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INVESTIGATING THE RELATIONSHIP OF PREVENTIVE AND CORRECTIVE MAINTENANCE IN CHILLER ASSETS USING LINEAR REGRESSION ANALYSIS

THESIS

Jacob A. Franke, Captain, USAF

AFIT-ENV-MS-22-M-195

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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AFIT-ENV-MS-22-M-195

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THESIS

Presented to the Faculty

Department of Engineering 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 Engineering Management

Jacob A. Franke, BS

Captain, USAF

March 2022

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AFIT-ENV-MS-22-M-195

Abstract

Asset managers responsible for maintaining portfolios of built infrastructure assets across large campus areas seek to make informed decisions to reduce their maintenance needs. One widely-accepted approach to reducing unwanted corrective maintenance is the incorporation of a preventive maintenance plan. While these preventive plans have been a maintenance staple for decades, the benefits achieved have not been thoroughly examined at the asset specific level. This study focuses on the U.S. Air Force built infrastructure portfolio to better understand the relationship between preventive maintenance, i.e., scheduled maintenance meant to preserve system performance while preventing system failures, and corrective maintenance, i.e., unscheduled repairs, in chiller assets. Through multiple stages of linear regression modeling and utilizing maintenance data from 14 U.S. Air Force installations from across the contiguous United States, preventive maintenance is used to explain the variance experienced in corrective maintenance. This study found that preventive and corrective maintenance are positively correlated. More importantly, preventive maintenance was found to account for relatively small portions of corrective maintenance. This suggests that targeting preventive maintenance may not be the only solution to reducing corrective maintenance on an asset. Moreover, this study highlights the value of collecting and maintaining portfolio maintenance data at the asset level to improve database utility. Finally, this paper suggests ways to improve data management practices to enhance an asset managers ability to properly maintain large portfolios of built assets.

Acknowledgments

I would first and foremost like to thank my academic advisor, Lt Col Justin Delorit, for all his support and understanding throughout this process. I will remember your mentorship and leadership long after this process concludes. Next, I would like to thank my committee members, Maj Patrick Grandsaert and Dr. Christopher Chini, for your willingness to help me succeed with this endeavor. In addition, thank you to Maj Grandsaert and his team at Air Force Civil Engineer Center, especially Bryan Muller, for their support of my research. Though our experience has been different than expected in this pandemic environment, thank you to my classmates for the support throughout this experience. Finally, I want to thank my wife, whose love and support kept me focused on the end goal.

Jacob A. Franke

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INVESTIGATING THE RELATIONSHIP OF PREVENTIVE AND CORRECTIVE MAINTENACE IN CHILLER ASSETS USING LINEAR REGRESSION ANALYSIS

I. Introduction

Background

Maintenance portfolios are commonly split into two large categories of activities: preventive maintenance, i.e., recurring maintenance activities designed to prolong asset or system performance and prevent premature failure, by replacing and maintaining components (Zhu et al., 2021), and corrective, unscheduled, maintenance activities. Proper management of these preventive and corrective maintenance activities for built assets has been widely accepted as a key to effective operations of mechanical systems over large physical campuses. These substantial built infrastructure portfolios require asset management plans to sustain operations, regardless of a firm's industry or purpose. One aspect of these plans is the incorporation of a preventive maintenance plan, that is a recurring maintenance playbook designed to prevent system failures before they occur. However, large campus areas layer additional constraints on asset managers as more facilities lead to more assets that need to be maintained. As technologies, data, and maintenance capabilities continue to improve, asset managers gain more tools to assist in maintaining these large built infrastructure portfolios.

The U.S. Department of Defense is no different than any other organization, operating substantial built infrastructure portfolios, spread across one or multiple campus areas. As of 2017, the U.S. Department of Defense (2017) operated nearly 4,800 sites, with over 275,500 buildings worldwide. Of that, the United States Air Force (USAF)

owns or operates out of 47,750 facilities, worth over $194 billion (U.S. Department of Defense, 2017). Most of these facilities require climate control systems, such as chillers, to protect assets from overheating and enable operations. These systems drive a large portion of a facility's operational costs. In fact, heating, ventilation, and air conditioning (HVAC) systems account for anywhere from 32-51% of a facility's energy consumption (U.S. EIA, 2016), based on facility usage, and consumption is expected to rise in the future, based on current climate predictions (Weiss, 2021). While heating demands may decrease in the winter, cooling demands will increase throughout the year (Weiss, 2021), creating a need for more cost-effective management of cooling generation systems. Additionally, a recent study analyzing military dormitory facilities found that costs to maintain HVAC systems were among the highest of all facility systems (Weeks & Leite, 2021).

The Air Force Civil Engineer Center (AFCEC) has enabled installations to sole-source chiller system requirements based on a simple economic analysis, with the intent of moving to an enterprise category management model. The belief of AFCEC is that category management would allow USAF installations to limit chiller brand diversity, which would, over the long-term, limit costs associated with preventative and corrective maintenance, parts stocking, and technician training. However, the proposed framework does not currently require installations to consider asset performance or life-cycle costs. One of the many aspects of life-cycle costs is preventive maintenance. Though the Air Force emphasizes the importance of preventive maintenance as holding the potential to reduce unscheduled maintenance, the current economic analysis for facility systems lacks the granularity required to capture the benefit achieved through preventive maintenance

across the asset's life cycle, especially with respect to preventing corrective, or unscheduled, maintenance.

Through a literature review (Chapter 2), it is identified that a gap exists within the body of knowledge as it pertains to modeling the benefits of preventive maintenance for built infrastructure systems, e.g., reducing corrective maintenance demand. Moreover, there is even less focus at the facility or facility-installed-asset levels. While it seems intuitive to believe that if preventive maintenance benefits one mechanical system, it will benefit other systems in the same way, there are few studies in the literature that delve into analyzing chiller assets, and confirming—or failing to confirm—the hypothesis. Despite the fact that this "one size fits most" approach to chiller maintenance, or any mechanical system, may be valid, it is hard to maximize the efforts of Airmen and taxpayer dollars without understanding the reasoning behind, or sources of, the benefits.

Problem Statement

The Air Force is constantly managing staffing limitations and budgets constraints pertaining to maintenance of built infrastructure. Because of this, AFCEC has expressed interest in "giving back" time and money to Civil Engineer technicians wherever possible, to enable mission success. With this mindset, the large economic investment and gaps in literature surrounding chillers and the built environment drive the question:

Are attributes of preventive maintenance in built infrastructure systems, namely chillers, related to reductions in corrective maintenance?

Based on the literature and common knowledge of preventive maintenance of other systems, e.g., oil changes on vehicles, a relationship does exist between preventive and corrective maintenance. Therefore, it is hypothesized that:

Corrective maintenance is negatively correlated with preventive maintenance.

In other words, as aspects of preventive maintenance increase, a decrease in corrective maintenance is expected.

Research Objectives

To address the proposed research question and hypothesis, the following research objectives are proposed:

1. Identify chiller systems to evaluate based on data currently available within the Air Force Asset Management Portfolio.
2. Develop a systematic methodology to screen and aggregate data retrieved from BUILDER and NexGen IT.
3. Design a framework to evaluate the relationship between preventive maintenance and corrective maintenance.

Case Study

To test the hypothesis that corrective and preventive maintenance performed on built infrastructure assets are negatively correlated, Air Force chillers assets will be analyzed. Data obtained from the Air Force's built infrastructure databases NexGen IT and BUILDER will be considered, as all installation asset managers have access to this information. A random sampling of installations, chosen by AFCEC, from the contiguous

United States is used to identify whether trends in relationships between preventative and corrective maintenance are spatially consistent.

Thesis Organization

This thesis follows a traditional format to address the problem statement and achieve the research objectives. Chapter 2 provides a literature review of the expected benefits of preventive maintenance, focused on the relation to reducing corrective maintenance. Chapter 3 examines and outlines the data utilized in the case study. Chapter 4 provides an in-depth overview of the methods used to analyze the data provided by AFCEC. In Chapter 5, results of the analysis are detailed, leading into discussion in Chapter 6. Finally, Chapter 7 provides conclusions from the research, identifies the significance of this case study, and provides future recommendations.

II. Literature Review

An all-encompassing theme flowed throughout the body of knowledge evaluated in this thesis; that is, recurring preventive maintenance programs are widely advertised as beneficial. Both commercial enterprises and government entities alike view preventive maintenance as a cost avoidance mechanism, though very few quantifiably validated the claims made. Many sources identified what steps should be implemented to achieve a beneficial preventive maintenance program. In addition, benefits of a preventive maintenance plan were detailed, and industry solutions were identified.

Recurring Maintenance Programs

The utilization of preventive maintenance plans to keep equipment operational is not a new concept. In the mid-1980s, heavy construction contractors sought ways to ensure their equipment operated at peak performance to prevent additional costs, schedule delays, or disruptions to future projects (Ibbs & Terveer, 1984). Because of the benefits, preventive maintenance plans are common across many industries, but are most common in vehicle fleet management (Killeen et al., 2019; Markudova et al., 2021) and manufacturing (Neto et al., 2021; Su et al., 2022). Yet very few studies focus on preventive maintenance benefits in built-infrastructure assets that support facility operations. A similar gap was identified in analyzing the preventive maintenance plans used to maintain equipment at wastewater treatment plants (Hernández-Chover et al., 2020); however, the study focused more on the efficiency gain of the systems, instead of cost savings.

Research in facility management has identified that system maintenance is crucial for extending the lifespan of the assets, and thereby, the facility (Grussing & Liu, 2014). Additionally, adherence to preventive maintenance plans should help reduce the amount of corrective maintenance required as mechanical systems contain parts with a "finite-life" (Mobley, 2014). This relationship was illustrated in a recent study of military dormitories, where preventive maintenance across all systems in the facility was inversely related to corrective maintenance (Weeks & Leite, 2021). The study also found that HVAC systems were among the largest contributors to overall facility maintenance costs. In addition, across all systems, labor hours had the greatest impact on overall cost. This sentiment is echoed by others, who estimate that labor costs should account for around 90% of the total cost of preventive maintenance (Mobley, 2014).

Not surprisingly, there appears to be agreement that a chiller system's life cycle can be increased by reducing system failures (Coe, 2014; Harris, 2019; Rogers, 2013; *TRANE*, 2014). This reduction is commonly targeted by adhering to a strong preventive maintenance plan, generally consisting of routine maintenance and frequent inspections, ensuring the asset is performing at optimum levels for both energy efficiency and to avoid catastrophic failure. However, the development and execution of preventive maintenance plans are varied across the literature.

Frequency

In 2010, the U.S. Department of Energy published its third iteration of the Operations and Maintenance Best Practices Guide (Sullivan et al., 2010). This report made several recommendations for improving chiller efficiency, including steps to improve chiller performance, as well as maintenance best practices. Maintenance actions

were listed in a checklist which categorized them by frequency, varying between daily, weekly, semi-annually, and annually. Daily actions included simple tasks such as visual inspection to ensure the chiller is operating correctly. Weekly actions focused on quality control testing, whereas semi-annual and annual tasks focused on optimization strategies aimed at retaining efficiency (Sullivan et al., 2010).

A similar message was identified in TRANE's Installation and Operation Maintenance manuals (*TRANE*, 2014). The manual for Series R chillers states that performing maintenance actions at the identified intervals, i.e., weekly, monthly, or yearly, will increase the life of the chiller and "minimize the possibility of costly failures" (*TRANE*, 2014). The manufacturer did not provide an analysis to support these claims. Additionally, the manual recommends accurate logging of maintenance activities to enable trend analysis and prediction of likely problems prior to system failure (*TRANE*, 2014). The frequency and scope of chiller maintenance is a limiting factor for USAF technicians (see Discussion).

