**AIR FORCE CORPORATE EXPOSURE ASSESSMENT STRATEGY: UNDERLYING COST BEHAVIORS & VISIBILITY**

THESIS


Bradley M. Duncan, 1st Lieutenant, USAF



AFIT-ENV-MS-18-M-196



**DEPARTMENT OF THE AIR FORCE**
**AIR UNIVERSITY**

# AIR FORCE INSTITUTE OF TECHNOLOGY

**Wright-Patterson Air Force Base, Ohio**

AFIT-ENV-MS-18-M-196

AIR FORCE CORPORATE EXPOSURE ASSESSMENT STRATEGY: UNDERLYING COST BEHAVIORS & VISIBILITY

THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Cost Analysis

Bradley M. Duncan

1st Lieutenant, USAF

March 2018

AFIT-ENV-MS-18-M-196

AIR FORCE CORPORATE EXPOSURE ASSESSMENT STRATEGY: UNDERLYING COST BEHAVIORS & VISIBILITY

Bradley M. Duncan, BS

1st Lieutenant, USAF

Committee Membership:

Lt Col Robert M. Eninger
Chair

Dr. Robert D. Fass
Member

Lt Col Brandon M. Lucas
Member

AFIT-ENV-MS-18-M-196


## Abstract

The research conducted in this thesis is an initial attempt to identify the costs associated with occupational exposure assessments within the Air Force. Using cost estimation methodologies, a cost model was created to predict the total costs of occupational hazard assessments focused on air sampling. Data was gathered from bioenvironmental engineering databases and subject matter experts for analysis. The data required extensive curation before running a mixed step-wise regression. The major cost drivers for occupational exposure assessments were identified as the sample time and pre-calibration time for conducting an air sample. The average predicted cost was $183.47 with 80% of predicted costs falling between $71.12 and $321.85. It was discovered that much of the data that is applicable to cost was unclear or unrecorded. As changes are implemented to the regulation for conducting these events, this research can provide decision support to Air Force leadership. The Air Force can also use this research's findings to improve upon budgetary tracking and fiscal transparency.

## Acknowledgments

Thank you to my classmates for their unconditional support throughout this process.

Bradley M. Duncan

## Table of Contents

## List of Figures

## List of Tables

# AIR FORCE CORPORATE EXPOSURE ASSESSMENT STRATEGY: UNDERLYING COST BEHAVIORS & VISIBILITY

## I. Introduction

### Background

The United States Air Force is currently revising Air Force Manual (AFMAN) 48-146, Occupational & Environmental Health Program Management, to better align the current methodology of assessing occupational hazards with the industry guideline set by the American Industrial Hygiene Association. Despite having data collected through a variety of information systems such as the Defense Occupation and Environmental Health Readiness System (DOEHRS) and the United States Air Force School of Aerospace Medicine's Laboratory Information Management System (LIMS), there is no current practice for addressing, predicting, and tracking the enterprise-wide costs associated with Department of Defense or corporate policy on exposure assessments. The number of exposure assessments conducted annually, and the amount of data collected is, *prima facie*, enough to conclude that there is a large expense associated with the assessment practices. The impact on future costs by changing the AFMAN are unknown. Information on the cost efficiency of exposure assessments and the optimal design for equitable resource usage is limited.

The Air Force and its employees are mandated to comply with the risk management framework established in AFI 91-202, The US Air Force Mishap Prevention Program. AFI 91-202 provides an overview of what control measures are implemented in order to maximize the ability to identify and assess hazards in order to apply risk management techniques that are designed to protect employees. Figure 1.1 illustrates how the five step risk management process continuously monitors and addresses threats.


**Figure 1 5 Step Risk Management Process (Department of the Air Force, 2009)**

Within the risk management framework, there are disciplines (Aviation, Occupational, Weapons, Space, etc.) that follow the guidance of the risk management program but have direct regulations for their specific function. This research focuses on the occupational and environmental health discipline but is being conducted in response to the fifth step of Figure 1, Supervise and Evaluate. Due to the aforementioned changes to the specific regulation, AFMAN 48-146 Occupational & Environmental Health Program Management, it is important to consider the costs associated with the improvements for budgeting and transparency.

Ultimately, the goal of the Air Force's risk management program should not be to mitigate all risk, but instead to use the optimal amount of resources to minimize and manage risk to an acceptable level. There is a point that it would take an inordinate amount of resources to reduce just a small amount of risk; however, that is not a clearly defined point and due to budget constraints, it is important that the optimal amount is determined. There is tension on what might be considered an acceptable level of risk and because there is a defined constraint on resources, some risk needs to be accepted. The question that has yet to be answered, is how much risk is acceptable? In order to determine the optimal level of risk and resources the costs of mitigation must be identified and the system performance must be tracked. There have been two published attempts to find the answer for optimization of risk in the occupational and environmental health sector to minimal avail.

Mahmoud Rezagholi (2010) analyzed how different design methods for measuring the exposure variables, the number of samples, and the statistical efficiency of the estimated variables contribute to the total cost of assessments. Mathiassen (2011) author built on Rezagholi's analysis and addressed how a larger number of samples were observed to lead to more accurate results, but inevitably increased costs. The authors searched for a framework that provided the best statistical efficiency within a given constrained budget. Because there is an inherent gap in knowledge on the cost of assessments, the underlying determinants of cost behavior, and likely costs the Air Force will bear with the proposed changes, it is practical to create a cost model that will provide a better understanding of current and potential future expenses.

## Problem

As a steward of the taxpayers' dollars, the Air Force is required to treat every expense as efficiently as possible. The overarching problem this research is designed to analyze the optimization of risk acceptance and cost. Changes to AFMAN 48-146 may consequently affect the total costs of Air Force Exposure Assessment Strategy so it is essential to define how current practices impact the budget. The analysis conducted attempts to address the knowledge gap for current costs of exposure assessments and identify the driving factors that will affect the total cost attributed to modifications of the current practices. In order to capture the impact of current Air Force exposure assessments strategies on the budget, a model was designed using a mixture of qualitative and quantitative techniques. Because there are a variety of strategy categories (air, water, radiation, etc.) this research was scoped to focus on occupational health air sampling. By finding the important indicators of cost for air sampling, future research can be conducted to find the relationship for other strategy categories.

## Justification

This research is an initial attempt at predicting the cost of Air Force occupational exposure assessments. A model has yet to be created that can predict or analyze the costs of assessments. Visibility into the costs has never been investigated because the exposure assessments are required by regulation and are an operational necessity for a healthy workforce. Because there is very little visibility on how much these assessments currently cost and little consideration is given to how much the proposed changes will impact the budget, this research is likely to improve Air Force forecasts cost assessments.

## Assumptions

Cost modeling and analysis may elucidate unexpected cost-activity associations which may not be explanatory, but may still useful and applicable for cost prediction. The investigators understand that DOEHRS data—in particular for early adoption years (2009 – 2012 or 2013)—may have missing or inconsistent quality across the installation records therefore the years 2014-2017 were selected for analysis. The sample size for this analysis is rather large as the databases hold over 100,000 records. For the 2014-2017 range, we were able to pull approximately 10,000 complete records that were reported in both databases. Sufficient statistical power to detect effects is certain. However, results were monitored to ensure that there was not too much statistical power which can potentially make insignificant differences seem significant. Part of the methodology includes sanitizing the data into an appropriate size for analysis. This will be taken into consideration as predictor variables are scrutinized.

## Approach or Methodology

The specific aims of this research were accomplished starting with data collection from DOEHRS and LIMS. First, data was aggregated for current practices of air sampling events from years 2014 through 2017. Despite having two large databases for air sample events, there is no actual cost data within the systems. However, many of the line items were converted to costs through the use of cost estimating practices discussed later in Chapter III. Also, the systems are relatively new and do not have uniform inputs which resulted in a major data cleansing effort. For events in the air sampling process that we determined to be important cost surrogates, which neither system tracked, communication with subject matter experts was utilized to simulate data. The primary data collected included the number of past exposures assessments, dates of sample events, the associated analytical methods (since the analytical methods vary in resources required), sample times, media type, media size, and the hazard tested. After the data was sanitized, baseline costs were determined through continuous and categorical (where appropriate) multiple regression analysis in a statistical software package for the contributing variables.

The researchers view a mixed-effects model as the most appropriate method. The primary predictor variables of interest include number of discrete samples collected, types of samples (to include partial or full period, screening), chemical analytes, media type, and sample time. A correlation matrix was used on input variables to identify potential multicollinearity. Additionally, variance inflation factor was used to assess the degree of multicollinearity. A mixed elimination stepwise process was used to find a parsimonious yet statistically sound model. Control variables may be needed to account for possible systematic errors related to locations, commands, methods, etc.

The outcome variable of interest was predicted cost. The best cost predictor variables were defined through an exploratory process. This is “inductive theory building” and future researchers can verify the model with a different data set. The data set was large enough to allow model development on a subset of the data (training data), then verification on the larger remaining data set. More specifically, the data was randomly split into a variable determination dataset and a variable verification dataset.

Because there are a variety of exposure assessment types and complexity levels, subject matter experts were interviewed in order to derive rough order-of-magnitude cost ranges that were applied to the unique variables. Elicitation of subject matter opinion is an established approach to preliminary data collection in the discipline of cost analysis. Once the model for current practices was accurate to a pre-defined threshold, it was considered complete. The model should be scrutinized in order to predict how the changes to the AFMAN will impact the total cost of assessments. The threshold will be based on researcher judgment as data is curated and model selection considered. The researchers view an R squared of .6 or greater as acceptable. An $R^2$ of .8 or greater is preferred.

A portion of the data collection involved ethnographic observation of exposure assessment activity in various settings. The researchers visited occupational health locations such as the bioenvironmental (BEE) flight on Wright-Patterson Air Force base and the United States Air Force School of Aerospace Medicine in order to observe and interact with experts. The BEE flight was able to provide data related to the actual sampling events while the professionals at USAFSAM were able to provide insights to the laboratory work related to processing samples.

## Hypothesis and Specific Aims

Research Question: Do the cost structure of current occupational hazard assessments and the proposed strategy for differ significantly?

Specific aim #1: Identify cost determinants and drivers for exposure assessments as currently conducted.

Specific aim #2: Determine or model total exposure assessment costs as currently conducted.

Specific aim #3: Determine how proposed changes to the AFMAN 48-146 will affect the identified cost drivers.

Specific aim #4: Determine projected or modeled costs for the proposed exposure assessment strategy.

## II. Literature Review

### Chapter Overview

The purpose of this literature review is to provide a background of the resources utilized to accomplish the predictive cost model for occupational exposure assessments. Because this research is a collaborative effort between the cost estimation and bio-environmental engineer (BEE) communities, there was a wide scope of articles studied in this chapter. The literature review introduces the past exploration and important focuses on the subject and connects how they are relevant to this research. Also, it establishes the current state of exposure assessments in the United States Air Force and addresses what potential changes may occur to realign current practices with the commercial industry.

### Background of Exposure Assessments

The Occupational and Health Administration defines exposure assessments as the charge that "employers must make a 'reasonable estimate' of the employee exposures anticipated to occur as a result of those hazards, including those likely to be encountered in reasonably foreseeable emergency situations, and must also identify the physical state and chemical form of such contaminant(s) ("Exposure Assessment," n.d.)." A major challenge in the current exposure assessment operations for the United States Air Force is a lack of uniformity in data recording across the locations performing these tests. There has not been an established exposure assessment strategy to determine how many of a specific assessments that need to be accomplished in order to adequately assess industrial workplace hazards (Batten, 2009). The current AFMAN 48-146 is undergoing revision that may clear up some of the issues of poor performance in the work place as it shifts towards the American Industrial Hygiene Association strategy shown in Figure 2. However, it is difficult to accurately describe all occupational exposure assessments because there are many sample methodologies with few data points, the inability to quantify exposure assessments because of their inherent uniqueness qualities, and a lack of aggregated data. Other concerns with accurately identifying costs of occupational health exposure assessments stem from the ever-changing gold standards, reporting bias, the inability to make timely changes to procedures, and the natural errors that occur within assessment methods (McGuire, Nelson, Koepsell, Checkoway, & Longstreth Jr., 1998)."

