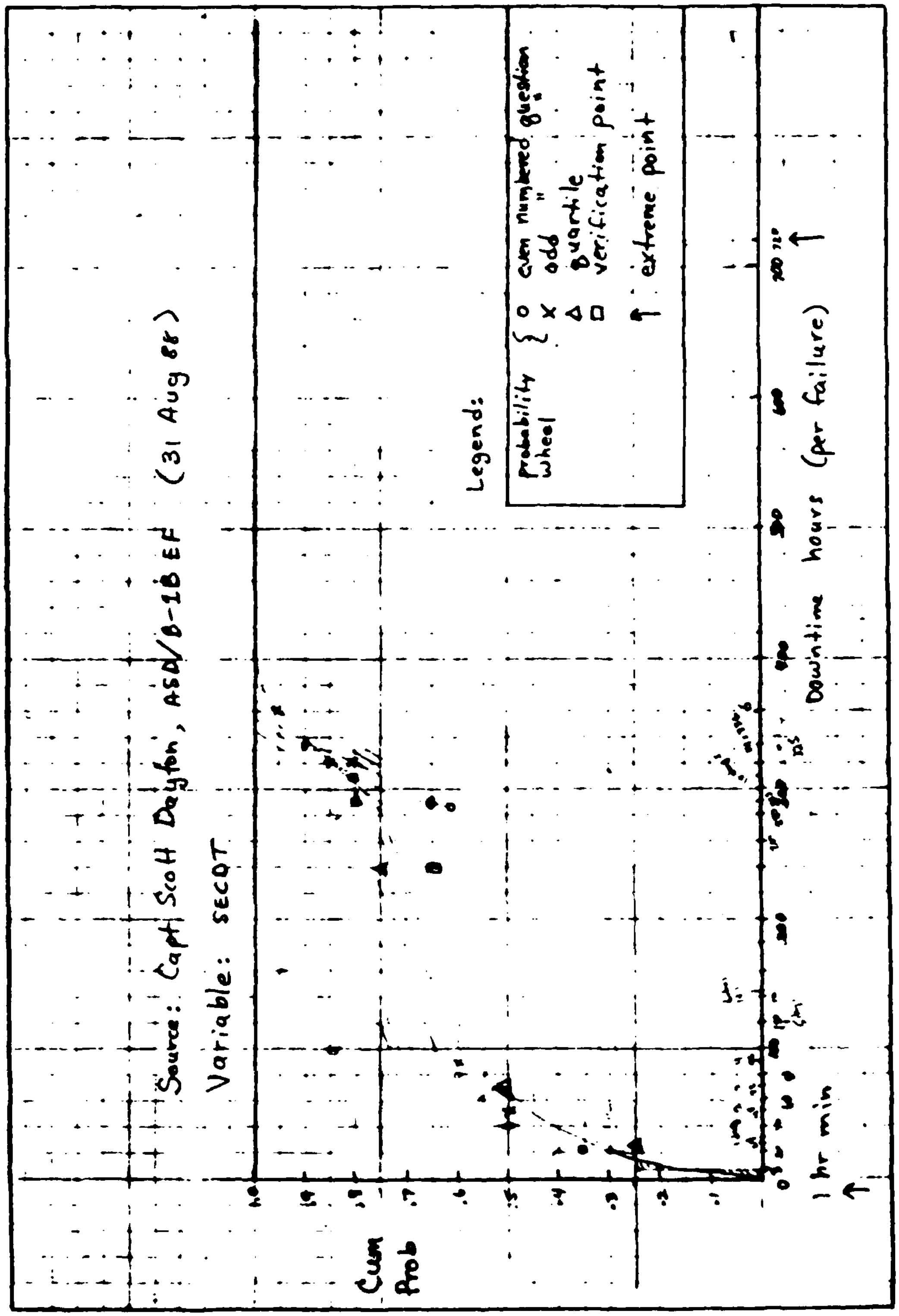
```
OPTIONS LINESIZE=80;
FILENAME RSM 'SAS1.DAT';
DATA RSM;
INFILE RSM;
INPUT INT OPF ASRC ASDT CVAL;
IO = INT * OPF;
IARC = INT * ASRC;
IADT = INT * ASDT;
OARC = OPF * ASRC;
OADT = OPF * ASDT;
ARCDT = ASRC * ASDT;
PROC PRINT DATA=RSM;
VAR INT CPF ASRC ASDT IO IARC IACT OARC CADT ARCCT OVAL;
PROC REG DATA=RSM;
 MODEL DVAL = INT OPF ASRC ASDT IO IARC IADT OARC OADT ARCDT /P;
 OUTPUT OUT=Z R=RESICUAL;
PROC PLOT DATA=Z;
   PLOT RESIDUAL * DVAL = '*';
PROC STEPWISE DATA=RSM;
   MODEL CVAL = INT OPF ASRC ASDT IO IARC IADT OARC OADT ARCDT/STEPWISE
               SLENTRY = .10;
```