Relationship of Cost to Risk and Uncertainty

In addition to frequency of recurring maintenance, asset managers must determine a level of acceptable risk to allow should labor, budget, or other constraints force deferment of maintenance activities. As identified by Rogers (2013), different levels of preventive maintenance are used to meet different levels of acceptable risk. For example, in a facility that must remain operational at all times, a more stringent, proactive maintenance model may be required, whereas a facility that houses an activity with less direct impact on a firm's operations may be chosen for deferred maintenance, if operational budgets require savings be generated. The author also expounds on the

reinvestment rates required to return a facility or system back to a “like-new level of service.” This takes place over a period of time at a given budgetary rate. The higher the rate, the shorter the time period required (Rogers, 2013). The idea that there are varying levels of preventive maintenance is echoed by well-known chiller manufacturers. McQuay National Service Management acknowledged that facilities that house critical operations should receive “additional and more frequent testing in order to provide a higher level of performance and reliability” (Coe, 2014). However, there is no discussion about deferring maintenance for low-priority facilities.

Over the past several decades, asset managers have focused on trying to improve asset life by focusing on maintaining the initial condition of assets; however, there is uncertainty in each system that is not easily accounted for in traditional models. Each built infrastructure system may require a different approach. For example, a study on underground pipe replacement utilized elements of spatial analysis and network theory to augment the traditional trial and error approaches that focus on asset age and condition (Silinis & Franks, 2003). Another study used structured query language (SQL) to identify patterns in component failures within systems or systems within a facility (Bartels et al., 2020). Regardless of the uncertainty accounting method, asset managers with large portfolios of built infrastructure systems will struggle to maintain an effective preventive maintenance plan if budgetary and staffing requirements are not met. Based on traditional models, the probability of reactive or corrective repairs increases as asset age increases, thus making replacement a viable option over repair, in some cases (Silinis & Franks, 2003).

Benefits of Preventive Maintenance in Chillers

Multiple benefits of a preventive maintenance plan were identified in the literature. The anticipated benefit of reducing unexpected repairs, i.e., corrective maintenance, was identified as a primary product of a well thought out and executed preventive maintenance plan (Dotzlaf, 2009; Schwartz, 2013). However, other benefits of preventive maintenance were identified, including improved system efficiencies (Coe, 2014; Harris, 2019; McQuay, 2014; Sullivan et al., 2010), as well as other, second- and third-order effects.

According to chiller manufacturers, recurring preventive maintenance can assist in avoiding “catastrophic breakdowns” (Coe, 2014). In fact, Coe finds that unexpected repairs can be reduced by as much as 75% if a preventive maintenance plan is followed. Coe also claims that routine preventive maintenance can reduce the length of system downtimes by 35-40%. Moreover, the cost of repair is not the only cost associated with corrective maintenance. Lost productivity during system outages should also be taken into account (Coe, 2014). In non-manufacturing fields, quantifying these losses for minor jobs may not be necessary or worthwhile, but long system downtimes could produce a sizeable decrease in worker performance or system output. In addition to repair costs, improved asset efficiency was linked to preventive maintenance. According to manufacturers, the increase in efficiency leads to reduced energy consumption (Coe, 2014). Decreased energy consumption can reduce carbon emissions, providing “green credit” if the decrease is large enough. Regular maintenance will also ensure the system remains within government regulations (Coe, 2014).

These benefits were also present in the U.S. Department of Energy's best practices. Chiller maintenance is broken into two tasks: bringing the chiller to peak efficiency, and second, maintain that peak efficiency (Sullivan et al., 2010). The importance of maintaining chiller efficiency is highlighted through cost and energy efficiency. For example, a few degree difference in water temperature flowing through the condenser could affect the system's efficiency by 2-3% (Sullivan et al., 2010).

Industry Solutions

Depending on the scope, preventive maintenance can account for large portions of cost, both monetary and time, associated with maintaining a portfolio of assets. Several companies offer preventive maintenance contracts to remove the additional burdens of performing in-house preventive maintenance-related activities, such as training personnel, reviewing data, or simply the amount of time it takes to run an effective preventive maintenance program. Many of these contracts are tailorable to the needs of the customer (Coe, 2014; S. Kachmar, personal communication, October 20, 2021), enabling organizations to make decisions at a higher level. For example, in 2014, McQuay began providing new customers with one year of free maintenance on scroll and screw chillers. This service included three visits throughout the year, with routine maintenance completed and recommendations for any additional issues, i.e., corrective maintenance, identified during the maintenance call (McQuay, 2014).

Other companies also provide various degrees of preventive maintenance packages. Johnson Controls offers fixed-cost services that are tailored to the customer's needs (Johnson Controls, 2021). For users who have York® chillers, but desire to

complete the maintenance in house, Johnson Controls offers Chiller Preventive Maintenance Kits that contain all the parts needed for annual preventive maintenance, based on the specific chiller model (Johnson Controls, 2015). In a personal interview with Mr. Stephen Kachmar, a senior director at Johnson Controls, he identified programs that helped government organizations upgrade and modernize assets related to energy consumption without upfront capital (S. Kachmar, personal communication, October 20, 2021). These programs, called Energy Savings Performance Contracts (ESPCs), allow federal agencies to work with an energy service company (ESCO) to update and modernize facility assets by utilizing the money gained from utility savings (*ESPCs for Federal Agencies*, 2021). The ESCO bears the burden of producing enough savings in energy costs to offset the cost of the new equipment. Often, ESCOs require a preventive maintenance plan for the assets to ensure their investment is properly protected throughout the ESPC. For example, Johnson Controls not only requires a plan, but the majority of their ESPCs require that Johnson Controls technicians complete the preventive maintenance (S. Kachmar, personal communication, October 20, 2021). Even for the skeptic, ESPCs show that at least some of the claims of preventive maintenance benefits must be true. Why else would a company risk their assets and investments?

Another company, Integrated Facility Services (IFS), is a “full-service mechanical contractor” that provides a variety of levels of recurring maintenance services (Integrated Facility Services, 2019). All plans include preventive maintenance and inspections; however, customers have the option to add corrective maintenance into the contract (Integrated Facility Services, 2019). IFS works to train their technicians for various elements of preventive maintenance across multiple brands (Harris, 2019). Training is

constantly changing as new models arrive with the latest technology advances. This continuous training mindset ensures that IFS can provide service to any customer because, while all chillers are similar by type, each brand may have proprietary differences. In addition to technician knowledge and proficiency, maintaining tools and equipment to perform preventive maintenance can be a sizeable investment, especially as technologies continue to improve and the diversity of software to run electronics increases (Harris, 2019). With large amounts of brand diversity inside of the chiller portfolio, the USAF HVAC technicians must maintain the same level of proficiency as companies such as IFS (see Discussion).

Literature Review Summary

While a consensus was found throughout the literature that preventive maintenance is beneficial, different studies focused on different benefits (e.g., maintained efficiencies, prevention of catastrophic failure, reductions in energy cost). Across the HVAC industry, both manufacturers and repair contractors provide varying levels of service that promote preventive maintenance. While one could argue that this is profit driven, the level of dedication and risk companies are willing to take provides a strong counter claim. Therefore, the literature seems to support the hypothesis that preventive maintenance should reduce the amount of corrective maintenance required over an asset's life cycle. However, the lack of focus on chillers, and built infrastructure systems in general, leads to the research question posed in this study

III. Data

Air Force Facility Database Overview

The United States Air Force has invested in two separate database systems to manage built infrastructure: BUILDER™ Sustainment Management System (SMS) and IBM TRIRIGA, known in the Air Force as BUILDER and NexGen IT, respectively. BUILDER is a web-based software application that was developed by the U.S. Army Corps of Engineers' Engineer Research and Development Center (ERDC), that stores built infrastructure data such as asset age, condition, and condition inspection dates (*BUILDER™ SMS*, 2012; U.S. Army Corps of Engineers, 2012). Assets are catalogued in BUILDER using a classification system adopted from the UNIFORMAT II hierarchy, which separates facilities into categories, based on the systems, components, and sections (Charette & Marshall, 1999). For instance, a chiller would fall under System D30 – Heating, Ventilation, and Air Conditioning (HVAC), Component D3030 – Cooling Generation Systems, and Section D303001 – Chilled Water Systems (Fig. 1).

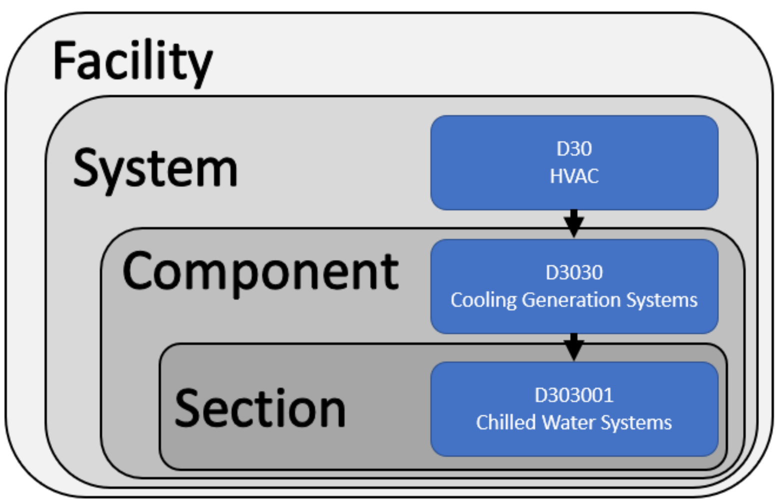


Figure 1: BUILDER Hierarchy for Chiller Assets

Using this hierarchy enables Air Force asset managers to make data-informed maintenance decisions for installation built infrastructure, based on asset condition and remaining expected service life. For example, recent research developed a performance metric using BUILDER data, to inform chiller manufacturer selection (Brown, 2021). While BUILDER is undoubtedly useful, as it has been implemented across the Department of Defense and other federal government agencies, and is actively used to inform decisions, the system lacks the ability to capture maintenance tasks and costs associated with built infrastructure maintenance. The Air Force has turned to NexGen IT to address this issue.

The Air Force began using NexGen IT in 2016. Over the following years, bases slowly transitioned from using the Interim Work Information System (IWIMS) and Automated Civil Engineer System (ACES) to manage their work tasks and facility maintenance portfolios (316th Wing Public Affairs, 2016). IWIMS and ACES were both developed in the 1980's and were standalone systems, inhibiting collaboration and work task tracking. The need to upgrade systems was apparent. NexGen IT has become the Air Force's primary integrated workplace management system, providing asset managers a single program that supports work task management from customer submittal to task completion, monitors preventive maintenance actions and plans, and tracks cost and material requirements (AFCEC Public Affairs, 2016).

NexGen IT Work Task Management

NexGen IT is used to capture and track work task information from the time of customer request, i.e., identification of a maintenance need, to final completion of work

by civil engineer technicians. A facility manager can submit a work task, reporting a deficiency in their facility. This work task is then routed to the installation's Civil Engineer Squadron, where, through a series of internal processes, it is assigned to a responsible technical shop or shops, e.g., electrical and/or plumbing. That shop, or combination of shops, uses NexGen IT to track the status of the work task, and work aspects like labor hours spent on the work task, cost of materials and labor, and work task priority.

In the Air Force, maintenance activities are assigned a work priority, based on the type of work being performed and the urgency of the repair need. Prioritization helps technicians better prioritize the work based on mission requirements. There are four levels of priority: Emergency (1), Preventive Maintenance, Plant Operations and Contingency Construction Projects (2A and 2B), Scheduled Sustainment Work (3A, 3B, and 3C), and Enhancements (4A and 4B) (Fig. 2).