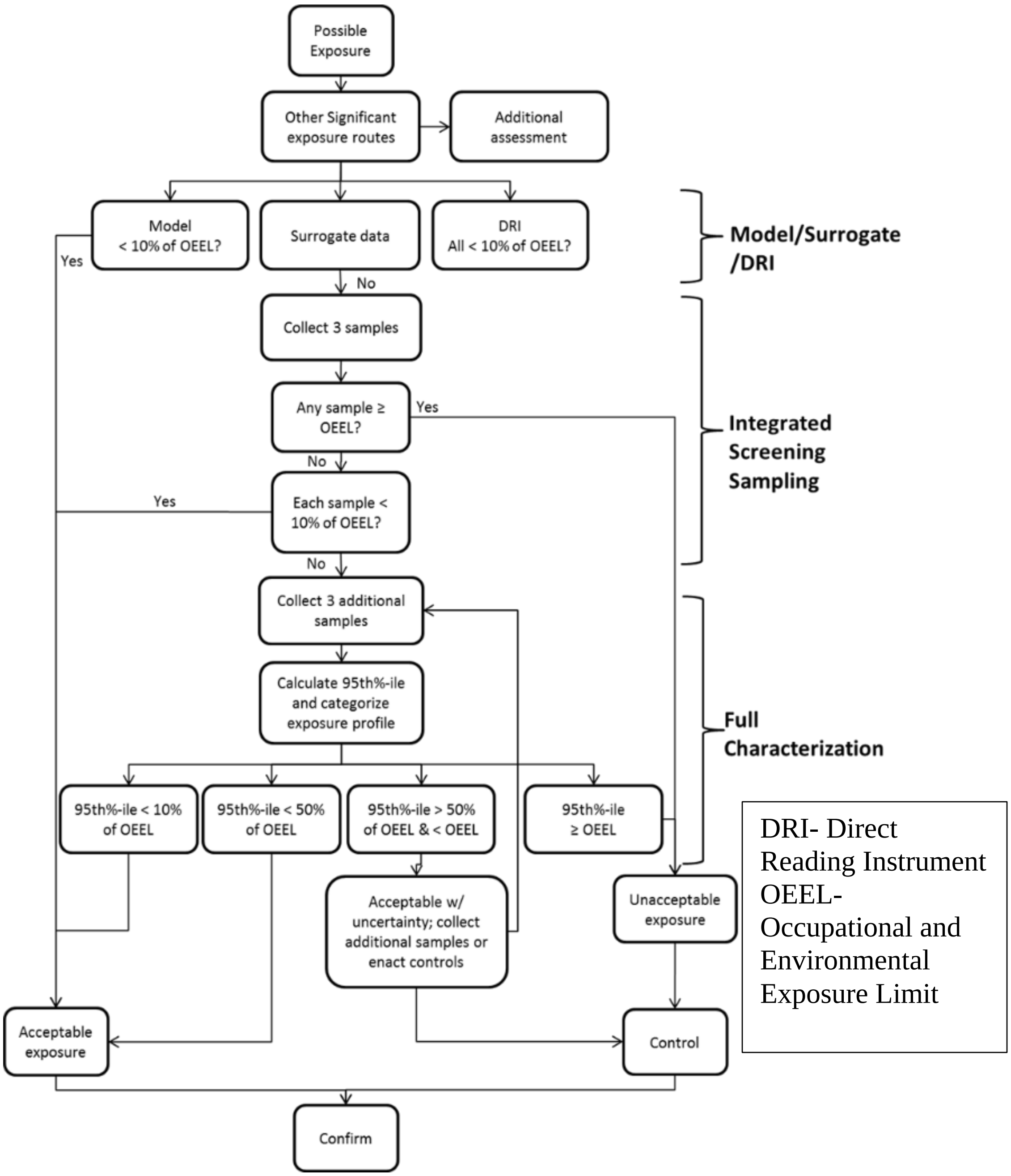



**Figure 2 Proposed Changes to AFMAN 48-146**

There has yet to be any tracking or modeling of how much it costs to do each exposure assessment.

Although the Department of Defense has not been tracking costs, there has been some research on the cost efficiency of exposure assessments in commercial industry. Rezahgholi (2010) began his research on optimization of exposure assessments by reviewing literature on the economic and statistical performance of exposure assessments. Rezagholi was able to find nine pieces of literature; however, the articles he cited lacked an examination of the costs tied to exposure assessments and focused primarily on the error models and statistical interpretations. Ultimately, he concluded that there had not been any applicable research in the 21st Century addressing an accurate cost model but since there was an initial interest in the undeveloped topic, there is value and need in pursuing cost efficient exposure assessment strategies (Rezagholi & Mathiassen, 2010).

Mathiassen continued his work in 2011 by taking the previous studies' optimization strategies that were based on simplified cost models and expanded the scope to cover non-linear cost scenarios (Mathiassen & Bolin, 2011). He describes the relationship of cost and statistical efficiency for optimal exposure assessments via a frontier curve shown in Figure 3. Mathiassen explains that all the previous literature has made the assumption that the price of a measurement is constant which leads to a linear relationship between cost and number of assessments. One source of error in the previous studies is that the relationships studied were not identified as feasible on the frontier curve in Figure 3. Mathiassen's paper "explores optimal cost-efficiency even when cost functions are not linear and budget constraints apply, and the study also identifies alternative optimization procedures in those cases where analytical closed-form solutions cannot be developed" (Mathiassen & Bolin, 2011). The conclusions drawn from his research include a demonstration of how the non-linearity of cost functions influences the optimal allocation of measurements between assessments and frequency of assessments. Finally, he concluded that there is a large gap in empirical data for cost functions supplementary to exposure assessments and costs tied to different stages of exposure assessments but the strategies he developed in his paper should be applied to exposure assessment strategies in order to have better informed decisions on for strategies that aim to optimally use monetary resources (Mathiassen & Bolin, 2011).

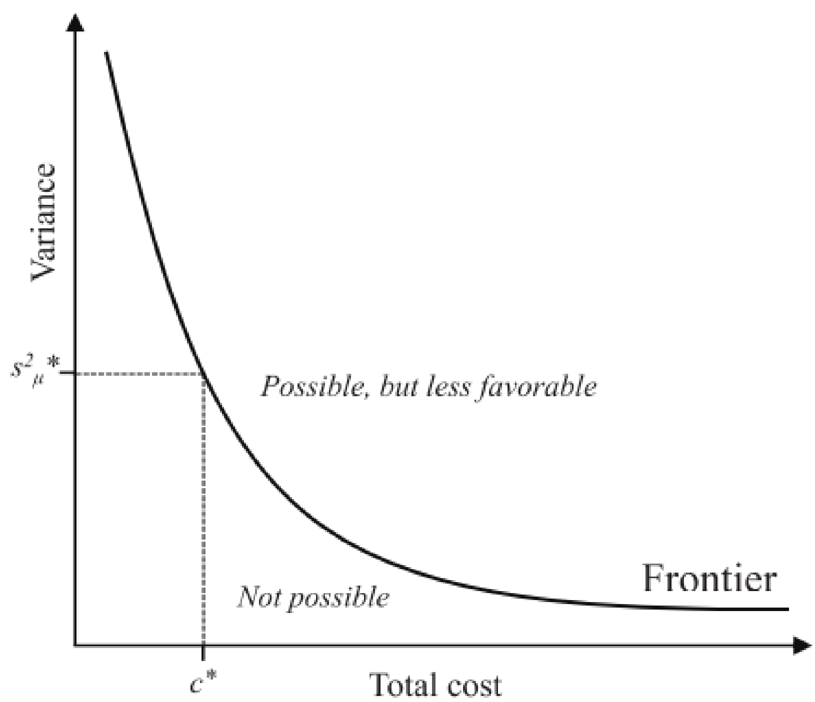



**Figure 3 Frontier Curve (Mathiassen & Bolin, 2011)**

**Cost Estimation**

Cost estimation within the Department of Defense (DoD) and United States Air Force is an essential tool utilized by leadership in decision support. Cost estimates are primarily used in the acquisition field and provide quantitative data between the different options (Thomas, 2006). This research is not a typical cost estimate in the sense that it is aiming to find the best option between different potential acquisitions but instead it is aimed at providing visibility of costs for a process that is well established and recognized within the Air Force.

The Government Accountability Office (GAO) has established a 12-step best practice for developing a cost estimate. Despite the GAO's guidance being aimed at major acquisition programs, there are many applicable aspects that are translated to this research. The GAO Cost Estimating and Assessment Guide discusses the importance and best practices for creating sound estimates through "an overall process of established, repeatable methods that result in high-quality cost estimates that are comprehensive and accurate and that can be easily and clearly traced, replicated, and updated." (Richey, 2009) Figure 2.3 outlines the GAO's twelve steps:

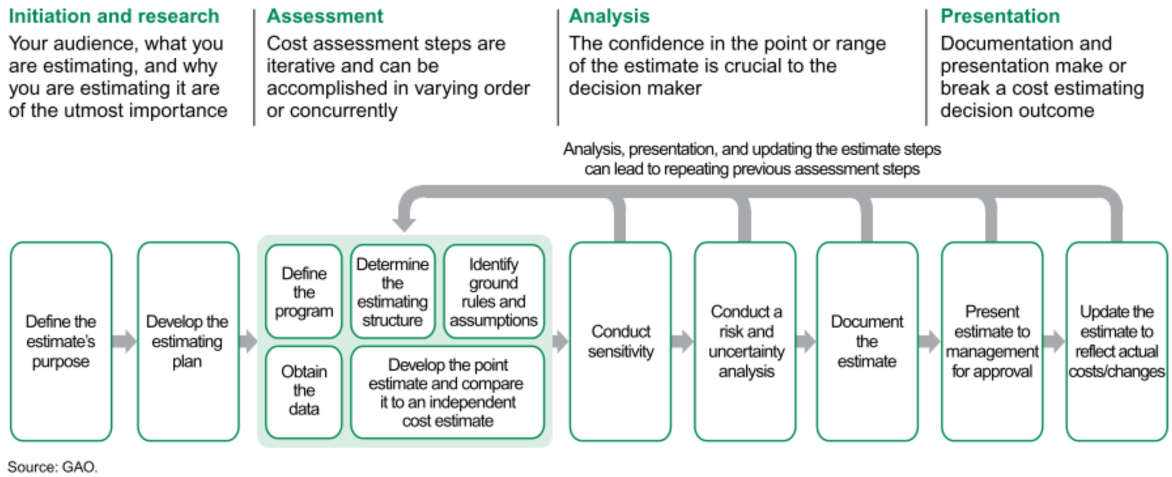



**Figure 4 GAO 12-Step Process (Richey, 2009)**

This section will analyze the 12 steps depicted in Figure 4. The first two steps address the who, how, and when of the cost estimate. The estimator should define who the estimate is for, what is being estimated, and why the estimate is being conducted (Thomas, 2006). This estimate is for, on the lowest level, the aerospace medicine leadership. As previously stated, we are estimating the cost of exposure assessments (scoped to air samples) because there has previously been little to no analysis within the Air Force on how assessments impact the budget. As changes to the governing regulation are being developed, it is important to have visibility on how the changes affect the budget and future costs of exposure assessments. The next step for creating a cost estimate is to develop the estimating plan. This step establishes who is on the cost estimating team, what approach will be taken to accomplish the estimate, and a timeline for completing the estimate (Thomas, 2006). For this research, the cost estimate team is composed of the AFIT Graduate Cost Analysis department and the Bio-environmental engineer experts. The first step in trying to determine the cost of exposure assessments was to down scope what we were trying to analyze. Because the bioenvironmental flights test for such a wide variety of hazards, we determined that it would be important to focus on only one of sampling categories, air, and determine the major surrogates of cost for an air sampling event. The team set a goal of completing this research by February of 2018.

The following steps were tailored to better fit our estimate since the GAO's guidance was written for acquisition programs. However, it is still important for us to review the technical definitions, characteristics, and features of the exposure assessment strategy (Richey, 2009). This part of the estimation strategy is completed with in-depth research and guidance from the subject matter experts in the BEE community. Interviews were conducted and a relationship with the United States Air Force School of Aerospace Medicine was developed which provided a wealth of knowledge on the internal processes on how exposure assessments are conducted. A major difference in this estimate and one typically outlined by the GAO's guidance is the lack of analogous programs that provide links for developing cost estimating relationships (Richey, 2009).

The next step in the cost estimating process is to determine the estimating structure establish ground rules and assumptions. Because this is not a typical cost estimate, the estimating structure does not follow the standard use of a work breakdown structure. "The ground rules, or the agreed upon estimating standards for the cost estimate, that are derived from the technical baseline are clearly spelled out" (Thomas,

2006) in Chapter three of this paper. It is important to note that excessive assumptions are added risk to a potential dilution of the validity of the cost estimate and each assumption needs to have an explicit purpose. Before the final six steps of building the cost estimate, we needed to obtain data. Our data was derived from the BEE data systems DOEHRS and LIMS. The two systems, which data passes between, contain every recorded detail of exposure assessments and the associated testing. In order to be able to use the data, we met with a subject matter expert and sanitized the data before inputting the data into our cost model.

**Expert Opinion Elicitation**

Using subject matter experts is a tool often used by cost estimators. The Air Force Cost Analysis Agency produced a Cost Risk and Uncertainty Handbook that is used for guidance across the cost analysis community. For multiple data points using expert opinions, the researchers relied on guidance from Air Force Cost Analysis Agencies' (AFCAA) handbook. The purpose of AFCAA's guidance is to establish that although elicitation is a valuable tool, there is the need to account for some bias in the expert's opinion shown in Table 1. Referred to as the 15/85 rule, AFCAA provides best practices and a step-by-step guide for using subject matter expert data.