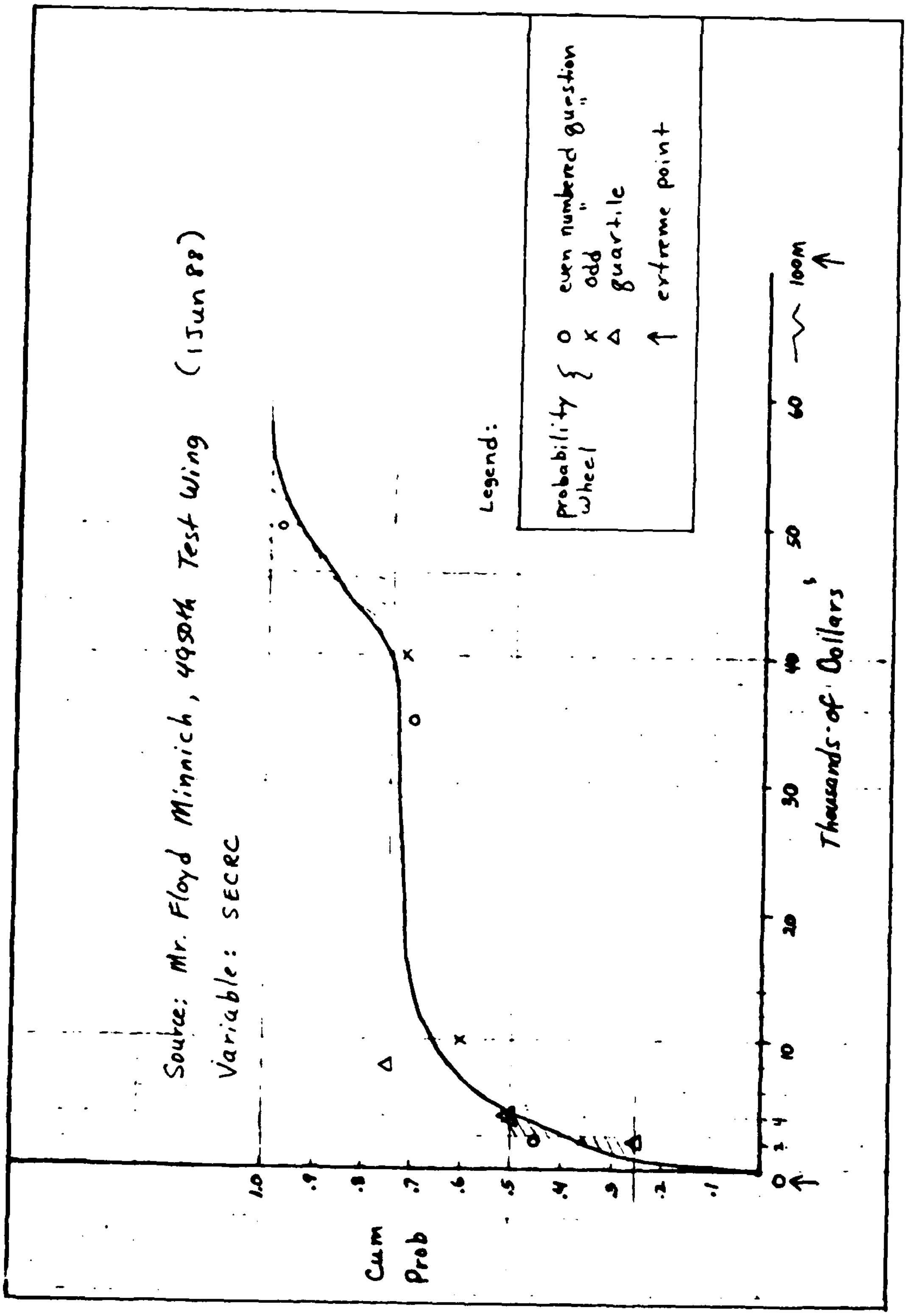
Key

INT = INSPUCT   ASRC = AVGSECRC

OPF = OPFAIL   ASDT = AVGSECDT


Source: Capt John Wilder, AFOTEC, Dyess AFB (31 Aug 88)
Variable: MTBF
Legend:
Probability wheel
o even numbered question
x odd "
Δ quartile
□ verification point
↑ extreme point
CUM Prob
Flying Hours
1.0
.5
250
300
350
400
450
500
550
600


Source: Capt Scott Dayton, ASD/B-1B EF (31 Aug 88)
Variable: SECDT
Legend:
Probability wheel
even numbered question
odd
quartile
verification point
extreme point
Downtime hours (per failure)
Cum Prob
1 hr min


Source: Mr. Floyd Minnich, 4950th Test Wing (1 Jun 88)
Variable: SECRC
Legend:
Probability Wheel
o even numbered question
x odd "
Δ quartile
↑ extreme point
Cum Prob
1.0
.9
.8
.7
.6
.5
.4
.3
.2
.1
0
10
20
30
40
50
60
100M
Thousands of Dollars

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Using decision analysis techniques, a general model was developed for base-level aircraft inspection interval decisions. This model differs from current methods such as actuarial analysis and the Computer Monitored Inspection Program in that it is designed to define and measure the significance of the subjective uncertainties and risks inherent in inspection interval decisions. Failure data, cost data, expert opinion, and decision maker preferences are brought together in a single, unified decision-making framework. Decision alternatives are evaluated based on the entire "cost" picture (i.e. repair costs, opportunity costs, and inspection costs). The general model developed in this thesis can serve as a starting point for the analysis, but it must be tailored for the actual subsystems to which it is applied. Once the specific model for a given subsystem is built, it can be analyzed using existing software packages. An example of how the tailoring and analysis may be accomplished is provided in a detailed study of the B-1B Anti-Skid subsystem. The decision analysis approach will be most advantageous when used on subsystems which have potentially serious failure consequences or economical concerns. Keywords.

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