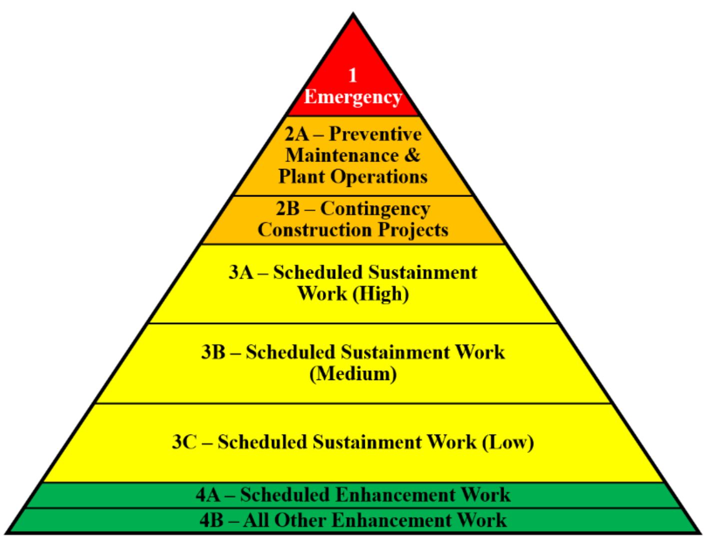


Figure 2: Air Force Work Task Priorities

Subcategories, identified by letters following the major numeric designator, exist within most of the priorities further dividing the work based on mission impact. In this framework, most work tasks are expected to occur as either preventive maintenance or scheduled sustainment work; between 2A and 3C. Priority 1 emergencies—unscheduled work that threatens life, safety, and health, or risks mission failure—can never be fully eliminated from the maintenance plan (AFCEC, 2021); however, the expectation is that they may be mitigated by proper management of the built asset portfolio, through preventive and scheduled maintenance. Preventive maintenance activities, priority 2A, are designed to manage mission risks, maximize the life cycle of assets by performing maintenance before system failure, and ultimately minimize life-cycle costs as compared to a run-to-failure model. Priority 2A Plant Operations and 2B Contingency Construction Projects are outside of the scope of this thesis. Priority 3 encompasses all scheduled sustainment work, with three subcategories based on risk to mission success, Risk Assessment Codes, and Fire Safety Deficiencies (AFCEC, 2021). All repair work other than emergencies is designated as a Priority 3. The final category, Priority 4, is enhancement work. This work may improve quality of life, but has no direct effect on the sustainment of the asset or mission success. Priority 4 work tasks may be funded by the requesting unit (AFCEC, 2021). All work tasks logged in NexGen IT are assigned one of these priority levels.

NexGen IT Data Screening: A generalized approach for asset and installation intercomparison

For this study, Air Force Civil Engineer Center (AFCEC) provided NexGen IT reports for fourteen installations, from the continental United States (Fig. 3). Each dataset included all work tasks performed at a specific installation, regardless of responsible shop or priority level. The first step taken was to subset the data to isolate only those work tasks related to chiller maintenance, given the Air Force's active position on category management for these systems.

Figure 3: Location of Installations Provided

To begin, the data were filtered to only include work tasks assigned to the installation's Heating, Ventilation, and Air Conditioning (HVAC) shop, as this shop has primary, and generally exclusive, ownership of chiller-related tasks. Next, data were sorted by work priority level. Those work tasks designated as Plant Operations, Contingency Construction Projects, and all Enhancement work tasks were removed from

the data set. These work tasks are not classified as preventive or corrective maintenance, and were not considered in this study. The remaining work tasks were aligned with the following work priority levels:

Level 1 – Emergency

Level 2A – Preventive Maintenance

Level 3A/B/C – Scheduled Sustainment Work (High/Medium/Low)

For this study, whether a work task was categorized as a Level 1 Emergency or any subcategory of Level 3 Sustainment was not important. The focus was to evaluate the relationship between the attributes of preventive and corrective maintenance as a whole. All repairs are corrective, or unscheduled work, regardless of the urgency needed to bring the asset back to an operational state. Therefore, all emergency and sustainment work tasks were classified as corrective maintenance and would need to be combined before analysis could begin (see Methods).

Next, work tasks associated with chillers were isolated. This process is more complicated than the previous steps. Two columns of data from the NexGen IT reports contained chiller identifiers: "Task Name" and "Name Asset." These columns were filtered using keyword searches. First, "chiller" was searched in the "Task Name" column. The resulting work tasks were marked with an identifier. Then, the filter was cleared, and the process was repeated for the "Name Asset" column. The process was also conducted using a keyword search for the UNIFORMAT II identifiers of "D3030" and "D3035" in both columns, as not all installations identified their work tasks in the same manner. It was noted that while "D3035" is not a standard UNIFORMAT II identifier (Charette & Marshall, 1999), several installations used it as a subcategory for

Cooling Generation Systems; however, the uses also varied between locations. These inconsistencies are a key factor limiting the utility of NexGen IT data for installation intercomparison (see Discussion). Additional screening was required to ensure the work tasks were assigned to chillers. For example, "chiller" keyword searches identified work tasks assigned to other pieces of equipment in the chiller room, or the distribution systems connected to the chiller. This approach provided a composite list of all work tasks identified as a task related to chillers.

The final steps in the screening process were formatting changes to prepare the data for analysis. Excess columns defining the costs as "US Dollars" were deleted as no other currency was used. The facility number and all cost columns were formatted as numeric data to enable descriptive statistical analysis and modeling processes required to answer the research question proposed above. With screening completed, each line item, in the dataset identified a single work task, assigned to a chiller asset in a specific facility.

NexGen IT Data Screening Results

As NexGen IT has only been implemented in Air Force Civil Engineer community since 2016, the data for each installation is limited based on when that installation transitioned from IWIMS and ACES to NexGen IT. Therefore, data was variably available by installation (2016-2019, start date). Table 1 provides a summary of the data screening process. Each "hit" identifies a work task where the keywords "chiller", "D3030", or "D3035" are listed in either the Task Name or Asset Name columns. Some work tasks were identified in multiple column keyword searches. Therefore, the "Total Unique Hits" column identifies each work task that meets one of

the eligibility criteria. This total includes all preventive and corrective maintenance work tasks, i.e., Level 1 Emergency, Level 2A Preventive Maintenance, Level 3A/B/C Sustainment.

Table 1: NexGen IT Data Screening Results

Installation	NexGen IT Transition Date	Total WT	HVAC WT	Chiller Hits in Task Name	Chiller Hits in Asset Name	D3030/ D3035 Hits	Total Unique Hits
Barksdale	Nov-16	45,190	9,256	702	467	---	736
Cannon	Apr-18	30,527	6,782	562	161	---	591
Columbus	Dec-16	36,716	6,514	224	15	378	565
Dover	Sep-16	55,063	11,268	719	296	---	869
Edwards	Feb-19	22,043	3,164	110	2	128	237
Ellsworth	Nov-16	68,660	16,280	826	863	426	1689
Fairchild	Jul-16	49,737	7,075	89	103	520	564
F.E. Warren	Dec-16	56,994	13,223	181	0	1224	1405
Goodfellow	Dec-16	45,069	11,915	831	0	673	831
Luke	Aug-16	47,868	15,955	1040	699	---	1049
Offutt	Feb-17	108,992	28,748	571	45	890	903
Scott	Jul-16	44,959	19,557	755	298	---	887
Shaw	Feb-18	23,397	8,795	669	320	---	672
Travis	Nov-16	70,739	19,014	276	279	---	552

*Note: HVAC = *Heating, Ventilation, and Air Conditioning* and WT = *Work Task*

IV. Methods

Overview

Once NexGen IT data screening was complete, a systematic, multi-step framework was built to evaluate the relationship between preventive and corrective maintenance for each installation, shown in Figure 4.

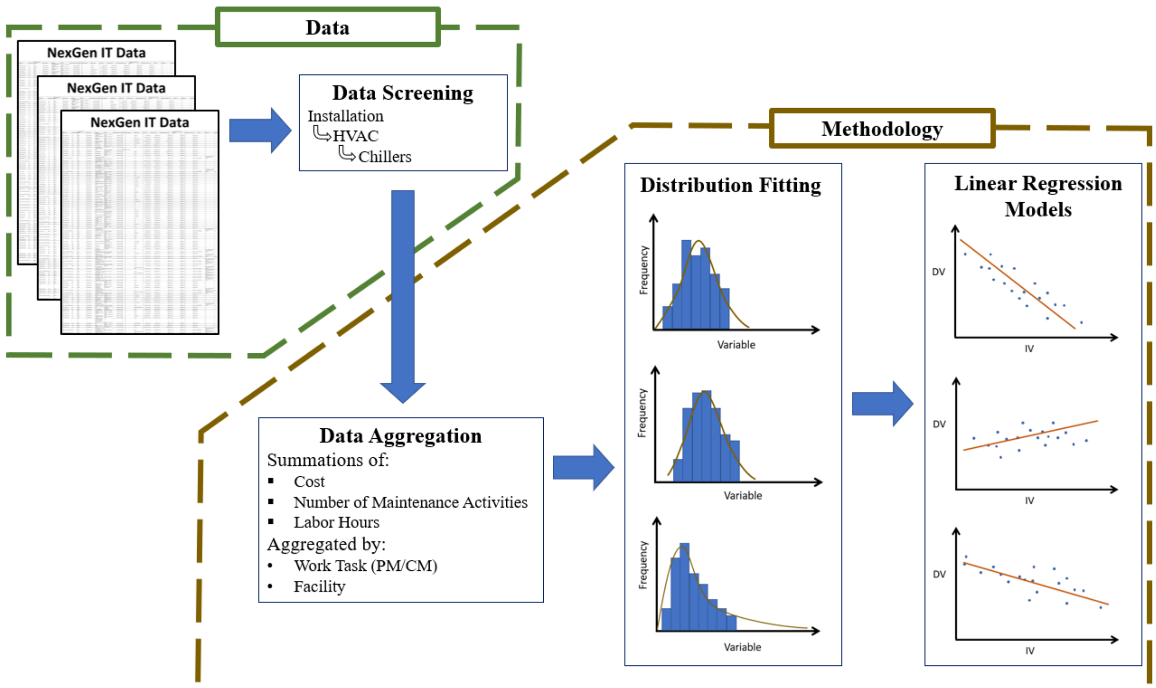


Figure 4: Systematic Methodology

The end goal of this study is to create linear, multi-linear, and multi-linear with interaction regression models comparing preventive and corrective maintenance through cost, number of maintenance activities, and labor hours spent. Ideally, the Air Force desires to view work tasks assigned to a specific chiller and analyze if preventive maintenance conducted on that asset affect the corrective maintenance burden. However, the data from NexGen IT is not organized to evaluate these relationships at the desired level of analysis. The screened data lacked the granularity necessary to make

comparisons at the asset level for facilities with multiple chiller assets. That is, not all work tasks identified the specific asset being repaired in a way that was conducive to data analysis. For example, a facility with three chillers could have preventive maintenance logged against the facility, and not against the chiller or chillers on which maintenance was performed. Similarly, a corrective maintenance activity at that same facility may list the asset's serial number in a column with other information, making it difficult to query, or the serial number may have been left out all together when the work was logged in NexGen IT; therefore, the analysis presented here was aggregated to the facility level.