**Table 1 Subject Matter Expert Biases (AFCRUH, 2015)**

| Motivational Bias | Cognitive Bias |
|---|---|
| Social pressure (face to face) | Inconsistency (opinion changes over time) |
| Impression (not face to face) | Anchoring |
| Group Think | Relating to irrelevant analogies |
| Wishful thinking | Underestimation |
| Career goals | Human Nature |
| Misunderstanding | |
| Project Advocacy | |
| Competitive Pressures | |

The best practices for including the use of multiple experts and their upper and lower estimates is outlined in the Air Force Cost Risk and Uncertainty Handbook. It is beneficial to encourage them to think of scenarios that could cause the two extremes of their estimate. The best way to draw this information from the experts is to have a dialogue to identify the upper and lower bounds that have a 20% chance of being exceeded. Also, the dialogue should include the most likely value for the data sought by the researcher.  Once that information is gathered, the estimator should select the most appropriate distribution shape. Without any other information the estimator should apply upper and lower bounds of 15% and 85%; the 15% accounting for the underestimate and the 85% accounting for the overestimate. It is always important to cross-check an expert's opinion in order to avoid gross over- or under-estimates (AFCRUH, 2015).

## Building a Cost Model

In order to understand what the cost of exposure assessments truly are, a parametric cost model that identifies cost estimating relationships of individual assessments was established. "They (parametric models) identify major architectural cost drivers and allow high-level design trades; enable cost-benefit analysis for technology development investment; and, they provide a basis for estimating total project cost for budgetary planning and procurement activities (Stahl, Henrichs, & Msfc, 2016)." Cost estimating relationships or cost drivers were the desired outcome of the cost estimating model but creating accurate CERs is only as reliable as the data set from which they come (Stahl et al., 2016).

An effective method for identifying predictor variables for the criterion variable, is through a multiple regression model. Multiple regression and correlation is a useful tool because its flexibility with linear data sets. Regression worked well with our model because "predictor variables in multiple regression analyses may be correlated with one another, and they may be continuous, categorical, or a combination of the two"(Hoyt, Leierer, & Millington, 2006) and our data set is a mixture of both. An analysis of variance was conducted in order to determine the statistical significance of our predictor variables that would be implemented in our model. Statistical significance of the predictor variables was determined through an effect size of .80 because "having a high internal consistency is desirable when a researcher has developed a test designed to measure a single unitary variable"(Mildred L. Patten, 2009). Using a statistical software package, Equation 1 was derived where $\hat{Y}$ is the dependent variable and $X_n$ are the independent variables. $B_n$ are the coefficients that each independent variable is multiplied by to determine how much it contributes to the predicted cost and $B_0$ is a constant specific to this model.

**Equation 1**

$$\hat{Y} = B_1X_1 + B_2X_2 \ldots + B_0$$

Because JMP (JMP®, 1989-2007) provides a *t statistic* and *p-value* for each of the independent variables, we were able to determine the predictive quality for each variable. If the *p-value* is less than the designated alpha, there is a significant statistical association between the independent and dependent variables (Hoyt et al., 2006). Finally, the model needs to be able to predict if there is any correlation between the predicted cost and the actual cost. In order to do so, the *F test* determines the significance of $R^2$ or proportion of variance accounted for by the predictor variables.

To ensure that our model would include even small effects, power analysis was conducted. “Statistical power analysis exploits the relationships among the four variables involved in statistical inference: sample size (N), significance criterion (ft), population effect size (ES), and statistical power (Cohen, 1992).” Table 2 in Cohen’s article on statistical power provides insight to how data was required in order for our model to be include effects.

**Table 2 Cohen's Table for Effect Size (Cohen, 1992)**

*N for Small, Medium, and Large ES at Power = .80 for $\alpha$ = .01, .05, and .10*

| | $\alpha$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | .01 | | | .05 | | | .10 | | |
| Test | Sm | Med | Lg | Sm | Med | Lg | Sm | Med | Lg |
| 1. Mean dif | 586 | 95 | 38 | 393 | 64 | 26 | 310 | 50 | 20 |
| 2. Sig *r* | 1,163 | 125 | 41 | 783 | 85 | 28 | 617 | 68 | 22 |
| 3. *r* dif | 2,339 | 263 | 96 | 1,573 | 177 | 66 | 1,240 | 140 | 52 |
| 4. *P* = .5 | 1,165 | 127 | 44 | 783 | 85 | 30 | 616 | 67 | 23 |
| 5. *P* dif | 584 | 93 | 36 | 392 | 63 | 25 | 309 | 49 | 19 |
| 6. $\chi^2$ | | | | | | | | | |
| 1*df* | 1,168 | 130 | 38 | 785 | 87 | 26 | 618 | 69 | 25 |
| 2*df* | 1,388 | 154 | 56 | 964 | 107 | 39 | 771 | 86 | 31 |
| 3*df* | 1,546 | 172 | 62 | 1,090 | 121 | 44 | 880 | 98 | 35 |
| 4*df* | 1,675 | 186 | 67 | 1,194 | 133 | 48 | 968 | 108 | 39 |
| 5*df* | 1,787 | 199 | 71 | 1,293 | 143 | 51 | 1,045 | 116 | 42 |
| 6*df* | 1,887 | 210 | 75 | 1,362 | 151 | 54 | 1,113 | 124 | 45 |
| 7. ANOVA | | | | | | | | | |
| $2g^a$ | 586 | 95 | 38 | 393 | 64 | 26 | 310 | 50 | 20 |
| $3g^a$ | 464 | 76 | 30 | 322 | 52 | 21 | 258 | 41 | 17 |
| $4g^a$ | 388 | 63 | 25 | 274 | 45 | 18 | 221 | 36 | 15 |
| $5g^a$ | 336 | 55 | 22 | 240 | 39 | 16 | 193 | 32 | 13 |
| $6g^a$ | 299 | 49 | 20 | 215 | 35 | 14 | 174 | 28 | 12 |
| $7g^a$ | 271 | 44 | 18 | 195 | 32 | 13 | 159 | 26 | 11 |
| 8. Mult *R* | | | | | | | | | |
| $2k^b$ | 698 | 97 | 45 | 481 | 67 | 30 | | | |
| $3k^b$ | 780 | 108 | 50 | 547 | 76 | 34 | | | |
| $4k^b$ | 841 | 118 | 55 | 599 | 84 | 38 | | | |
| $5k^b$ | 901 | 126 | 59 | 645 | 91 | 42 | | | |
| $6k^b$ | 953 | 134 | 63 | 686 | 97 | 45 | | | |
| $7k^b$ | 998 | 141 | 66 | 726 | 102 | 48 | | | |
| $8k^b$ | 1,039 | 147 | 69 | 757 | 107 | 50 | | | |

**Value Focused Thinking**

Another tool considered for this research was value-focused thinking. Using value-focused thinking would improve both decision making and identification of situation where decisions can affect the outcome. Because there are many qualitative aspects to how exposure assessments are conducted in the bio-environmental engineer career field, we needed to state the objective explicitly with Keeney's three features of "decision context, an objective, and a direction of preference (Keeney, 1996)." Keeney also published an article in 2008 that discusses the key concepts in application of value focused thinking and the three ways it can lead to better decisions: better objectives for evaluating alternatives, creation of alternatives, and outlines superior decision opportunities (Keeney, 1996). As the researchers began to analyze the data collected, we determined that using value focused thinking would not be required. The researchers decided to take a more quantitative and statistical approach to their analysis and using a method such as value focused thinking potentially threatened the validity of the analysis by making too many changes to the raw data.

**Summary**

This chapter investigated the major sources of information used to complete this research. First, we looked at the current state of exposure assessment strategies in the Air Force and the lack of any formal recording of the costs that these assessments are having on the budget. Figure 2 outlines the changes to the Air Force regulation as it shifts to match the industry standard. Next, we took a look at the first half of the GAO's 12 steps for the best practice of completing a cost estimate. Despite not being an ordinary acquisition cost estimate, most, if not all, of the GAO's guidance has some applicability that was at least taken into consideration throughout this research. The actual estimate was completed through a model that uses multiple regression and correlation calculated in JMP statistical software. We also use Cohen's power analysis to ensure that there is adequate power for statistical significance in the model. Finally, we addressed the qualitative aspects of the model and determined that we could normalize the data without the use of value focused thinking.

# III. Methodology

## Chapter Overview

The purpose of this study is to create visibility on the costs of occupational hazard assessments in the United States Air Force as processes are being modified in order to adopt industry best practices. The purpose of this chapter is to outline the methods used throughout this research, explain the sample data, outline the procedure for collecting the data, and explain the statistical analysis conducted on the data.  It is important to show how the methodology is adequate and repeatable for this type of research. This chapter addresses how the data was collected, sanitized, and normalized and how we conducted the analysis.

**Research Design**

This study uses a mixture of descriptive and analytical research methodology. Data was collected from two Air Force automated information systems (AIS) and subject matter experts. DOEHRS is a system utilized by the BEE flights to record information pertinent to sampling events. LIMS is a system used by the laboratories to record the results of processed samples. The data is connected between the two systems by a unique identification code that we were able to use to compile all of the data into a usable workbook. Before acquiring data from the owners of each system, we determined what information we thought would be useful cost surrogates. Figure 5 was the initial roadmap for determining what information would be major cost elements and useful to collect.

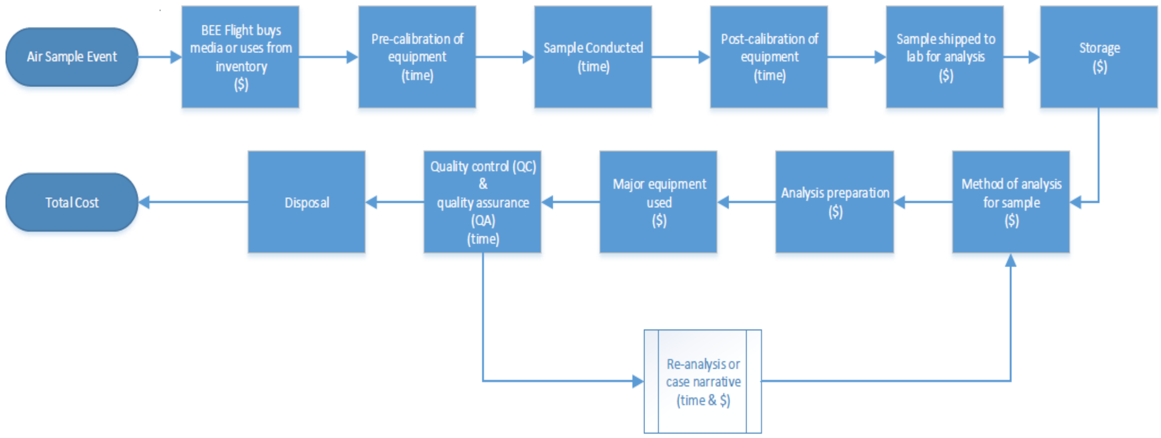



**Figure 5 Cost Model Road Map**

Each block identifies whether there is a direct cost or time (manpower), which was converted to a cost, associated with that part of the roadmap.

We examined the data to find trends that might be useful for analysis. After organizing the data in Excel, analysis was conducted to create a cost estimate model. The United States Air Force maintains meticulous records of all exposure assessments conducted. By acquiring and sanitizing records, we were able to import and analyze the data in statistical software. Modeling is a valuable technique for estimating costs and it is the seventh step in the GAO's Twelve Steps of a High-Quality Quality Cost Estimating Process (Richey, 2009). Models are widely accepted in the cost analysis community as a viable tool for creating cost estimates.

Models are frequently used throughout the Air Force for major acquisition programs. For such programs, a model is built to estimate the cost of each element of a work breakdown structure (WBS). However, this study is not estimating a major acquisition program; therefore, rather than estimating the cost of a WBS element, we are focusing on the cost of air sampling events. Using the results, future research can compare our findings to the cost of the new air sampling methods after the modifications are implemented.

For these reasons, we chose a mixture of descriptive and analytical research methodology approaches to create a cost estimate of exposure assessments in the Air Force. The estimate(s) will provide analytical decision support to Air Force leadership on the efficacy of changing current regulations to match industry practices. Also, because there is a knowledge gap on this topic, it will provide framework for future research on the subject.

**Research Questions and Hypotheses**

This thesis attempts to answer or build a foundation to answer the research questions of the proposed hypothesis that the cost structure of current operations and proposed strategy for occupational hazard assessments will differ significantly. The research questions that this thesis will answer are:

- What are the cost determinants and drivers for exposure assessments as currently conducted?
- What do exposure assessments cost as currently conducted?
- How do proposed changes to the AFMAN 48-146 affect the identified cost drivers?
- What are projected or modeled costs for the proposed exposure assessment strategy (EAS)?