Data Aggregation Technique

Each dataset was aggregated in three different ways, based on work priority level and facility number. First, the *number of maintenance activitie*s were summed into a facility-level total based on work priority. Second, the *total cost of maintenance activities* was summed. Next, the *labor cost of maintenance activities* was divided by the *HVAC shop rate* for the installation, a standard hourly cost notionally billed for time spent working on a task, to find the number of *labor hours* spent on each work task (Eq. 1).

$$Labor\ Hours = \frac{Labor\ Cost}{HVAC\ Shop\ Rate} \qquad \text{(Eq. 1)}$$

The resultant numbers, labor hours per activity, were summed to find the total labor hours spent per work priority. The three aggregated datasets were merged into a single sheet that identified the *total cost*, *total number of maintenance activities*, and *total labor hours* spent on those activities based on task priority and facility number (Fig. 5).

WT Priority	Total Cost	Number of Mx Activities	Total Labor Cost	Total Labor Hours
1-Emergency	$ 300.01	1	$ 300.01	4.00
2A - Preventive Maintenance	$ 2,400.07	1	$ 2,400.07	32.00
2A - Preventive Maintenance	$ 375.01	1	$ 375.01	5.00
2A - Preventive Maintenance	$ 675.02	1	$ 675.02	9.00
2A - Preventive Maintenance	$ 525.01	1	$ 525.01	7.00
2A - Preventive Maintenance	$ 600.02	1	$ 600.02	8.00
3A - High Sustain	$ 2,009.88	1	$ 300.01	4.00
3A - High Sustain	$ 225.01	1	$ 225.01	3.00
3A - High Sustain	$ 150.00	1	$ 150.00	2.00
3A - High Sustain	$ 3,787.61	1	$ 3,787.61	50.50
3A - High Sustain	$ 2,925.08	1	$ 2,925.08	39.00
3B - Medium Sustain	$ 225.01	1	$ 225.01	3.00
3B - Medium Sustain	$ 225.01	1	$ 225.01	3.00
3C - Low Sustain	$ 1,753.69	1	$ 300.01	4.00
3C - Low Sustain	$ 6,350.05	1	$ 1,725.05	23.00
3C - Low Sustain	$ 300.01	1	$ 300.01	4.00
3C - Low Sustain	$ 35,967.90	1	$12,206.59	162.75
3C - Low Sustain	$ 44,449.60	1	$16,650.46	222.01
3C - Low Sustain	$ 825.02	1	$ 825.02	11.00

WT Priority	Total Cost	Number of Mx Activities	Total Labor Hours
1-Emergency	$ 300.01	1	4.00
2A - Preventive Maintenance	$ 4,575.13	5	61.00
3A - High Sustain	$ 9,097.58	5	98.50
3B - Medium Sustain	$ 450.02	2	6.00
3C - Low Sustain	$89,646.27	6	426.76

Figure 5: Example of First Aggregation for a Single Facility

Next, all emergency and sustainment work tasks were subset into a single, corrective maintenance dataset. The aggregatations were based on the same categories as the main dataset: *total cost of the activies combined, total number of maintenance activities, and the total number of labor hours*. This processes combined all emergency and scheduled sustainment work tasks assigned to a facility into three corrective maintenance values for that facility: *total cost*, *number of activities*, and *labor hours*. This corrective maintenance data was then merged together with the preventive maintenance, based on the facility number (Fig. 6).

WT Priority	Total Cost	Number of Mx Activities	Total Labor Hours
1-Emergency	$ 300.01	1	4.00
2A - Preventive Maintenance	$ 4,575.13	5	61.00
3A - High Sustain	$ 9,097.58	5	98.50
3B - Medium Sustain	$ 450.02	2	6.00
3C - Low Sustain	$89,646.27	6	426.76

WT Priority	Total Cost	Number of Mx Activities	Total Labor Hours
Corrective Maintenance	$ 99,493.88	14	$ 535.27
Preventive Maintenance	$ 4,575.13	5	61.00

Figure 6: Second Aggregation for a Single Facility

Only facilities that had both preventive maintenance and corrective maintenance activities assigned to their chillers were merged into this final dataset. That is, if a facility

had only corrective or preventative maintenance, it was excluded due to the fact this work seeks to identify the relationship between corrective and preventative maintenance.

Statistical Modeling

The data filtering and aggregation resulted in the production of inputs for statistical models. The modeling effort focused on using three independent variables and identfying the degree to which each, and combinations of the three, account for variability in aspects of chiller corrective maintenance. The independent variables investigated are the *total cost of maintenance*, the *number of maintenance activities*, and the *labor hours* spent performing maintenance activites. Single, multiple, and multiple with interaction regression models, using the three independent variables defined above, are created to analyze the relationship between preventive maintenance and corrective maintenance. However, before selecting a regression technique, it is appropriate to approximate the distribution of the model inputs. Normally-distributed data can be directly analyzed using a linear model framework, but any diversions from normality could affect the overall skill and validity of the model. For any inputs that were not normally distributed, the data was transformed in a way that a simple linear regression could be used, e.g., a log-normal transformation of independent and dependent variables enables linear regression.

Distribution fitting was completed to determine the distribution of each dataset. Some installations in this study had facilities that received disproportionate amounts of maintenance, both corrective and preventive; therefore, the potential of outliers skewing

the distributions was a concern. Because of this, the Freedman-Diaconis rule was used to calculate histogram bin width. The general equation for this rule is shown in Equation 2:

$$h = 2\frac{IQR(x)}{\sqrt[3]{n}} \qquad \text{(Eq. 2)}$$

where *h* is the bin width; *n* is the number of observations in the sample; and *IQR(x)* is the interquartile range of the dataset, *x* (Freedman & Diaconis, 1981). By calculating the bin width using the interquartile range rather than as a function of standard deviation as used in other bin calculations, such as Scott's rule (Scott, 1979), the histogram is less likely to be affected by outliers in the data. Distribution fitting was completed three times for each installation, comparing preventive maintenance and corrective maintenance *costs, number of activities*, and *labor hours*, respectively.

For each installation, three linear regressions were completed to estimate how effective preventive maintenance was in predicting the need for corrective maintenance. The first model compared preventive maintenance costs to corrective maintenance costs, the second activity count, and the third labor hours. Explained variance was evaluated using the adjusted R-Squared values from the linear models. Significance was determine using the *p*-value. Next, three multiple linear regression models were completed per installation, each predicting corrective maintenance, either cost, activity count, or labor hours. Each of these models used preventive maintenance cost, number of preventive maintenance activities completed, and labor hours spent on preventive maintenance to predict one of the three aforementioned aspects of corrective maintenance. Explained variance and significance were determined in the same manner as the single linear regressions. Finally, multiple-linear regression models were constructed to test for

interactions between the independent variables. Table 2 provides a summary of all the regression models completed. In total, 126 different linear regressions were completed, three single and six multiple linear regressions per installation (14 installations).

Table 2: Summary of Linear Regression Models

	Dependent Variable	Independent Variable(s)
Linear Regression	CM Cost	PM Cost
	Number of CM Activities	Number of PM Activities
	CM Labor Hours	PM Labor Hours
Multiple Linear Regression and Interactions Models	CM Cost	PM Cost, Number of PM Activities, PM Labor Hours
	Number of CM Activities	
	CM Labor Hours	

V. Results

Data Aggregation

Data aggregation took the data obtained from NexGen IT and compiled it into model inputs for linear regression analysis. As mentioned in the Chapter 4, only facilities that had both preventive and corrective maintenance activities assigned to chillers were compiled into the final model inputs. The results of the data screening and aggregation are shown in Table 3.

Table 3: Data Aggregation Results

Installation	NexGen IT Transition Date	Total Unique Chiller Hits	Number of Facilities
Barksdale	Nov-16	736	59
Cannon	Apr-18	591	31
Columbus	Dec-16	565	25
Dover	Sep-16	869	59
Edwards	Feb-19	237	15
Ellsworth	Nov-16	1689	71
F.E. Warren	Dec-16	1405	37
Fairchild	Jul-16	564	49
Goodfellow	Dec-16	831	23
Luke	Aug-16	1049	37
Offutt	Feb-17	903	21
Scott	Jul-16	887	32
Shaw	Feb-18	672	38
Travis	Nov-16	552	21

In general, the installations that transitioned to NexGen IT in 2016 contained more total work tasks; however, the total number of work tasks assigned to the installation's HVAC Shop varied between 14.2% and 43.5% (Table 4). On average from this sample, 25% of an installation's work tasks were assigned to their HVAC shop.

Work tasks assigned to chillers accounted for, on average, just over 7% of HVAC work tasks (see Discussion).

Table 4: Percentage of HVAC and Chiller Work Tasks (WT) by Installation

Installation	Total WT	HVAC WT	Total Unique Chiller Hits	HVAC WT (% of Total)	Chiller WT (% of Total)	Chiller WT (% of HVAC)
Barksdale	45,190	9,256	736	20.48%	1.63%	7.95%
Cannon	30,527	6,782	591	22.22%	1.94%	8.71%
Columbus	36,716	6,514	565	17.74%	1.54%	8.67%
Dover	55,063	11,268	869	20.46%	1.58%	7.71%
Edwards	22,043	3,164	237	14.35%	1.08%	7.49%
Ellsworth	68,660	16,280	1689	23.71%	2.46%	10.37%
Fairchild	49,737	7,075	564	14.22%	1.13%	7.97%
F.E. Warren	56,994	13,223	1405	23.20%	2.47%	10.63%
Goodfellow	45,069	11,915	831	26.44%	1.84%	6.97%
Luke	47,868	15,955	1049	33.33%	2.19%	6.57%
Offutt	108,992	28,748	903	26.38%	0.83%	3.14%
Scott	44,959	19,557	887	43.50%	1.97%	4.54%
Shaw	23,397	8,795	672	37.59%	2.87%	7.64%
Travis	70,739	19,014	552	26.88%	0.78%	2.90%
			AVERAGE	25.04%	1.74%	7.23%

Distribution Fitting

The distributions of preventive and corrective maintenance for each installation were plotted together for each set of independent variables (i.e., *cost*, *number of activities*, and *labor hours*). A sample of the results for select installations is shown in Figure 7, with the remainder of the results shown in Appendix A.

These distributions show the differences in the quantities spent on each aspect of preventive maintenance compared to corrective maintenance, with the “Frequency” shown in the histogram as the number of facilities that fall within that bin. Plots are color

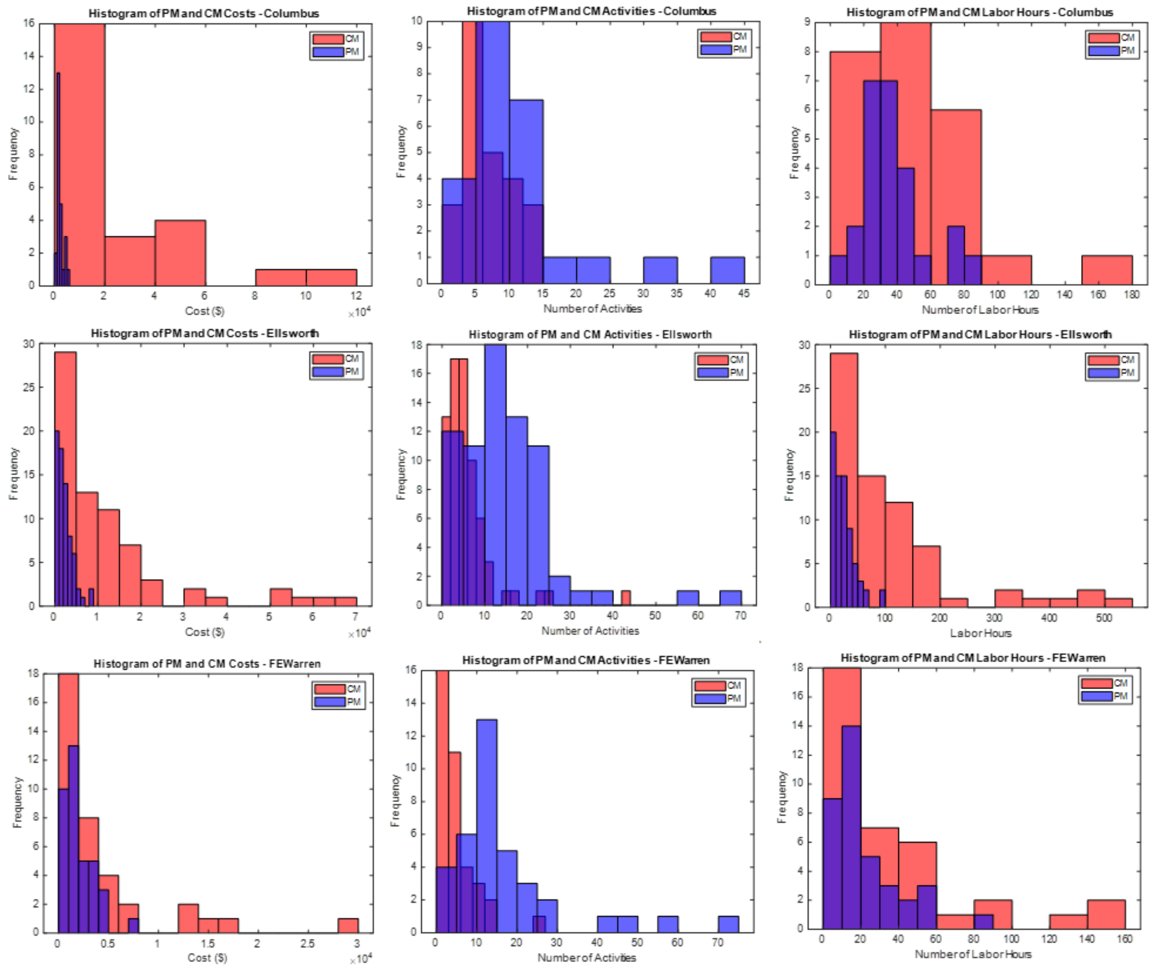


Figure 7: Model Input Distribution Sample. Each row contains a different installation: (top) Columbus AFB, (middle) Ellsworth AFB, (bottom) FE Warren AFB. The columns illustrate aggregated PM and CM comparisons: (left) costs, (middle) activities, (right) labor hours.

coded, with all preventive maintenance values shown in blue, and all corrective maintenance shown in red. Throughout the distribution fitting process, it became apparent that the aggregated chiller data for the majority of installations most closely followed a log-normal or exponential distribution. Therefore, it was necessary to perform a log-normal transformation of both independent and dependent data inputs to linearize the data inputs, thus enabling linear regressions. There were two installations, Barksdale

and Fairchild, whose data inputs may have followed a different distribution (see Discussion).

The distributions in Figure 7 show some trends across installations. First, the total preventive maintenance costs per facility are generally much lower than those incurred by corrective maintenance, as expected. Second, most facilities experience few cases of recurring corrective maintenance actions. There are a few facilities across the installations that seem to be serious “repeat offenders”, but for most facilities, chillers receive far more preventive maintenance than corrective, in terms of *number of maintenance activities*. Lastly, corrective maintenance activities are generally more time consuming, taking more *labor hours* to complete. These three trends are visible across all installations in Appendix A, with few exceptions.

Linear Regression Analysis

Single Linear Regression Analysis

Transforming the model inputs into a logarithmic space allowed for linear regression analysis to take place. Figure 8 shows some of the statistically significant results produced in the single linear regression after the logarithmic transformation. The remainder of the single linear regression results are shown in Appendix B. Most models showed positive correlation between preventative and corrective maintenance, rather than the expected negative relationship originally hypothesized (see Discussion).

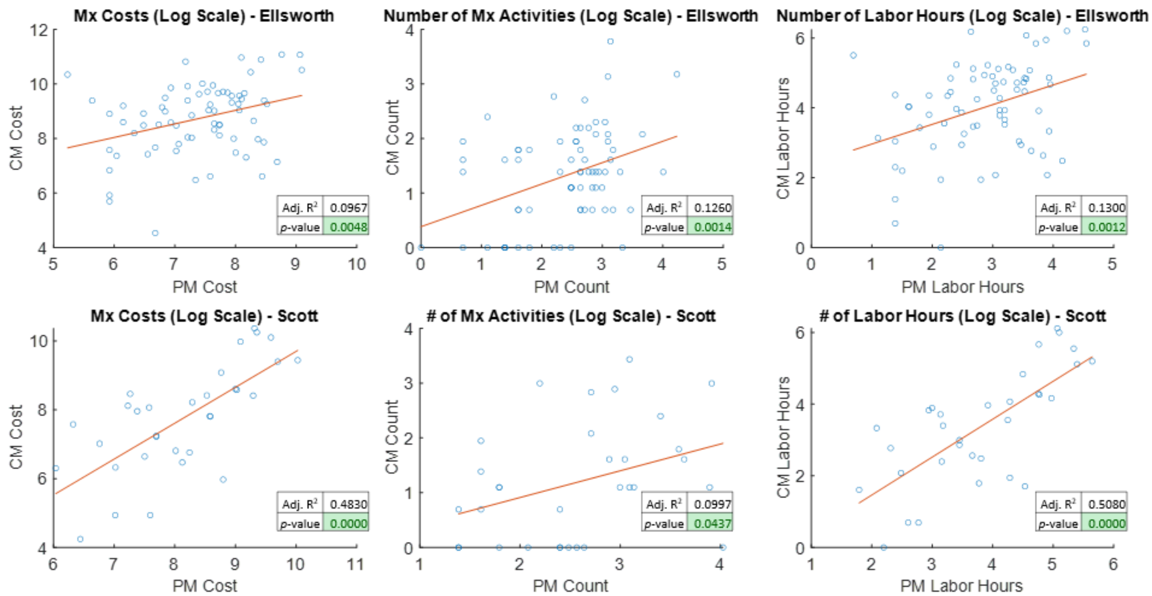


Figure 8: Sample of Single Linear Regression Relationships in Logarithmic Space

Equation 3 shows a first-order probabilistic model used in single linear regression analysis, where β_0 is the intercept, and β_1 is the change in the dependent variable, y (i.e., corrective maintenance), for every one-unit increase of the independent variable, x (i.e., preventive maintenance) (McClave et al., 2016).

$$y = \beta_0 + \beta_1 x_1 \qquad \text{(Eq. 3)}$$

Since the linear model was conducted in a logarithmically-transformed space, it was necessary to re-transform the model back to normal space. This was accomplished using Equation 4,

$$y = e^{\beta_0 + \beta_1 x_1} \qquad \text{(Eq. 4)}$$

where β_1, β_0, and x are the logarithmic values. This transformation returned the best fit line back to untransformed space using the fit parameters to show the true relationship between variables. The resulting model framework showed that the rate of change is, in

fact, non-linear. An example of these results is shown in Figure 9. Model frameworks for each installation can be found in Appendix B.

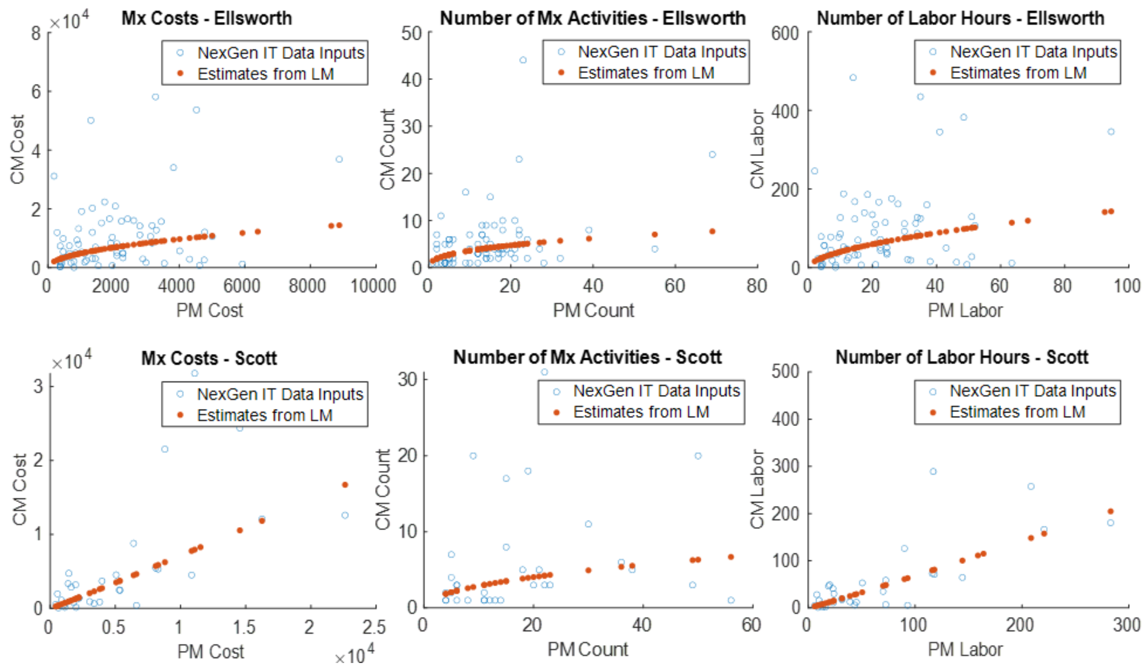


Figure 9: Example of Model Framework

Figure 10 provides a summary of single linear regression models, based on their statistical significance. An installation specific summary is provided in Appendix B. For this analysis, *p*-values for each model were compared against ranges of significance. Models which provide 95% confidence in results (i.e., $\alpha \leq 0.05$) are highlighted green, those with slightly less significant results which provide an 85-95% confidence (i.e., $0.05 < p\text{-}value \leq 0.15$) are highlighted yellow, and all others are highlighted red. The boxplots (Fig. 10 and 11) show adjusted R^2 values across all installations. Each box identifies the interquartile range (i.e., the values between the 25th and 75th percentiles), with the red line indicating the median adjusted R^2 value. Dashed lines extend to the most extreme data points that are not considered statistical outliers. Outliers are identified by

the ‘+’ symbol. Figure 10 summarizes all models based on statistical significance, with the three levels of significance on the horizontal axis. Explained variance, in the form of adjusted R^2 value, is shown on the vertical axis.