It is imperative to determine the cost drivers for the cost estimate. Cost surrogates were determined by meeting with experts and using the cleansed data (Richey, 2009). Once a multiple regression was conducted on the cost surrogates and statistically significant variables, two of the four research questions were answered. The last two research questions were answered with an analytical approach. Using the data we acquired from the cost estimate, we then analyzed how the proposed changes affect the cost drivers. Using subject matter experts, we interpolated the effects on the total cost to determine a projected cost for the proposed exposure assessment strategy.

## Instrumentation

The primary data set was sanitized and normalized in Excel using functions that exist in the basic software package. The Data Analysis add-in to Excel was used for many of the histograms and multi-collinearity matrix. We also used @RISK (@RISK, 2016) to fit a triangle distribution to the subject matter expert data and conduct the Monte Carlo simulation. In order to complete analysis on the data that we gathered, we utilized statistical software JMP. It provided us the capability to complete a multiple regression on the data.

## Population and Sample

The data used from this research consists of the reports from individual exposure assessments and the subsequent testing conducted on the samples taken. Each exposure assessment has a report generated that outlines the sample taken by the bio-environmental engineers. After input into the BEE’s system, DOEHRS, it is then pulled into the laboratory’s system, LIMS, where it is updated with the work conducted on the sample by the chemists. The final result for an exposure assessment is a portfolio that describes all of the work and resources used to accomplish the individual test.

**Data Collection**

Relying on experts in DOEHRS or LIMS, we conversed with corresponding system owners and users to determine the type of data we should pull and had the USAFSAM DOEHRS support office run a query. The first source of expertise came from a DOEHRS user who had experience inputting exposure assessment data into the system as a BEE. He provided us insight on what kind of data would be relevant to this research so that we could formulate the query for the USAFSAM DOEHRS support office partner. The support office was then able to run an Air-Force-wide report for all of the data we had outlined.

The next source of the data came from the LIMS system. Because DOEHRS and LIMS communicate between each other, we were able to provide the DOEHRS query results to the chemists who then provided us details on the resources used to process each of the samples. The final result from the data collection was two sets of data, one from DOEHRS and one from LIMS that represented the same exposure assessments.

We chose to use data from years 2014-2017 because LIMS went through a restructuring process that potentially would change the format of any early data. The owners were able to provide us with approximately 41,000 lines and 38,000 lines of raw data between DOEHRS and LIMS, respectively. However, using the unique identification code, only 9,824 lines were represented in both systems. The raw data needed significant cleansing before it was able to be used for any analysis.

In order to cleanse the data, we pulled the DOEHRS and LIMS numbers into an Excel workbook where we organized and reduced the data pool to what was needed for a multiple regression. We chose to do this because Excel has a more user friendly user interface for moving and sorting data compared to JMP. Excel has the ability to pull data from tables using functions such as VLOOKUP and it is more versatile in its ability to sort large data sets. Once we were able to complete the cleansing process, we imported the data into JMP.

**Data Sanitization and Normalization**

One major difference in the data sets linked through the unique identification code was that LIMS did not identify if there were multiple analytes tested during the same sample event. This proved to be a concern because there are pre-calibration, post-calibration, and sample times that were being double counted. In order to mitigate this issue, we had to determine what times were being double counted. The process for identifying the duplicates was to use the date, location, and exact sample times. The data set was modified to divide each analyte sampled into its own event and apply an average time to each category based on how many were sampled.

Another area of concern was the lack of cost recorded with any of the data provided. The first block of Figure 5 addresses the media or equipment requirement for each sample. However, there is no cost data in DOEHRS for the media used. Using the media type and media size, the researcher found the commercial cost of purchasing the minimum quantity. Once compiling a list of all of the media costs, it was applied to the data set under the assumption that the military does not receive discounts for their large purchases and that enough media is purchased in one order that shipping is negligible.

The next two blocks on the road map that were tackled were the pre- and post-calibration times. Both of these times are not recorded in either of the AISs so expert opinion elicitation techniques discussed in chapter two were utilized. The first expert, a Technical Sergeant and teacher at USAFSAM, agreed to help us create these data points. The expert sat down with the researcher and laid out all the steps involved in pre- and post-calibration to ensure he was giving the most accurate estimate for the times involved. Appendix A shows his high, low, and normal estimate for both large (greater than three air pumps) and small (less than three air pumps) sample events. He also provided a percentage for how often an event was either large or small. Before using the expert's information to create the data, his opinion was cross checked with three other experts that currently work in the local BEE shop.

In order to use the subject matter expert's opinion, we chose to use a triangular distribution and apply the 15/85 guidance from the Air Force Cost Risk Uncertainty Handbook. Next, we conducted a Monte Carlo simulation in @Risk with 10,000 iterations. Doing so provided us with the expected calibration times for large and small air sample events.

All of the data points were normalized into a cost in order to create an aggregate cost that would later become the dependent variable in the regression. Many of the data points where recorded in time or man hours, so the researchers needed to find the cost of employing those who conducted the sample events. First we consulted an expert and determined the ranks of those who conduct air sample events range from E-1 to E-6 and O-1 to O-3. Using a 2014 composite pay and reimbursement rate memorandum, we calculated the average cost per minute for those ranks. The fully burdened rates are shown in Appendix B (Roth, n.d.). We determined the cost per minute to be $0.63485. That rate was applied to all times in the data set.

The last data point we were able to acquire was the blanket purchase agreement prices from the laboratory. This information was a list of all of the preparation and analysis costs for the various testing methods if the Air Force was going to utilize private labs. However, there were many variances in the format of the titling of the methods in the purchase agreement than how it appears in DOEHRS and LIMS. Therefore, we needed to cleanse the blanket purchase agreement so that it would align with the automated information systems and then match the prices. We were unable to acquire any further data from contacts at USAFSAM, which will be addressed in the assumption and limitations portion of this thesis, so the purchase agreement prices were ultimately the total costs attributed to the lab.

## Data Analysis

After collecting the appropriate data to conduct the research, the analysis consisted of three major steps: cleansing, multiple regression and correlation, and distribution fitting. These three steps resulted in a model that is able to predict, with confidence, the cost of a particular exposure assessment.

The majority of the analysis was conducted in JMP. With the cleansed data, we began by testing for statistical significance for each of the variables we thought might be a good predictor of cost in the data set. If the variable proved to be statistically insignificant, it was removed through a mixed elimination stepwise process. Many statistical tests, discussed in Chapter Four, such as the Bruesch-Pagan, Shapiro-Wilks, and Cook's Distance were conducted. Once we found the best predictors, we let the statistical software run the multiple regression. The output of the regression was a balanced equation that output the predicted cost. Finally, we wanted to assign a distribution to the predicted costs. In order to do so, we utilized @RISK by importing the results from JMP and to determine the most appropriate distribution of fit.

**Conclusion**

This chapter highlights the processes used to obtain and analyze the data in order to create a predictive model for the cost of exposure assessments in the United States Air Force. This research followed the standard cost estimating protocol and the methodology used was sufficient for creating a model. The majority of effort for this research was spent on gathering and cleansing the data as it was not readily available nor directly applicable to statistical analysis.

# IV. Results and Analysis

## Chapter Overview

This chapter provides an examination of the results from the methods addressed in Chapter III. A preliminary step-wise multiple regression model was created with the sanitized data set to identify the cost driving independent variables for total cost. Once, the multiple regression model was finalized, the independent variables' statistical significance and their ability to explain variance was examined. Finally, a predictive equation was established that could identify the total cost of future air sample exposure events for the current practices. The equation identified what variables are major cost drivers and may provide decision support to potential changes of the Air Force regulation.

## Correlation Matrix

Before the research team began the multiple regression process, a correlation matrix was created to better understand how points in the data set interacted with each other. This matrix provided insights to the researchers for variables that would potentially be removed by the mixed step-wise regression. The researchers noted high correlation between NIOSH 7605 and NIOSH 1501/1550 Air Force and None and the HEXAMETHYLENE DIISOCYANATE MONOMER variables. The decision to remove or keep those variables will be discussed later in this chapter.

| | Total Cc | Correct | Correct | Correct | CHROMIUM(VI | COPPER | CADMIU | HEXAME | BENZEN | ALUMIN | Hazard | NIOSH 7 | NIOSH 7 | NIOSH 1 | NIOSH 1 | Method | 37 mm, | 37 mm, | None | 100 mg, | Size oth |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Total Cost | 100% | | | | | | | | | | | | | | | | | | | | |
| Corrected Sample Time (Min) | 72% | 100% | | | | | | | | | | | | | | | | | | | |
| Corrected Pre-Calibration (Min) | 86% | 53% | 100% | | | | | | | | | | | | | | | | | | |
| Corrected Post-Calibration (Min) | 86% | 53% | 100% | 100% | | | | | | | | | | | | | | | | | |
| CHROMIUM(VI) | 40% | 7% | 22% | 22% | 100% | | | | | | | | | | | | | | | | |
| COPPER | -4% | 9% | 1% | 1% | -20% | 100% | | | | | | | | | | | | | | | |
| CADMIUM | -12% | 3% | -4% | -4% | -23% | -10% | 100% | | | | | | | | | | | | | | |
| HEXAMETHYLENE DIISOCYANATE MONOMER | 8% | -11% | -8% | -8% | -14% | -6% | -7% | 100% | | | | | | | | | | | | | |
| BENZENE | -26% | -10% | -22% | -22% | -25% | -11% | -12% | -7% | 100% | | | | | | | | | | | | |
| ALUMINUM | -5% | -5% | -5% | -5% | -14% | -6% | -7% | -4% | -8% | 100% | | | | | | | | | | | |
| Hazard Other | -13% | 0% | 1% | 1% | -45% | -19% | -22% | -13% | -24% | -14% | 100% | | | | | | | | | | |
| NIOSH 7605 | 38% | 6% | 21% | 21% | 95% | -20% | -22% | -14% | -25% | -14% | -41% | 100% | | | | | | | | | |
| NIOSH 7300 | -10% | 14% | 2% | 2% | -44% | 43% | 50% | -13% | -24% | 32% | -5% | -45% | 100% | | | | | | | | |
| NIOSH 1501/ 1550 Air Force | -25% | -13% | -22% | -22% | -20% | -8% | -10% | -6% | 62% | -6% | -7% | -20% | -19% | 100% | | | | | | | |
| NIOSH 1550 | -7% | -5% | -1% | -1% | -13% | -6% | -6% | -4% | 1% | -4% | 24% | -13% | -13% | -6% | 100% | | | | | | |
| Method Other | -12% | -11% | -10% | -10% | -37% | -17% | -20% | 33% | 13% | -13% | 42% | -41% | -40% | -18% | -12% | 100% | | | | | |
| 37 mm, 5 um | 30% | 8% | 18% | 18% | 74% | -5% | -12% | -19% | -34% | -9% | -28% | 73% | -20% | -27% | -18% | -31% | 100% | | | | |
| 37 mm, 0.8 um | -4% | 16% | 5% | 5% | -35% | 30% | 42% | -10% | -19% | 28% | -3% | -35% | 76% | -15% | -10% | -29% | -48% | 100% | | | |
| None | 12% | -5% | -5% | -5% | -15% | -6% | -7% | 84% | -5% | -5% | -6% | -15% | -14% | -6% | -4% | 36% | -20% | -11% | 100% | | |
| 100 mg/50 mg | -34% | -20% | -23% | -23% | -37% | -16% | -18% | -11% | 65% | -12% | 22% | -37% | -35% | 54% | 35% | 27% | -50% | -28% | -12% | 100% | |
| Size other | -6% | -4% | -4% | -4% | -16% | -7% | -8% | 2% | -8% | -5% | 32% | -16% | -15% | -7% | -4% | 38% | -22% | -12% | -5% | -13% | 100% |

**Figure 6 Correlation Matrix**

## Predicting Air Sample Costs Using Multiple Regression

The researchers developed a model using commonly practiced multiple regression techniques. Due to the iterative nature of multiple regression, the initial step-wise regression yielded a model that needed to be adjusted to account for statistical validation tests such as Variance Inflation Factors, Cook's Distance Test, Shapiro-Wilk Tests, and Breusch-Pagan Tests. If a specific independent variable failed one of the validations, corrective action such as removal was taken. Table 3 provides the tests, purposes, and results conducted.

**Table 3 Statistical Tests**

| Test | Purpose | Result |
|---|---|---|
| Bonferroni Correction | Detect Type I Error | NIOSH 1501/1550 Air Force did not meet threshold |
| Variance Inflation Factors | Detect Multicollinearity | -Removed NIOSH 7605<br>-NIOSH 1501/1550 Air Force Removed |
| Cook's Distance | Test Influence of Data Points | Pass |
| Shapiro-Wilk | Testing for Normality | Failed, Data is Centered Around Zero |
| Breusch-Pagan | Testing for Constant Variance | Failed, No Trend |

### Dependent Variable

The dependent variable in the multiple regression model was total cost of air sample exposure assessments. As discussed previously, the total cost was a data point created in accordance to the roadmap the research team created in Chapter 3. Due to the nature of using a dependent variable that is derived from the data set, the research team could expect the model to output a relatively large $R^2$.

### Independent Variables

The following independent variables were used in the team's preliminary model. Most of the variables came directly from the data set with the use of dummy variables while pre-calibration times were obtained through expert opinion elicitation and sample time was adjusted to mitigate double counting. Sample time needed to be adjusted because it was possible for the BEE shop to have tested multiple hazards with the same test and the data set would represent and individual sample time for each event. To avoid double counting the man hours for some exposure assessments, the researchers used the location, date, and sample time as indicators if the events were conducted simultaneously. If an event was discovered to be done simultaneously with another, the average time was taken and applied to each event. Dummy variables were created for the analytes being tested, sample method used, and media size. The researchers did not want to over fit the results of the analysis with too many dummy variables so approximately the smallest ten percent of variables were grouped together with their own dummy variable for each category.

1. *Corrected Sample Time (Min)* – This variable was derived from the raw sample times acquired in the data set by taking all of the average time for analytes tested on the same day, in the same location, with identical sample times. Therefore, if there were two samples such as SILICA, CRYSTALLINE CRISTOBALITE that were tested on 9 August 2017 at 244A-58th MXS ACFT Structural Maint & Corr Control and both had identical sample times, the average sample time would be used for each event.
2. *Corrected Pre-Calibration (Min)* – The same technique was used for this variable as *corrected sample time (min)* except only location and date were used to uniformly distribute the time spent pre-calibrating for that day's work.
3. *CHROMIUM(VI)* – This identifies if chromium was the analyte being tested.

4. *HEXAMETHYLENE DIISOCYANATE MONOMER* – This identifies if hexamethylene diisocyanate monomer was being tested.
5. *BENZENE* – This identifies if benzene was being tested.
6. *ALUMINUM* – This identifies if aluminum was being tested.
7. *NIOSH 7605* – This identifies if NIOSH 7605 methods were being used.
8. *NIOSH 1501/1550 Air Force* – This identifies if the NIOSH 1501/1550 for the Air Force were being used
9. *37mm, 5um* – This identifies if the size of the media used in the sample event was 37mm in diameter with a 5um pore
10. *None* – This identifies if there was no media size available for a particular sample event
11. *100mg/50 mg* – This identifies if the media size was 100mg/50mg.
12. *Size other* – This identifies if the media size was one of the sizes not assigned as an individual variable.

**Validation Pool**

The data set was randomly split into a model set and a test set, 80% and 20% accordingly. Of the 9,824 lines of data, 7,859 were used to create the model and 1,965 were used for the test set. Once the model set was validated through statistical testing, the remaining test set was used to create the final predictive equation.

**Step-wise Multiple Regression**

Using 80% of the data, the independent variables were input into the step-wise function of JMP with a p-value of .01. A p-value of .01 was justified by Figure 7 the data set was so large. Below is the output for the first run of the team's model with a .93 $R^2$. The estimate column is the coefficient in the regression equation for that particular variable. The Prob > |t| column shows that each of the variables are statistically significant given the alpha of .01.

### Summary of Fit

| | |
|---|---|
| RSquare | 0.939499 |
| RSquare Adj | 0.939407 |
| Root Mean Square Error | 24.82102 |
| Mean of Response | 184.1207 |
| Observations (or Sum Wgts) | 7859 |

### Analysis of Variance

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 12 | 75062560 | 6255213 | 10153.20 |
| Error | 7846 | 4833786 | 616 | Prob > F |
| C. Total | 7858 | 79896345 | | <.0001* |

### Lack Of Fit

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Lack Of Fit | 2659 | 3027627.7 | 1138.63 | 3.2700 |
| Pure Error | 5187 | 1806158.0 | 348.21 | Prob > F |
| Total Error | 7846 | 4833785.8 | | <.0001* |
| | | | | Max RSq |
| | | | | 0.9774 |

### Parameter Estimates

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | VIF |
|---|---|---|---|---|---|
| Intercept | 31.687287 | 0.880106 | 36.00 | <.0001* | . |
| Corrected Sample Time (Min) | 0.6301964 | 0.005002 | 126.00 | <.0001* | 1.46095 |
| Corrected Pre-Calibration (Min) | 2.1472827 | 0.01221 | 175.86 | <.0001* | 1.4949391 |
| CHROMIUM(VI) | 39.746789 | 2.037735 | 19.51 | <.0001* | 11.489811 |
| HEXAMETHYLENE DIISOCYANATE MONOMER | 55.673354 | 2.704791 | 20.58 | <.0001* | 3.5250596 |
| BENZENE | -9.314325 | 1.257663 | -7.41 | <.0001* | 2.1519599 |
| ALUMINUM | 30.584505 | 1.470537 | 20.80 | <.0001* | 1.1257423 |
| NIOSH 7605 | 23.025494 | 2.004153 | 11.49 | <.0001* | 11.071259 |
| NIOSH 1501/ 1550 Air Force | 3.5061577 | 1.346661 | 2.60 | 0.0092* | 1.7230873 |
| 37 mm, 0.8 um | -4.990497 | 0.98407 | -5.07 | <.0001* | 2.035321 |
| None | 57.892603 | 2.606213 | 22.21 | <.0001* | 3.7771914 |
| 100 mg/50 mg | 8.9401773 | 1.144896 | 7.81 | <.0001* | 2.9891837 |
| Size other | 17.246341 | 1.425666 | 12.10 | <.0001* | 1.3498081 |

**Figure 7 Preliminary Regression Model**

In order to reduce Type I error, Bonferroni Correction was conducted. The correction consists of dividing the alpha by the total number of variables in the regression, 12, to lower the threshold for rejecting the null hypothesis. Therefore, using an alpha of .01 $.01 \div 12 = .008$. All of the variables meet this measure's requirements.

The next measure the researchers looked at was the Variance Inflation Factor or VIF. VIF is used to detect if there is multicollinearity in the model. Generally, any variables with a VIF greater than 10 are indicative of multicollinearity and should be removed or investigated. In Figure 7, Chromium (VI) and NIOSH 7605 have VIFs of 11; therefore, the researchers removed NIOSH 7605 from the regression model due to its lower impact on the model. When NIOSH 7605 was removed from the data set, NIOSH 1501/1550 Air Force became insignificant and was also removed from the model.

Cook's Distance is a check used to ensure that there are no overly influential data points. The Cook's Distance Test checks for any data point with a value greater than 0.5 which would indicate having too much influence on the model. The highest value Cook's Distance in the data set was .15 meaning all of the data passes the test. It was noted that it was unlikely to have any overly influential points due to how many points there are in the data set. Figure 8 shows the overlay plot of the Cook's Distance Test.

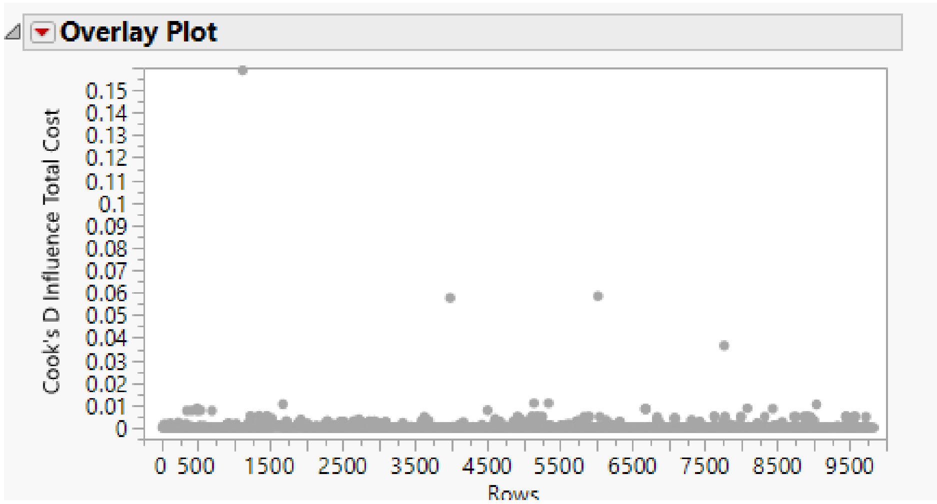



**Figure 8 Cook's Distance Test**

Next, a Shapiro-Wilks test was conducted using a histogram of the studentized residuals. The residuals were graphed in Figure 9 to show that there is a normal distribution of the data. A normal distribution includes that 95% of the data is within two standard deviations and 99.7% of the data is within three standard deviations. This data set was not exactly normal as only 96.7% was within three standard deviations and 94.5% were within two standard deviations. Figure 9 fails the Shapiro-Wilks Test for normal distributions but it is apparent that the majority of the data is centered on zero. If the large spikes had occurred outside the bell curve, it would be more of a hard statistical failure that would put a stop to any further analysis where this should be considered a soft failure because multiple regression is robust against departures from normality. Also, due to the central limit theorem, we considered the data set to be normal because it had an n greater than 30.

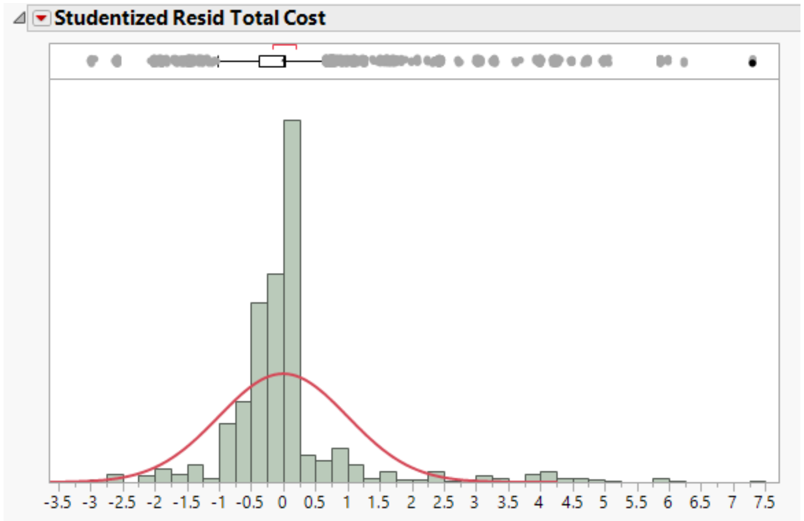



**Figure 9 Studentized Residuals**

**Quantiles**

| | | |
|---|---|---|
| 100.0% | maximum | 7.3074213382 |
| 99.5% | | 4.9827867481 |
| 97.5% | | 3.4579932396 |
| 90.0% | | 0.7381370568 |
| 75.0% | quartile | 0.0314450255 |
| 50.0% | median | -0.005104969 |
| 25.0% | quartile | -0.386119533 |
| 10.0% | | -0.749637778 |
| 2.5% | | -1.661939736 |
| 0.5% | | -2.579209287 |
| 0.0% | minimum | -3.001206845 |

**Summary Statistics**

| | |
|---|---|
| Mean | -1.81e-5 |
| Std Dev | 1.000795 |
| Std Err Mean | 0.0112892 |
| Upper 95% Mean | 0.0221116 |
| Lower 95% Mean | -0.022148 |
| N | 7859 |

**Fitted Normal**

**Parameter Estimates**

| Type | Parameter | Estimate | Lower 95% | Upper 95% |
|---|---|---|---|---|
| Location | μ | -1.81e-5 | -0.022148 | 0.0221116 |
| Dispersion | σ | 1.000795 | 0.9853911 | 1.0166916 |

-2log(Likelihood) = 22314.3670705782

**Goodness-of-Fit Test**

KSL Test

| D | | Prob>D |
|---|---|---|
| 0.267160 | < | 0.0100* |

**Figure 10 Shapiro-Wilks Results**

The final statistical test that the researchers conducted was a Breusch-Pagan to test for heteroscedasticity within the model. This test confirms that there is constant variance in the range of predicted values. In order to complete the Breusch-Pagan, the n, degrees of freedom, sum of squared errors, and sum of squared residuals were used. A low p-value rejects for the Bruesch-Pagan Test means that the variance is not constant in the model.  Table 4 shows the results.