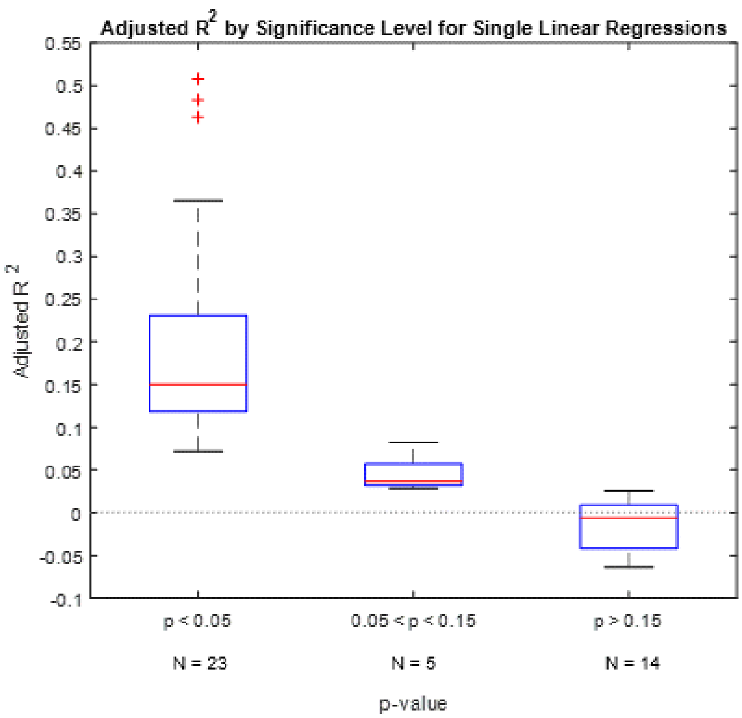


Figure 10: Boxplot of All Single Linear Regression Models

Figure 11 illustrates the efficacy of each model based on the model type, that is, cost, number of maintenance activities, and labor hours. The vertical axis remains explained variance through adjusted R2, and the horizontal axis is the model type. Models with a p-value between 0.05 and 0.15 did not provide a meaningful change. Likewise, models with a p-value > 0.15 had a median value close to zero; therefore, neither were not replotted by model type in Figure 11.

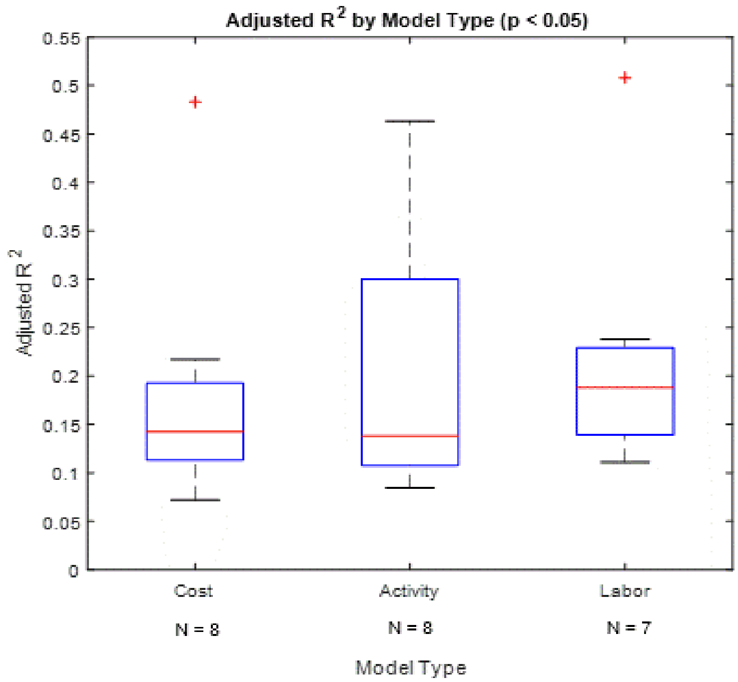


Figure 11 Boxplot of Significant Single Linear Regression Models ($p \leq 0.05$)

Multiple Linear Regression Analysis

Probabilistic models that contain multiple variables are called multiple regression models (McClave et al., 2016). Equation 5 shows a first-order, multiple linear regression model used in this study. The dependent variable, y, remains the aspect of corrective maintenance targeted by the model; however, the model now includes multiple independent variables. All three independent variables, x_1, x_2, and x_3, are aspects of preventive maintenance, *cost*, *number of maintenance activities*, and *labor hours*, respectively. Therefore, the aspect of corrective maintenance, y, targeted by the model changes by β_1 (*cost*), β_2 (*activities*), and β_3 (*labor hours*) for every one-unit increase of the respective independent variable, x_1, x_2, or x_3.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \qquad \text{(Eq. 5)}$$

As with the single linear regression analysis, it was necessary to perform a logarithmic transformation on the model inputs before running the multiple regression analysis, and then returning the model into normal space. This data transformation may influence the effectiveness of using the *β*-values to predict specific values of corrective maintenance based on linear increases in the dependent variables; nevertheless, the *β*-values remain a good indicator of the relationship between corrective and preventive maintenance, especially with respect to whether that relationship is positively or negatively correlated. Additionally, the model's adjusted R^2 values remain valid indicators of the model's overall effectiveness at explaining the variance in the dependent variable.

A summary of the multiple linear regression analysis is shown in Figure 12. As with the single linear regression analysis, results were categorized based on ranges of significance. An installation specific summary can be found in Appendix C. Similar to the single linear regression, boxplots illustrate the expected variance across all installations as a function of multiple variables. The vertical axis remains explained variance as adjusted R^2 values, with the horizontal axis changing between significance values (Fig. 12) and model type (Fig. 13). As all three independent variables were used in each multiple linear regression model, the model type (Fig 13.) refers to the aspect of corrective maintenance targeted by the model (i.e., *cost*, *number of maintenance activities*, or *labor hours*).

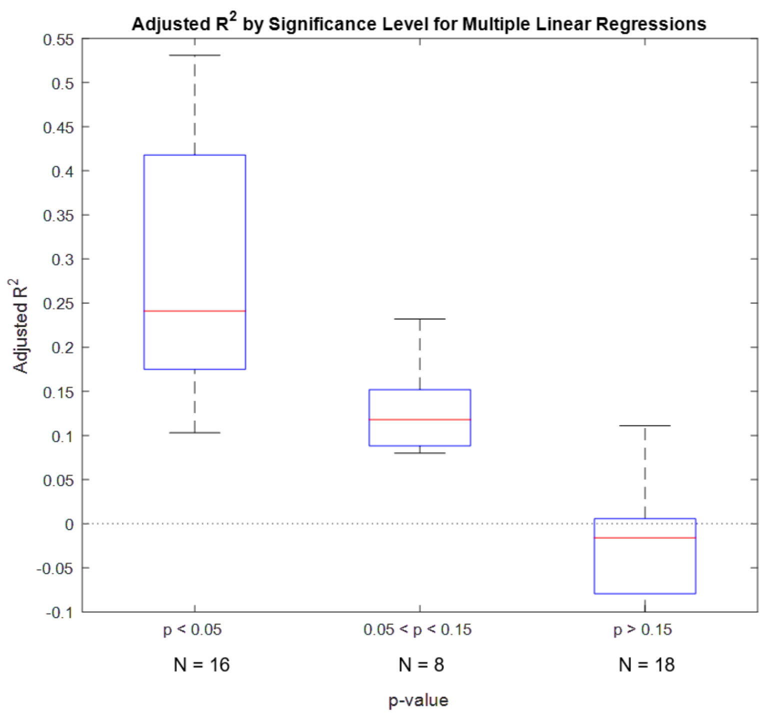


Figure 12: Boxplot of All Multiple Linear Regression Models

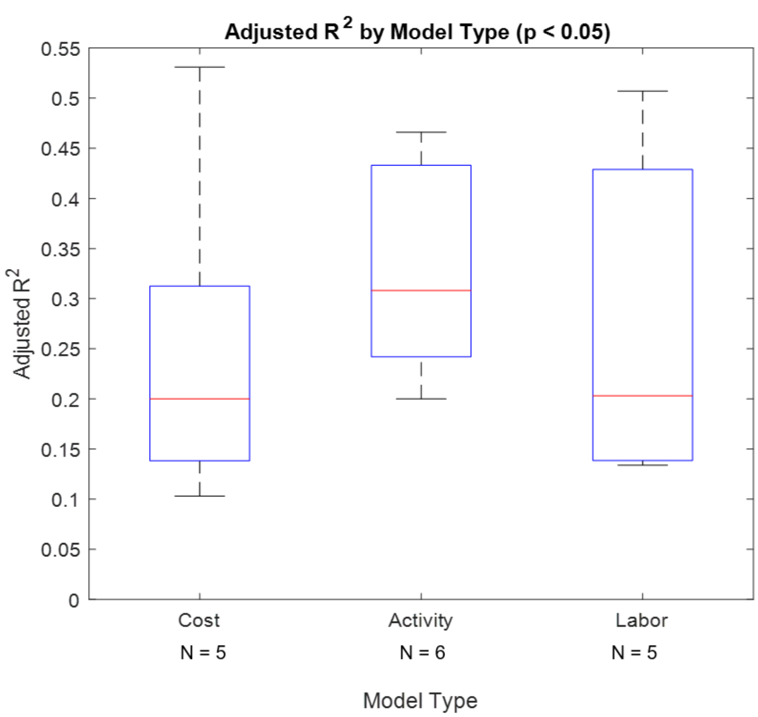


Figure 13: Boxplot of Significant Multiple Linear Regression Models ($p \leq 0.05$)

Multiple Linear Regression Analysis with Interactions

The multiple linear regressions conducted assume that each independent variable is independent of the other two. Logically this would not make sense. For example, as the *number of preventive maintenance activities* increases, the *cost* and *labor hours* spent should also increase. The increase may not be the same across all chillers in the installation's portfolio, but a change will exist, nonetheless. Therefore, interaction models were conducted to help identify how the independent variables interact with each other.

Equation 6 shows an example of a multiple linear regression model with interactions used in this study.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_1 x_2 + \beta_5 x_1 x_3 + \beta_6 x_2 x_3 \qquad \text{(Eq. 6)}$$

The dependent variable, y, remains the aspect of corrective maintenance targeted by the model. As with the multiple linear regression, all three independent variables, x_1, x_2, and x_3, are aspects of preventive maintenance, *cost*, *number of maintenance activities*, and *labor hours*, respectively. However, three additional terms are added to the model: x_1x_2, x_1x_3, and x_2x_3. These cross products will help determine how much each variable depends on the other. The change in the aspect of corrective maintenance, y, targeted by the model is slightly different than the standard multiple linear regression model (Eq. 4). To test for interactions, certain variables are held constant with others increased by 1. For example, to find the change in corrective maintenance (y) caused by preventive maintenance *cost* (x_1), x_2 and x_3 will be held constant; therefore, the changes in y due to x_1 are $\beta_1 + \beta_4 x_2 + \beta_5 x_3$ for every one-unit increase of x_1 (McClave et al., 2016).

Figure 14 summarizes the multiple linear regression interaction analysis with results listed by levels of significance. Installation specific results are detailed in Appendix D. The boxplots illustrate the expected variance across all installations as a function of multiple variables. The explained variance is expected to increase from the multiple linear regression models as each model now captures the dependency that each independent variable has on the others. For example, since labor cost usually accounts for most of the cost spent on preventive maintenance, it may depend, or interact, with the *number of activities* or *labor hours*. This interaction could be in addition to the variance removed from multicollinearity. The vertical axis remains explained variance as adjusted R^2 values, with the horizontal axis changing between significance values (Fig. 14) and model type (Fig. 15). The model type refers to the aspect of corrective maintenance targeted by the model (i.e., *cost*, *number of maintenance activities*, or *labor hours*).