**Table 4 Breusch-Pagan Results**

**Breusch-Pagan Test**

| | |
|---|---|
| N | 7858 |
| df(Exp) | 11 |
| SSE | 7483408 |
| SSR | 4115468694 |

| | |
|---|---|
| **T.S.** | **2268.895574** |
| **Pvalue** | **0** |

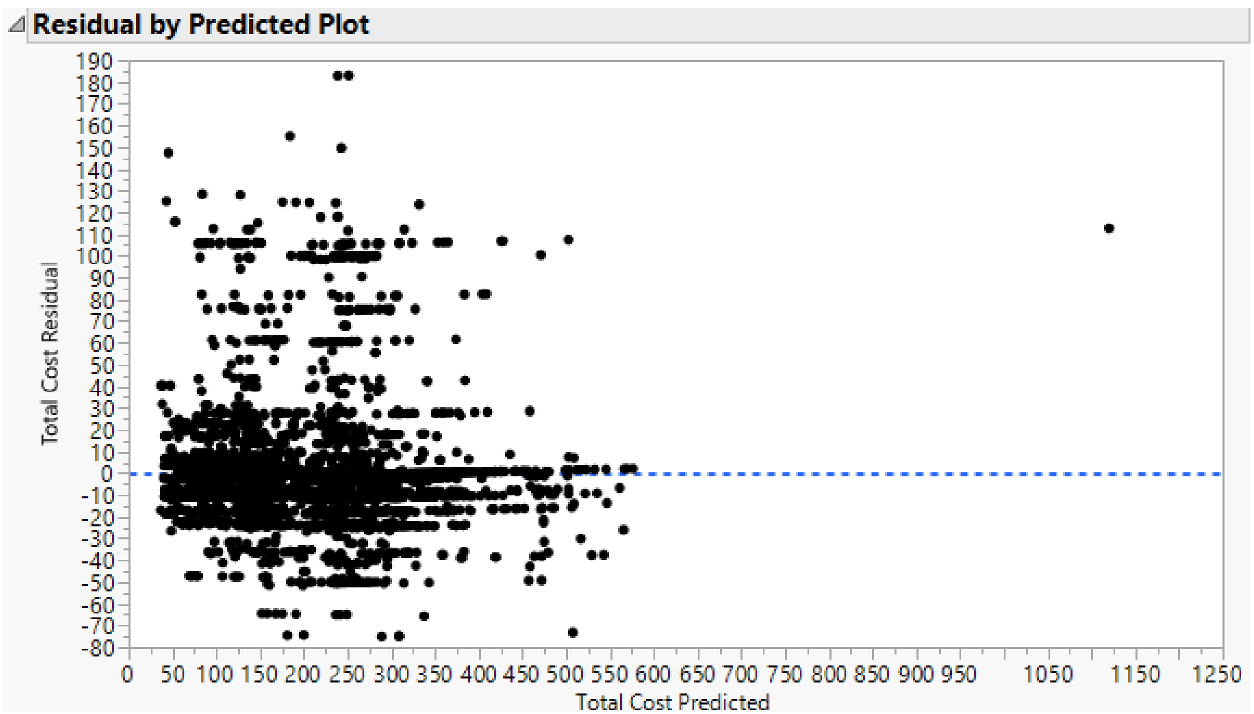



**Figure 11 Residual by Predicted Plot**

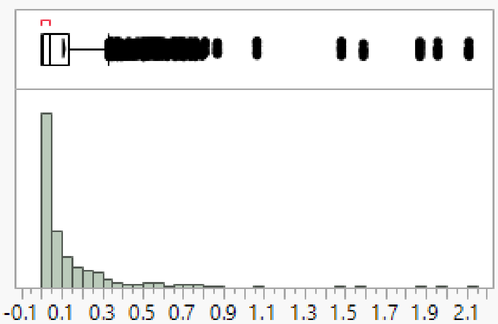
Figure 11 indicates that there is no trend. If the overlay plot showed signs of a trending V, it would result in a hard fail but because there was no trend, the data incurs statistically fails Breusch-Pagan but multiple regression is robust against deviations from constant variance.

## Model Validation

After creating the initial model, the research team began model validation with the remaining 20% of the data set. The team compared the Mean Absolute Percent Error and Median Absolute Percent Error from the 80% preliminary model with the 20% validation model. Figure 12 and 13 include the Absolute Percent Error of the preliminary model and the validation model respectively.

**Distributions**

**APE**




**Quantiles**

| | | |
|---|---|---|
| 100.0% | maximum | 2.1130119453 |
| 99.5% | | 1.5918675736 |
| 97.5% | | 0.6235923713 |
| 90.0% | | 0.2728975637 |
| 75.0% | quartile | 0.1351561858 |
| 50.0% | median | 0.0436381379 |
| 25.0% | quartile | 0.0031018564 |
| 10.0% | | 0.0008800715 |
| 2.5% | | 0.000207224 |
| 0.5% | | 0.0000473598 |
| 0.0% | minimum | 5.7269193e-6 |

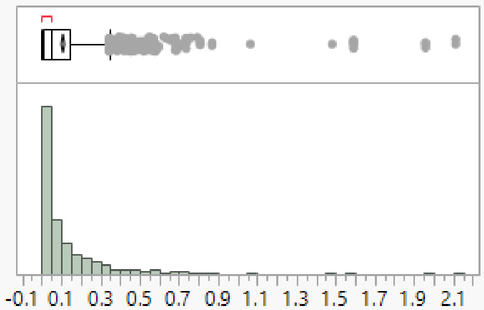
**Summary Statistics**

| | |
|---|---|
| Mean | 0.110794 |
| Std Dev | 0.2060261 |
| Std Err Mean | 0.002324 |
| Upper 95% Mean | 0.1153496 |
| Lower 95% Mean | 0.1062383 |
| N | 7859 |

**Figure 12 Summary of Statistics of Absolute Percent Error for Preliminary Model**

Distributions

APE




Quantiles

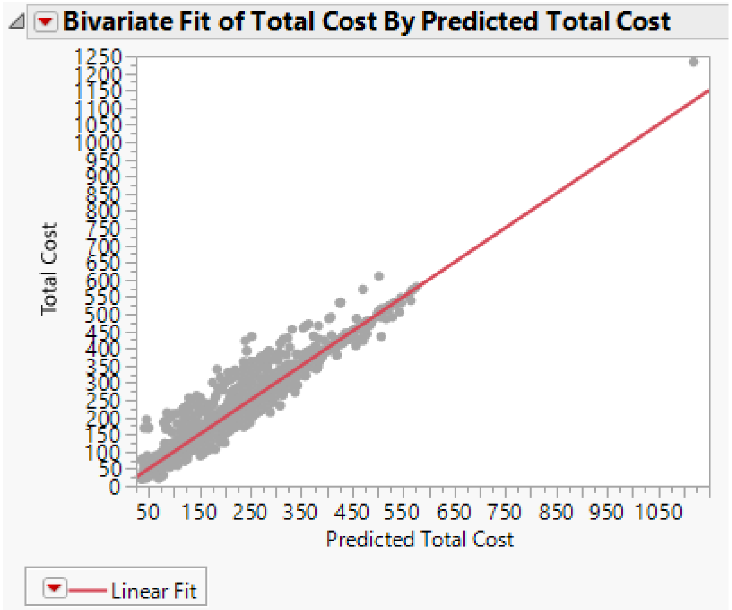
| | | |
|---|---|---|
| 100.0% | maximum | 2.1130119453 |
| 99.5% | | 1.5918675736 |
| 97.5% | | 0.5696154821 |
| 90.0% | | 0.2791596087 |
| 75.0% | quartile | 0.1393823359 |
| 50.0% | median | 0.0466320293 |
| 25.0% | quartile | 0.0036757755 |
| 10.0% | | 0.0009414848 |
| 2.5% | | 0.000212533 |
| 0.5% | | 0.0000435723 |
| 0.0% | minimum | 5.7269193e-6 |

Summary Statistics

| | |
|---|---|
| Mean | 0.1095324 |
| Std Dev | 0.1907466 |
| Std Err Mean | 0.004303 |
| Upper 95% Mean | 0.1179714 |
| Lower 95% Mean | 0.1010934 |
| N | 1965 |

**Figure 13 Summary of Statistics of Absolute Percent Error for Validation Model**

The Mean Absolute Percent Error is 11.07% in the preliminary model and 10.95% in the validation model. The Median absolute percent error is 4.36% in the preliminary model and 4.66% in the validation model. All of these numbers are very similar indicating the two sets are relatively the same.



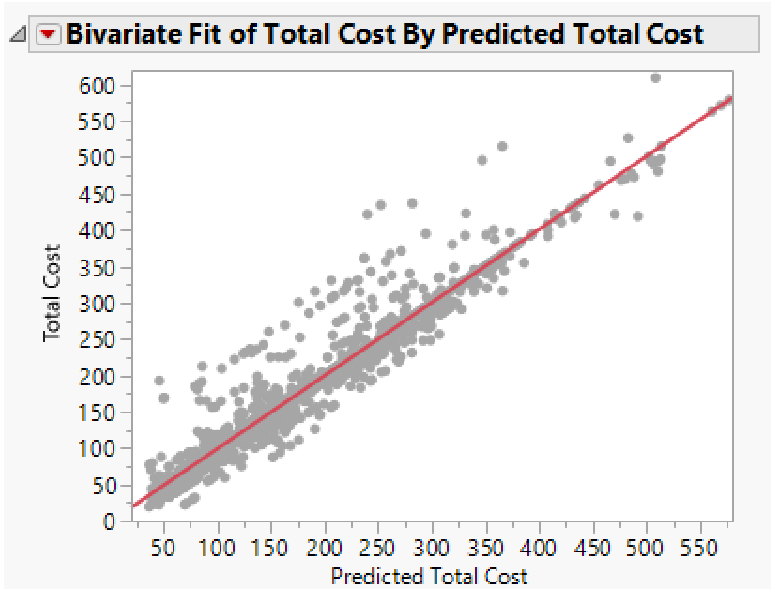

### Linear Fit

Total Cost = -4.21e-11 + 1*Predicted Total Cost

#### Summary of Fit

| | |
|---|---|
| RSquare | 0.938432 |
| RSquare Adj | 0.938424 |
| Root Mean Square Error | 25.0214 |
| Mean of Response | 184.1207 |
| Observations (or Sum Wgts) | 7859 |

**Figure 14 Bivariate Plot of Total Cost $ vs. Predicted Preliminary Model**




**Linear Fit**

Total Cost = -1.540768 + 1.0062473*Predicted Total Cost

**Summary of Fit**

| | |
|---|---|
| RSquare | 0.936976 |
| RSquare Adj | 0.936943 |
| Root Mean Square Error | 25.39233 |
| Mean of Response | 183.1723 |
| Observations (or Sum Wgts) | 1965 |

**Figure 15 Bivariate Plot of Total Cost $ vs. Predicted Validation Model**

Both bivariate plots for total versus predicted costs have an $R^2$ and adjusted $R^2$ of .93. This, with the mean and median actual percent error, concludes that both the preliminary model and the validation model are comparable and the research team was able to move on to the final regression model.

## Final Regression Model

The research team accepts that the regression model can be used without additional limitations. The final model was a regression with the same independent variables that included all of the data points. Figure 16 is the model:

**Summary of Fit**

| | |
|---|---|
| RSquare | 0.938198 |
| RSquare Adj | 0.938135 |
| Root Mean Square Error | 25.09327 |
| Mean of Response | 183.931 |
| Observations (or Sum Wgts) | 9824 |

**Analysis of Variance**

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Model | 10 | 93801197 | 9380120 | 14896.83 |
| Error | 9813 | 6178975 | 630 | Prob > F |
| C. Total | 9823 | 99980173 | | <.0001* |

**Lack Of Fit**

| Source | DF | Sum of Squares | Mean Square | F Ratio |
|---|---|---|---|---|
| Lack Of Fit | 2678 | 3415767.4 | 1275.49 | 3.2935 |
| Pure Error | 7135 | 2763207.7 | 387.28 | Prob > F |
| Total Error | 9813 | 6178975.1 | | <.0001* |
| | | | | Max RSq |
| | | | | 0.9724 |

**Parameter Estimates**

| Term | Estimate | Std Error | t Ratio | Prob>\|t\| | Std Beta | VIF |
|---|---|---|---|---|---|---|
| Intercept | 32.597726 | 0.78682 | 41.43 | <.0001* | 0 | . |
| Corrected Sample Time (Min) | 0.6272859 | 0.004526 | 138.58 | <.0001* | 0.421105 | 1.4660563 |
| Corrected Pre-Calibration (Min) | 2.1490066 | 0.011041 | 194.63 | <.0001* | 0.595498 | 1.4863597 |
| CHROMIUM(VI) | 61.11231 | 0.820853 | 74.45 | <.0001* | 0.281942 | 2.2771548 |
| HEXAMETHYLENE DIISOCYANATE MONOMER | 56.87331 | 2.475616 | 22.97 | <.0001* | 0.109259 | 3.5914245 |
| BENZENE | -6.785907 | 1.044082 | -6.50 | <.0001* | -0.02182 | 1.7895784 |
| ALUMINUM | 30.785103 | 1.32998 | 23.15 | <.0001* | 0.061452 | 1.1191233 |
| 37 mm, 0.8 um | -5.951841 | 0.878406 | -6.78 | <.0001* | -0.02405 | 1.9999607 |
| None | 59.090807 | 2.372932 | 24.90 | <.0001* | 0.122328 | 3.8316442 |
| 100 mg/50 mg | 7.738107 | 1.016458 | 7.61 | <.0001* | 0.032302 | 2.8587371 |
| Size other | 15.634786 | 1.288091 | 12.14 | <.0001* | 0.035168 | 1.3329465 |

**Figure 16 Final Regression Model**

The team's final regression model ended with an $R^2$ of .938 using 10 independent variable. There are some variables with negative coefficients because the intercept of the regression equation is higher than the value of the predicted cost if that variable were to be included. The final equation to predict the total cost of an occupational exposure assessment focusing on air sampling events is the following with $X_n$ starting with *Corrected Sample Time (Min)* and ending with *Size other*:

$$Y = 32.598 + .627X_1 + 2.149X_2 + 61.112X_3 + 56.873X_4 + -6.785X_5 + 30.785X_6 + -5.95X_7 + 59.091X_8 + 7.738X_9 + 15.635X_{10}$$

**Predicted Cost Distribution**

The final portion of the analysis that the researchers conducted was fitting the predicted outcomes to a distribution. @Risk provided the best fit distribution for the data as a Kumaraswamy distribution but the researchers chose to use the second best fit, Weibull distribution, because the differences were minute and it more widely recognized.

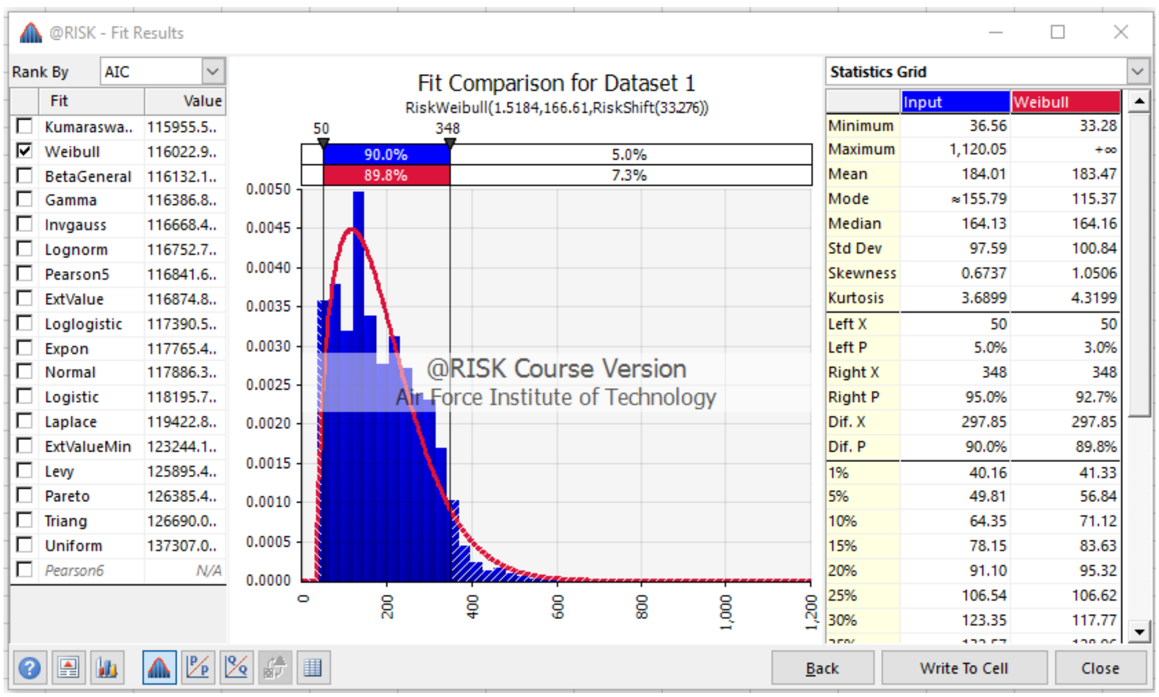



**Figure 17 Predicted Costs Distribution**

The descriptive statistics show that the predicted costs have a mean of $183.47 and a median of $164.16. The data is skewed to the right but the 80% of the predicted costs fall between $71.12 and $321.85 per sample.

## Raw Data Aggregation

The researchers also used coding (Appendix B) to look at averages of the largest 10 groups of different combinations of independent variables. The first table indicates the most common instances of a certain event. For example, the most prevalent air sampling event from out 9,824 lines of data used NIOSH 7605 methodology and a PVC filter for media. There were 3,052 occurrences of that particular combination and the average cost was $241.14 with an average sample time of 58.07 minutes.

# Groups: Method [73]

| | Method | `Media Type` | Total | Time | Count |
|---|---|---|---|---|---|
| | <chr> | <chr> | <chr> | <dbl> | <int> |
| 1 | NIOSH 7605 | PVC Filter | $241.14 | 58.07 | 3052 |
| 2 | NIOSH 7300 | MCE Filter | $174.52 | 71.44 | 2035 |
| 3 | NIOSH 7300 | PVC Filter | $164.95 | 60.10 | 780 |
| 4 | NIOSH 1501/ 1550 Air Force | Charcoal CB | $97.03 | 22.46 | 779 |
| 5 | NIOSH 1501 | Charcoal CB | $126.98 | 35.36 | 632 |
| 6 | NIOSH 1550 | Charcoal CB | $148.97 | 36.18 | 357 |
| 7 | NIOSH 1005 | Charcoal CB | $123.89 | 13.75 | 244 |
| 8 | ASTM D6561-00 | ISO-CHEK | $201.68 | 6.05 | 217 |
| 9 | NIOSH 2016 | Silica Gel Treated | $131.84 | 9.54 | 210 |
| 10 | NIOSH 0500 | PVC Filter, Matched | $71.75 | 23.51 | 159 |

**Figure 18 Most Common Combinations of Method and Media Type**

The team also identified what was the most frequent hazards being tested. In Figure 18, it is visible that events testing for Chromium (VI) made up nearly a third of the researchers data set.

| | Hazard | Total | Time | Count |
|---|---|---|---|---|
| | <chr> | <chr> | <dbl> | <int> |
| 1 | CHROMIUM(VI) | $242.45 | 58.80 | 3117 |
| 2 | BENZENE | $112.20 | 32.82 | 1174 |
| 3 | CADMIUM | $147.95 | 57.20 | 973 |
| 4 | COPPER | $171.27 | 73.29 | 753 |
| 5 | ALUMINUM | $158.49 | 34.90 | 416 |
| 6 | HEXAMETHYLENE DIISOCYANATE MONOMER | $221.93 | 15.39 | 384 |
| 7 | LEAD | $218.71 | 126.46 | 315 |
| 8 | PARTICULATES NOT OTHERWISE SPECIFIED | $110.02 | 36.79 | 274 |
| 9 | METHYLENE CHLORIDE | $128.72 | 17.36 | 252 |
| 10 | FORMALDEHYDE | $141.21 | 18.58 | 229 |

**Figure 19 Frequency of Hazard Being Tested**

**Fiscal Transparency**

A major reason for conducting this analysis was to highlight how much money is being spent on occupational exposure assessments in the Air Force. Changing anything, even minor, with a large budget, has the potential to be very costly. One of the steps in finding out the costs included finding the total budget for these processes. However, there was little information available. The researchers were able to get in contact with the USAFSAM budget analysts, the BEE Resource Advisor, and a Budget Analyst from the Pentagon. The information gathered led to the conclusion that either the finances, specifically for occupational exposure assessments, have not been adequately monitored or there is not enough training provided to those who are responsible for the budgets.

USAFSAM budget analysts, when contacted, were unable to provide any actual figures on how much money was spent from 2014-2017 on processing occupational exposure assessments or what factors go into the total costs. The information the researchers were able to obtain was that all occupational exposure assessment costs were purchased with the government purchase card. That information was valuable, but only for top-level analysis, because they budget analysts were unable to provide any information on how purchases were coded. Without the coding, the researchers were unable to decipher from the large government purchase card bill what was spent on occupational exposure assessments and what was spent on other supplies. The BEE resource advisor provided a similar response that the government purchase card holder purchases inventory when required. The researchers were unable to uncover any ledger or budget information.  Finally, the contact at the Pentagon was able to provide Air Force-wide budget reports that had all of the data for expenditures on occupational exposure assessments, but was unable to provide any specific coding because not all locations use the same specialty codes for their government purchase cards, or any at all.

The easiest remedy for simple budget transparency would be to create a uniform process across the Air Force for tracking and inputting government purchases pertaining to occupational exposure assessments. The solution would most likely be opposed for the reasoning that if specialty codes were required for occupational exposure assessments, why every individual purchase or expenditure would not have its own specialty code, which would potentially create an abundance of work. A more feasible solution would be to provide more training to the government purchase card holders and requiring a ledger to be maintained that tracks expenditures by activity.

## Conclusion

The research team was able to conduct a multiple regression on the data available. The results provided a relatively high $R^2$ of .938 and an equation that could be used to predict the rough cost of an air sampling occupation hazard assessment. However, it should be noted, that much of the road map discussed in chapter three was not completed. In order to find a more accurate representation of the total cost, effort should be made to identifty the true costs incurred by the laboratory when they process the samples taken by the BEE flights.

# V. Conclusion

## Chapter Overview

This chapter addresses the end results discussed in Chapter IV. The significance of the research is explained with the limitations and assumptions and any recommendations for follow-on research to this topic. The initial effort of this research was to identify how changes to the AFMAN 48-146 would affect the budget. Due to down scoping the research, the primary goal became to identify the costs of occupation exposure assessments for the current practices. The research team developed a roadmap, discussed in Chapter III, which identified the major surrogates for cost. The team set out to find data for each of the surrogates but due to limitations with the points of contacts, was only able to complete approximately 75% of the roadmap. With the data collected, the team developed a model using a mixed step-wise regression that predicted the total cost of an occupational exposure assessment.

## Conclusions of Research

As stated in Chapter IV, the model created by the research team was able to predict the costs of occupational exposure assessments with an $R^2$ of .934. Using approximately 10,000 lines of data, the team's model was robust and statistically significant for an alpha of .01. The team also provided an aggregation of data that shows the top 10 most frequent pairings of testing method and media type used and what the average cost was for those events. Also, a table for the top 10 hazards tested were created including the average sample time and cost respectively. A final conclusion from this research was that fiscal transparency has room for improvement. From a top-level, all of the data is tracked but not with precision. A process could be implemented that would allow all levels of budget analysis to break out and better understand the expenditures being made.

**Limitations**

It is valuable to understand the limitations of the research conducted when making conclusions or recommendations. There were multiple limitations to conducting this research. The first major limitation encountered was the lack of actual costs tracked in DOEHRS and LIMS. The entities conducting occupational exposure assessments do not currently track any costs despite the systems having the capability to do so. Because no costs were tracked by those conducting and processing exposure assessments, data needed to be sought out and pieced together. In doing so, the researchers were required to make assumptions such as the pay grades of those conducting the assessments and prices of media were as shown on commercial websites. The biggest assumption that the team made, was that cost of processing samples taken in the lab were the same as the prices listed on the blanket purchase agreement. It is almost certain that there are decreases in costs when conducting analysis in-house opposed to paying commercial companies to do the work. The team also assumed that the data input into the systems was accurate and inclusive.

## Recommendations for Action

The United States Air Force could use the findings of this research to better two different processes. First, the costs drivers addressed in this paper should be considered by leadership before making changes to the process of conducting occupational exposure assessments. If any of the potential changes were to affect the method of testing, media type, or hazards tested, it would be valuable to review the findings of this research and take appropriate action or acceptance. Second, the process of tracking costs incurred through bioenvironmental engineering activities, specifically occupational exposure assessments, could be improved upon. The systems already have the capability to record associated costs so it would be a matter of streamlining training to better utilize the tools available.

## Recommendations for Future Research

There are many opportunities to conduct follow-on research. First, the research conducted in this paper can be improved upon with a more complete data set. A more complete data set would include more actual data for the second half of our roadmap. This research is lacking in data from the labs at USAFSAM and inclusion of that data would provide a more valid cost model. Another facet of research that could be conducted would be to compare how the costs of current practices would be affected by the changes to AFMAN 48-146. Finally, research could be conducted on finding the optimal exposure assessment strategy that mitigates the most risk for the lowest cost – essentially the most bang for the buck.

## Summary

In conclusion, two of the four specific aims of this research were addressed. A statistically significant model that identifies the major cost drivers associated with occupational exposure assessments was created. The Air Force leadership can use the findings of this research to focus on how current practices are conducted and how changing regulations might impact the budget. Follow-on research would be valuable to the Air Force and would ensure that the tax payer’s dollars are being used optimally.

## Bibliography


@RISK, Version *7.5*. Palisade Corporation, Ithaca, NY, 2016

AFCRUH. (2015). U . S . Air Force Cost Risk and Uncertainty Analysis Handbook.

Batten, T. W. (2009). FIELD EVALUATION OF A NOVEL EXPOSURE ASSESSMENT STRATEGY.