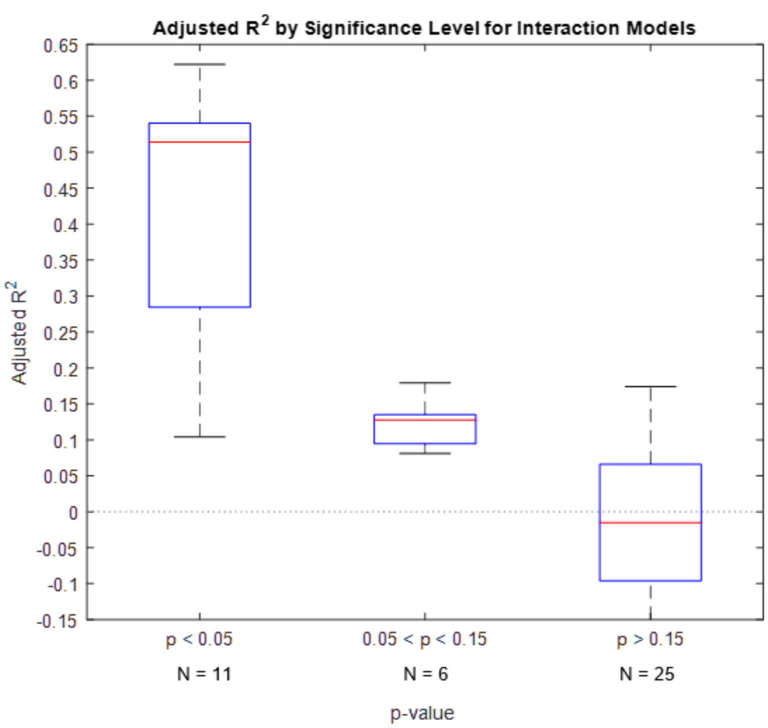


Figure 14: Boxplot of All Interaction Regression Models

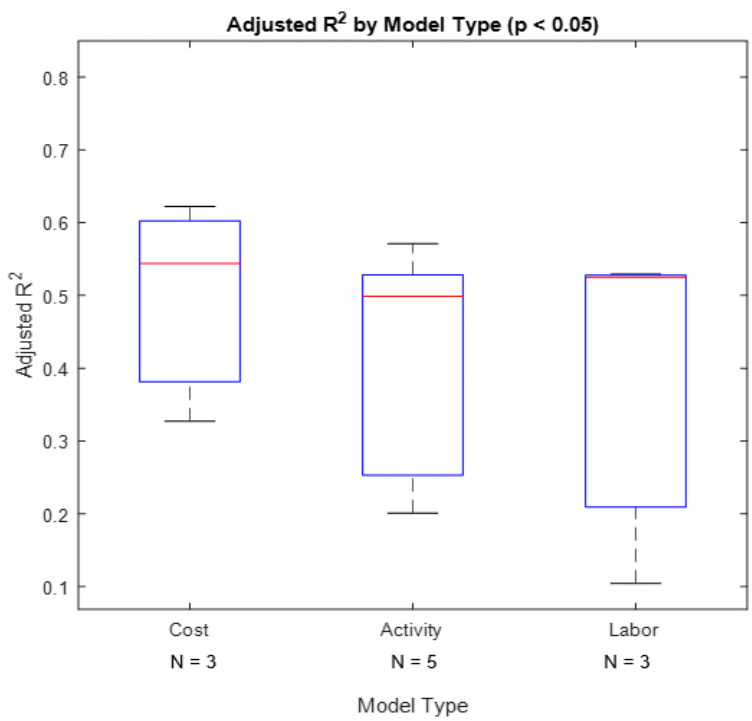


Figure 15: Boxplot of Significant Interaction Regression Models ($p \leq 0.05$)

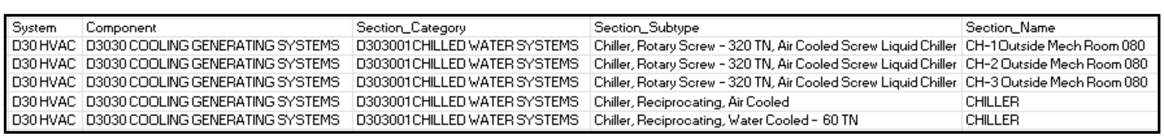
VI. Discussion

Data Aggregation

Data quality and the lack of connectivity between NexGen IT and BUILDER severely limited the ability to make a thorough evaluation of the impact preventive maintenance has on aspects of corrective maintenance. This was particularly evident during data aggregation. Additional variables outside of the scope of this study also play a large role in affecting the data used within this study.

Data Quality

The largest hurdle to overcome in this study was the data quality. While BUILDER maintains strict data entry procedures, NexGen IT does not. For example, in BUILDER, the UNIFORMAT II hierarchy is isolated into individual entries. This produces separate columns for the system, component, and section for an asset (Fig. 16) Additionally, the section is subdivided into three separate columns: category, subtype, and name. This structure inside the database enables users to easily filter data to the granularity they desire. As seen in Figure 16, three separate 320-ton chillers are identified from the same facility. This empowers asset managers to easily identify issues for a specific chiller asset, rather than limiting analysis at the facility level.



System	Component	Section_Category	Section_Subtype	Section_Name
D30 HVAC	D3030 COOLING GENERATING SYSTEMS	D303001 CHILLED WATER SYSTEMS	Chiller, Rotary Screw - 320 TN, Air Cooled Screw Liquid Chiller	CH-1 Outside Mech Room 080
D30 HVAC	D3030 COOLING GENERATING SYSTEMS	D303001 CHILLED WATER SYSTEMS	Chiller, Rotary Screw - 320 TN, Air Cooled Screw Liquid Chiller	CH-2 Outside Mech Room 080
D30 HVAC	D3030 COOLING GENERATING SYSTEMS	D303001 CHILLED WATER SYSTEMS	Chiller, Rotary Screw - 320 TN, Air Cooled Screw Liquid Chiller	CH-3 Outside Mech Room 080
D30 HVAC	D3030 COOLING GENERATING SYSTEMS	D303001 CHILLED WATER SYSTEMS	Chiller, Reciprocating, Air Cooled	CHILLER
D30 HVAC	D3030 COOLING GENERATING SYSTEMS	D303001 CHILLED WATER SYSTEMS	Chiller, Reciprocating, Water Cooled - 60 TN	CHILLER

Figure 16: Excerpt of BUILDER™ Section Details Report

Unfortunately, NexGen IT does not isolate the UNIFORMAT II hierarchy into separate data entries. In fact, a standard data entry procedure is not evident across a

random sample of installations. Most will identify the UNIFORMAT II hierarchy within the column called "Name Asset". Other installations listed the hierarchy within the "Task Name" column. This inconsistency limits the functionality of the data, forcing users to conduct additional data screening. Additionally, some installations identified chillers under the UNIFORMAT II subcategory "D3035", while others used "D3035" for other cooling generation systems. Most installations did not have "D3035" listed in their NexGen IT data. Again, inconsistencies within the data made it difficult to work with.

Data Quantity

The results in Table 3 highlight another key limitation: the number of data points. Fourteen installations were analyzed; however, only three-to-five years' worth of maintenance data was available based on when the installation transitioned to NexGen IT. Additionally, focusing the study on chiller assets limited the breadth of study. Many installations did not separate preventive maintenance hours between the different types of cooling generation systems in NexGen IT. It took additional data screening to sift through the NexGen IT data provided to identify those work tasks assigned to chillers. This process introduced more chances for human error. As a result, some installations did not have enough data points to provide statistically significant results in the linear regression analysis.

Additionally, only having 3-5 years of data available could affect how the total preventive maintenance cost is perceived. As an asset ages, the total cost spent on preventive maintenance will continue to increase. If the data logged in NexGen IT is predominantly from newer assets with higher conditions, then the preventive maintenance cost may be fairly low (Fig. 17). However, as the asset degrades over time,

the cost of maintaining the asset will increase. A more substantive dataset that encompasses larger portions of an asset's life cycle, or the ability to link asset condition to costs spent maintaining the specific asset, are necessary to understand the relationship between preventive and corrective maintenance.

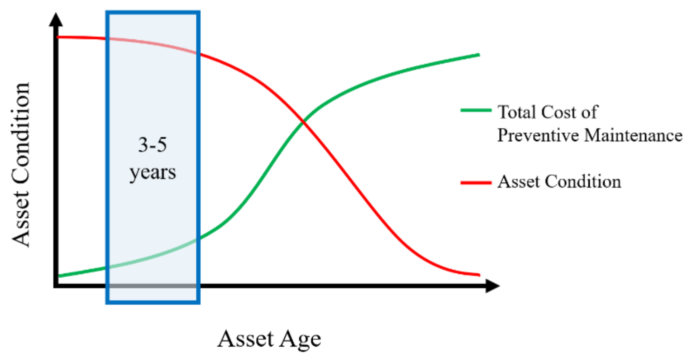


Figure 17: Theoretical Relationship Between Preventive Maintenance Cost and Asset Condition

The fact that chillers account for such a low percentage of total HVAC work task (Table 4) also illustrates that, while chillers are a major drain on time and budgetary constraints, they are only a portion of the portfolio managed by USAF HVAC technicians. This leaves best practices, such as the recommendation to conduct thorough data review to observe trends (*TRANE*, 2014), as lofty goals that are often outside the scope of an Airmen's day-to-day task list. If reviews were included in the preventive maintenance plan, trends could be reviewed by a competent HVAC Airman in the Requirements and Optimization (R&O) Section within the CE Squadron.

BUILDER/NexGen IT Connectivity

The two databases, BUILDER and NexGen IT, are both designed and maintained by separate proprietary companies. Because of this, data cannot be queried from one database to the other. Additionally, the limited data points and inconsistencies present

within NexGen IT make manual synchronization of the data within the two databases at the asset level unviable. This was a major limitation as it constrained the study to data available in NexGen IT only. As discussed previously, NexGen IT is still in its infancy as a USAF database, especially compared to BUILDER. This prevented the analysis of how a chiller's age and condition affected the corrective maintenance requirements.

Staffing Issues and Technician Experience

The analysis conducted in this study does not include variables such as technician experience levels, shop size and staffing percentages, or the effects of deployments and permanent changes of station. These variables are not stored in NexGen IT or BUILDER, but they are common limitations dealt with at the shop management level. Overall shop experience varies based on shop size and staffing levels. Smaller installations will have smaller shops with fewer technicians overall, decreasing the overall level of experience. Additionally, not all installations are fully-staffed. Deployments, temporary duties, and permanent changes of stations all affect the efficiency of a shop and its technicians. As Airmen move to a new installation, any nuances in assets from different manufacturers will need to be overcome. The original decision by AFCEC to sole-source chillers was designed to limit the brand diversity in an installation's chiller portfolio. This, in theory, is beneficial as it limits the proprietary training required for an installation's HVAC technicians and aims to streamline acquisition.

Distribution Fitting

Statistical software was not utilized to find the best fit for each individual distribution. Instead, an attempt was made using visual observation to find a good fit for

the model inputs as a whole. This could have affected the results in some cases due to small sample sizes; however, based on the number of models that were not statistically significant, it is assumed that the impact would be fairly small. As mentioned, Barksdale and Fairchild had preventive maintenance model inputs that appeared to follow a distribution other than log-normal (Fig. 18). All three of the independent variables for Barksdale appeared to have qualities of a normal distribution, though with some skewness, while at Fairchild, only the *number of preventive maintenance activities* appeared to show signs of normality; however, both the *cost* and *labor hours* models also show signs of log-normal or exponential distributions without the outliers. Because the vast majority of model inputs appeared to follow a log-normal or exponential distribution, a log-normal transformation was completed on all installations. This assumption could have affected the results, especially with respect to Barksdale. However, since most of the models followed a log-normal distribution, the transformation of model inputs is still estimated to provide a good fit.