Cohen, J. (1992). Quantitative Methods in Psychology. *Psychological Bulletin*, *112*(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Exposure Assessment. (n.d.). Retrieved November 8, 2017, from https://www.osha.gov/SLTC/etools/respiratory/change_schedule_exposure.html

Hoyt, W. T., Leierer, S., & Millington, M. J. (2006). Analysis and Interpretation of Findings Using Multiple Regression Techniques. *Rehabilitation Counseling Bulletin*, *49*(4), 223–233. https://doi.org/10.1177/00343552060490040401

JMP®, Version *13 Pro*. SAS Institute Inc., Cary, NC, 1989-2007

Keeney, R. L. (1996). Value-focused thinking: Identifying decision opportunities and creating alternatives. *European Journal of Operational Research*, *92*(3), 537–549. https://doi.org/10.1016/0377-2217(96)00004-5

Mathiassen, S. E., & Bolin, K. (2011). Optimizing cost-efficiency in mean exposure assessment--cost functions reconsidered. *BMC Medical Research Methodology*, *11*(1), 76. https://doi.org/10.1186/1471-2288-11-76

McGuire, V., Nelson, L. M., Koepsell, T. D., Checkoway, H., & Longstreth Jr., W. T. (1998). Assessment of occupational exposures in community-based case-control studies. *Annu.Rev Public Health*, *19*(0163–7525), 35–53.

https://doi.org/10.1146/annurev.publhealth.19.1.35

Mildred L. Patten. (2009). *Understanding Research Methods* (Seventh). Pyrczak Publishing.

Rezagholi, M., & Mathiassen, S. E. (2010). Cost-efficient design of occupational exposure assessment strategies - A review. *Annals of Occupational Hygiene*, *54*(8), 858–868. https://doi.org/10.1093/annhyg/meq072

Richey. (2009). GAO Cost Estimating and Assessment Guide. *US Government Accountability Office*, (March), 440. Retrieved from http://www.gao.gov/new.items/d093sp.pdf

Roth, J. P. (n.d.). *Burdened salaries.pdf*.

Stahl, H. P., Henrichs, T., & Msfc, N. (2016). Towards a multi-variable parametric cost model for ground and space telescopes, *9911*.

Thomas, C. M. (2006). FLEXIBLE ARCHITECTURE AND ITS IMPACT ON THE LIFE CYCLE COST OF AIR TO SURFACE MUNITIONS, (March), 1–148.

## Appendix A

Below are the notes taken when discussing pre- and post-calibration times for occupational exposure assessments with a subject matter expert.

Rank/Grade TSGT MARK OLSEN

As Subject Matter Experts, please provide your best estimates for the following actions for both large and small **air sample events**.

PRE-CAL

TASK ↓ ETHOD DETERMINE ↓ AB SELECTION ↓ EDIA CHECKS ↓ QUIP CHECKS ↓ AMPLE STRATEGY ↓ (CAN BE ABBREV. EXP.)

OLLECT MEDIA 1. ↓ OLLECT EQUIPMENT 2. ↓ LLECT CALIBRATOR 3. ↓ REATE SAMPLING TRAIN 4. WITH CAL MEDIA) ↓ UN CALIBRATOR ON 10 READ 5. AVERAGING CYCLE ↓ DJUST PUMP TO DESIRED 6. FLOW RATE ↓ RECORD FINAL AVERAGE 7. FOR PUMP ↓ REPLACE PUMP WITH NEXT PUMP 8. (LOOP FOR X-THE PUMPS) ↓ PUT INTO KIT FOR EVENT

POST-CAL

RETURN W/ SAMPLES ↓ CAL STEPS 1-8. ↓ TRANSFER PERSONNEL, PUMP, CAL INFO INTO DOEHRS ↓ GENERATE SAMPLES & SAMPLE IDs ↓ GENERATE DOEHRS XML FILE (1) ↓ GENERATE SAMPLE SUBMISSION FORM (3) ↓ LABEL SAMPLES (5) ↓ GENERATE SHIPPING LABEL (3) ↓ PACKAGE SAMPLES (5) ↓ EMAIL XML FILE (1) ↓ DRIVE SAMPLES TO FED-EX DROP-OFF (~60)

$>3$ PUMPS / $<3$ PUMPS

1. What is the **fastest** time you have completed pre-calibration before conducting **air samples** (minutes)?

   Large 20 MINUTES Small 15 MINUTES (15-45 MINS)

2. What is the **longest** time it has taken you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 150 MINUTES Small 120 MINUTES (15-30 MINS)

3. How long does it **normally** take you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 55 MINUTES Small 45 MINUTES (5-10)

4. What is the **fastest** time you have completed post-calibration, packaging, and shipping **for air samples** (minutes)?

   $>$ 3 MEDIA CASSETTES and/or PUMPS (~5-10 MEDIA) $\leq$ 3 MEDIA CASSETTES AND/OR PUMPS

   Large 1 hr 45 mins Small 1 hr 30 mins

5. What is the **longest** time it has taken to complete post-calibration, packaging, and shipping for **air samples** (minutes)?

   Large ~~1 hr 45~~ >8 hrs Small ~~1 hr 30 mins~~ 3 hrs 30 mins

6. How long does it **normally** take to complete post-calibration, packaging, and shipping **for air samples** (minutes)?

   Large 2 hrs 30 minutes Small 2 hrs 30 minutes

7. Out of 10 **air sample events**, what is your best estimate for the distribution between large and small (Large + Small = 10)?

   Large 2 Small 8

Rank/Grade E4/S, A

As Subject Matter Experts, please provide your best estimates for the following actions for both large and small **air sample events**.

1. What is the **fastest** time you have completed pre-calibration before conducting **air samples** (minutes)?

   Large 45 min　　　Small 15 min

2. What is the **longest** time it has taken you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 1hr 15min　　　Small 30 min

3. How long does it **normally** take you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 45min – 1hr　　　Small 20 min

4. What is the **fastest** time you have completed post-calibration, packaging, and shipping **for air samples** (minutes)?

   *2 - 3 days　　　*1 - 2 days

   Large 5 - 8 hrs　　　Small 3 - 5 hrs

5. What is the **longest** time it has taken to complete post-calibration, packaging, and shipping for **air samples** (minutes)?

   *5 days　　　*3 - 4 days

   Large 2 days　　　Small 1 day

6. How long does it **normally** take to complete post-calibration, packaging, and shipping **for air samples** (minutes)?

   *2 days　　　1 day

   Large 4 - 6 hrs　　　Small 3 hrs

7. Out of 10 **air sample events**, what is your best estimate for the distribution between large and small (Large + Small = 10)?

   Large 2　　　Small 8

Rank/Grade SrA O'Brien

As Subject Matter Experts, please provide your best estimates for the following actions for both large and small **air sample events**.

1. What is the **fastest** time you have completed pre-calibration before conducting **air samples** (minutes)?

   Large 45 Small 15

2. What is the **longest** time it has taken you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 60 Small 45

3. How long does it **normally** take you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 30 Small 20

4. What is the **fastest** time you have completed post-calibration, packaging, and shipping **for air samples** (minutes)?

   Large 4 hrs* Small 45 min*
   1 hr 20min

5. What is the **longest** time it has taken to complete post-calibration, packaging, and shipping for **air samples** (minutes)?

   Large 10hrs* Small 8hrs*
   6hrs. 2hrs

6. How long does it **normally** take to complete post-calibration, packaging, and shipping **for air samples** (minutes)?

   Large 5hrs* Small 3hrs*
   3hrs. 1hrs

7. Out of 10 **air sample events**, what is your best estimate for the distribution between large and small (Large + Small = 10)?

   Large 2 Small 8

Rank/Grade A1C Osborne

As Subject Matter Experts, please provide your best estimates for the following actions for both large and small **air sample events.**

1. What is the **fastest** time you have completed pre-calibration before conducting **air samples** (minutes)?

   Large 45 min    Small 15 min

2. What is the **longest** time it has taken you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 1hr 15 min    Small 45 min

3. How long does it **normally** take you to complete pre-calibration before conducting **air samples** (minutes)?

   Large 45 min    Small 15-30 min

4. What is the **fastest** time you have completed post-calibration, packaging, and shipping **for air samples** (minutes)?

   * with DOEHRS 8 hrs    5 hrs

   Large 5 hrs    Small 3 hrs

5. What is the **longest** time it has taken to complete post-calibration, packaging, and shipping for **air samples** (minutes)?

   * with DOEHRS 16 hrs    8 hrs

   Large 8 hrs    Small 6 hrs

6. How long does it **normally** take to complete post-calibration, packaging, and shipping **for air samples** (minutes)?

   Large 8 hrs    Small 4 hrs

7. Out of 10 **air sample events**, what is your best estimate for the distribution between large and small (Large + Small = 10)?

   Large 2    Small 8

## Appendix B

Below is the code used in R to aggregate data shown in figures 18 and 19:

```
library(tidyverse)
library(readxl)
library(scales)

 df <-  read_excel("C:/Users/James/Desktop/Class/Brad/Brad.Data.xlsx") %>%
  filter(Method != "#N/A")

df %>%
  group_by(Hazard) %>%
  summarise(Total = dollar(mean(`Total Cost`, na.rm = T)),
          Time = round(mean(as.numeric(`Corrected Sample Time (Min)`), na.rm = T),2),
          Count = n()) %>%
  arrange(desc(Count))

df %>%
  group_by(Method, `Media Type`) %>%
  summarise(Total = dollar(mean(`Total Cost`, na.rm = T)),
          Time = round(mean(as.numeric(`Corrected Sample Time (Min)`), na.rm = T),2),
          Count = n()) %>%
  arrange(desc(Count))
```

| REPORT DOCUMENTATION PAGE | *Form Approved OMB No. 0704-0188* |
|---|---|



| **1. REPORT DATE** *(DD-MM-YYYY)* | **2. REPORT TYPE** | **3. DATES COVERED** *(From - To)* |
|---|---|---|
| 23-04-2018 | Graduate Research Thesis | 01-08-2017 - 23-04-2018 |

| | |
|---|---|
| **4. TITLE AND SUBTITLE**<br>Air Force Corporate Exposure Assessment Strategy: Underlying Cost Behaviors & Visibilty | **5a. CONTRACT NUMBER** |
| | **5b. GRANT NUMBER** |
| | **5c. PROGRAM ELEMENT NUMBER** |
| **6. AUTHOR(S)**<br>Duncan, Bradley M., 1Lt | **5d. PROJECT NUMBER** |
| | **5e. TASK NUMBER** |
| | **5f. WORK UNIT NUMBER** |
| **7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)**<br>Air Force Institute of Technology<br>Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way<br>Wright-Patterson AFB OH 45433-7765 | **8. PERFORMING ORGANIZATION REPORT NUMBER**<br>AFIT-ENV-MS-18-M-196 |
| **9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)**<br>United States School of Aerospace Medicine 2510 North, 5th St,<br>Fairborn, OH 45324 | **10. SPONSOR/MONITOR'S ACRONYM(S)**<br>USAFSAM |
| | **11. SPONSOR/MONITOR'S REPORT NUMBER(S)** |

**12. DISTRIBUTION/AVAILABILITY STATEMENT**

Distribution Statement A. Approved for Public Release;Distribution Unlimited

**13. SUPPLEMENTARY NOTES**

This work is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

| 14. ABSTRACT | | | | | |
|---|---|---|---|---|---|

**14. ABSTRACT**

The research conducted in this thesis is an initial attempt to identify the costs associated with occupational exposure assessments within the Air Force. Using cost estimation methodologies, a cost model was created to predict the total costs of occupational hazard assessments focused on air sampling. Data was gathered from bioenvironmental engineering databases and subject matter experts for analysis. The data required extensive curation before running a mixed step-wise regression. The major cost drivers for occupational exposure assessments were identified as the sample time and pre-calibration time for conducting an air sample. The average predicted cost was $183.47 with 80% of predicted costs falling between $71.12 and $321.85. It was discovered that much of the data that is applicable to cost was unclear or unrecorded. As changes are implemented to the regulation for conducting these events, this research can provide decision support to Air Force leadership. The Air Force can also use this research's findings to improve upon budgetary tracking and fiscal transparency.

**15. SUBJECT TERMS**

Budget, Occupational Hazard Assessment, Cost, Regression

| 16. SECURITY CLASSIFICATION OF: | | | 17. LIMITATION OF ABSTRACT | 18. NUMBER OF PAGES | 19a. NAME OF RESPONSIBLE PERSON |
|---|---|---|---|---|---|
| a. REPORT | b. ABSTRACT | c. THIS PAGE | | | Lt Col Robert M. Eninger, AFIT/ENV |
| U | U | U | UU | 75 | 19b. TELEPHONE NUMBER *(Include area code)* (937) 785-3636 Robert.Eninger@afit.edu |

**Standard Form 298** (Rev. 8/98)
Prescribed by ANSI Std. Z39.18