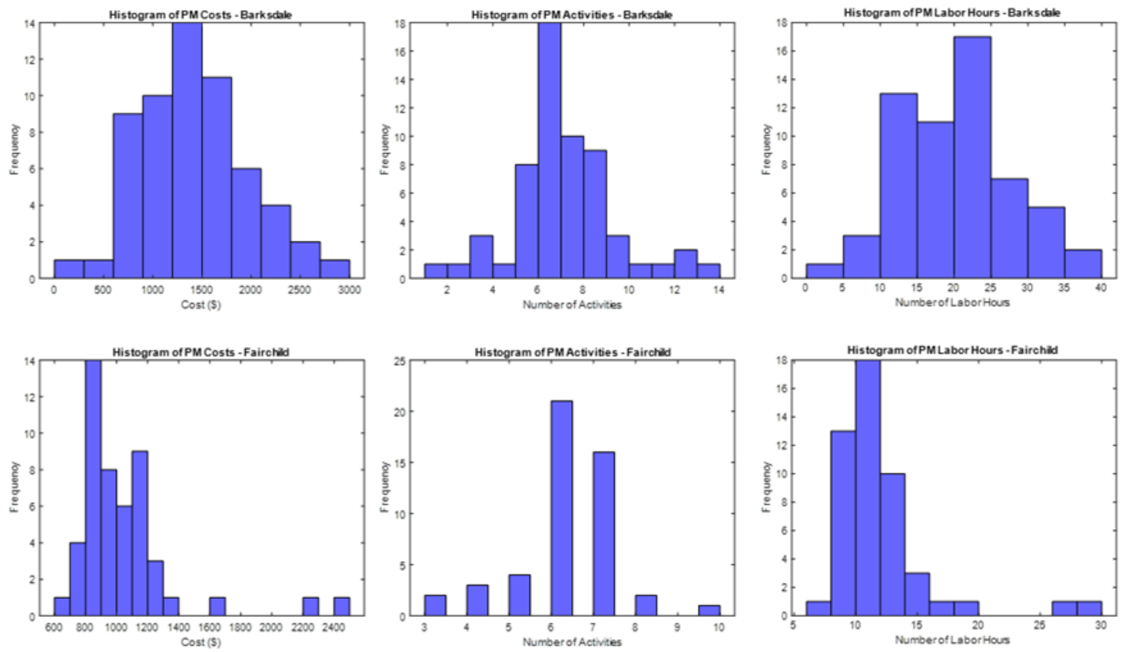


Figure 18: Model Input Distributions for Barksdale and Fairchild

Linear Regression Analysis

Single Linear Regression

The best fit lines from the linear models (Fig. 8) showed a positive relationship between preventive and corrective maintenance. That is, in all statistically significant models, increases in preventive maintenance caused corrective maintenance to also increase, regardless of the independent variable used. This positive relationship appears to reject the initial hypothesis that corrective maintenance decreases as preventive maintenance is completed on the asset. This is not entirely surprising. Preventive maintenance is cyclical, occurring on a recurring basis. Regardless of how frequently preventive maintenance occurs (e.g., weekly, quarterly, annually), the values of all aspects of preventive maintenance will increase with asset age, simply because of its recurring nature. Over time, systems naturally degrade; therefore, the probability of

failure increases. Furthermore, one of the main reasons for preventive maintenance is to prevent catastrophic, unscheduled maintenance activities. Not all corrective maintenance activities are catastrophic, though unscheduled maintenance will continue to occur due to risk and uncertainty. Therefore, the fact that corrective maintenance increases with preventive maintenance is not surprising, especially without a comparison to assets that are not maintained by a preventive maintenance plan.

Even though preventive and corrective maintenance are not negatively correlated as expected, preventive maintenance does explain some of the variability in corrective maintenance. The majority of models conducted, 23 of 42, were statistically significant to the $\alpha = 0.05$ level (Fig. 10). On average (median), these models explained roughly 15% of the variance in their respective aspect of corrective maintenance. The worst model explained only 7% of the variance in corrective maintenance cost, while the best model accounted for close to 51% of the variance in corrective maintenance labor hours. However, of the statistically significant models ($p \leq 0.05$), three produced R^2 values that were statistical outliers when compared with the rest of the models (Fig. 10). Removing these outliers, the best model falls close to 37% explained variance. Additionally, the interquartile range sits between 12-22%. So, though the models are statistically significant, the explained variance in corrective maintenance remains relatively low. Even when relaxing the significance constraint to p-values ≤ 0.15, the average explained variance would only decrease (Fig. 10). These low R^2 values signify that preventive maintenance is only a piece of the puzzle when trying to explain the variability in corrective maintenance. Nearly all the adjusted R^2 values for regression models with a *p*-

value > 0.15 were negative, effectively zero; therefore, they explained none of variance found in that specific aspect of corrective maintenance.

When analyzing the statistically significant models by model type, it is apparent that preventive maintenance *costs* and *labor hours* provide more reliable results than the *number of activities* (Fig. 11). Models focused on *costs* and *labor hours* had smaller interquartile ranges, and, apart from two outliers, total ranges. The median values for *cost* and *labor hours* models were approximately 14% and 19% explained variance, respectively. These models provided a more reliable estimation of the explained variation in corrective maintenance. It is worth noting that the third outlier from Figure 10 was not considered an outlier when analyzing the models by type; therefore, the overall range of the *number of activities* models would decrease if this outlier was removed. Nevertheless, the interquartile range remains much larger than that of the *cost* and *labor hours* models, maintaining that the *number of activities* model is the least effective.

Statistical significance of a model was not exclusively reliant on the sample size. Half of the installations had single linear regression models that fell into multiple significance ranges, varying by model type. Fairchild had two statistically significant ($p \leq 0.05$) single linear regression models, *cost* and *labor hours.* Because the model for *number of activities* was statistically insignificant ($p = 0.539$), it could have been left out of the multiple linear regression models. A similar approach could have been used for Cannon, where the same trends occurred. Interactions models were used to attempt to fine tune the models (discussed later); however, omitting the insignificant variable from the multiple linear regression would have increased the significance of the model without

adding additional variability. This is one example of how the systematic approach used may have hindered the results.

Multiple Linear Regression Analysis

The multiple linear regression analysis provided similar results to those produced by the single linear regression models, though changes did exist. Only 16 of the 42 models were statistically significant ($p \leq 0.05$), a 17% decrease from the 23 in the single linear regression analysis (Fig. 12). Nonetheless, with the decrease in significant models came an increase in explained variance. The median explained variance in corrective maintenance increased 7%, from 15% to 24%. Similar trends occurred as the significance constraint was relaxed to p-values ≤ 0.15. The explained variance from models falling within the significance range of $0.05 < p \leq 0.15$ are lower than the median of the more significant models (Fig. 12). When models were analyzed by type, the range of adjusted R^2 values is much larger than that found through the single linear regression (Fig. 13).

With multiple linear regression, there is a chance that variance explained by one independent variable overlaps with the variance explained by another, called multicollinearity. This multicollinearity causes the regression model to double-count the variance in corrective maintenance (Fig. 19). The coefficient of determination, or R^2, indicates the total variance explained by the regression model. In multiple regression models, the adjusted R^2 values provide a more accurate representation of the total variance explained by the sum of the variables, ensuring the variability in the dependent variable is only accounted for one time.

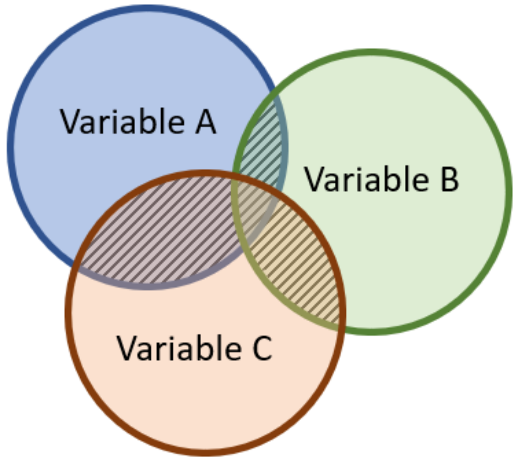


Figure 19: Example of Multicollinearity

Though the multiple linear regression produced several models that were statistically significant, multicollinearity was definitely a factor. The amount of multicollinearity present in a model can be roughly estimated using Equation 7.

$$Multicollinearity \approx (1 - \frac{Adj.R^2}{R^2}) \qquad \text{(Eq. 7)}$$

The multiple regression models run in this study were statistically significant as a whole, but few of the β-values were deemed significant using a *student's t-test*. For example, the multiple linear regression model for *cost* at Scott AFB had a p-value = 0.00002, and an adjusted R^2 = 0.531. The model was definitely statistically significant and explained the most variance out of any multiple linear regression. However, the only β-value that was statistically significant was β_3, *labor hours.* This was an indication that multicollinearity existed in the model. With an R^2 = 0.577, roughly 8% of the model's skill was due to multicollinearity. Considering the three independent variables used in this study, it is not surprising that multicollinearity exists. One of the primary costs of preventive maintenance is labor; therefore, it is only logical that the longer a maintenance activity

lasts, or the number of times preventive maintenance is completed at a facility, that the cost of maintenance would increase.

One likely cause for insignificant results in the β-values is simply the small number of data inputs. The average sample size per installation was 37 facilities, with Ellsworth providing the largest sample at 71. Sample size could be increased by focusing the models on each individual asset, rather than aggregating the data to the facility level. However, for this to be possible, assets must be more easily identifiable in NexGen IT. Additionally, improving the connectivity of BUILDER and NexGen IT would allow for different variables to be utilized. These additional variables may account for different parts of the variance in corrective maintenance, and would decrease multicollinearity for the model as a whole.

Multiple Linear Regression with Interaction Analysis

The trends observed moving from single linear regression to multiple linear regression occurred again when moving to interaction analysis. The total number of models that were statistically significant ($p \leq 0.05$) decreased from 16 to 11, and the median explained variance increased 25%, from 24% to 51% (Fig. 14). Additionally, the interquartile range shifted upward, meaning that, as a collective, more of the statistically significant models explained higher amounts of variance in corrective maintenance (Fig.; 14).This increase in explained variance indicates that the independent variables interact with each other. The interactions model captures this dependency, and, therefore, is able to explain more of the variance in the dependent variable. Models falling within the lower

significance level ($0.05 < p \leq 0.15$) remained well below the median value of the models in the $p \leq 0.05$ significance level.

The same issues with multicollinearity were present in the interaction models, with several models statistically significant, but few β-values passing the *student's t-test*. Scott AFB was one of the only installations to produce nine statistically significant models. However, a closer look at the adjusted R^2 values highlights the multicollinearity in the models. Especially with respect to the models for *cost* and *labor hours*, the change in adjusted R^2 between each model is very small (Table 5).

Table 5: Regression Results for Scott AFB

Model	Model Statistics	Cost	Activities	Labor Hours
Single Linear Regression	R^2	0.499	0.129	0.524
	Adj. R^2	0.483	0.100	0.508
	p-value	0.0000	0.0437	0.0000
Multiple Linear Regression	R^2	0.577	0.488	0.555
	Adj. R^2	0.531	0.433	0.507
	p-value	0.0000	0.0003	0.0000
Interaction Analysis	R^2	0.632	0.596	0.617
	Adj. R^2	0.544	0.499	0.525
	p-value	0.0002	0.0005	0.0003

The coefficient of determination, unadjusted R^2, in the three interaction models increased from the multiple linear regression models; however, the adjusted R^2 values remained fairly constant. This indicates that more multicollinearity is present in the interactions model. Across all models at Scott AFB, the number of *labor hours* spent conducting preventive maintenance remains the most significant variable based on β-values, on average.

VII. Conclusion

Research Conclusions

This thesis focused on research investigating the relationship between preventive and corrective maintenance, specifically with respect to the USAF built infrastructure portfolio. This emphasis led to the following research objectives:

1. Identify systems to evaluate based on data currently available within the Air Force Asset Management Portfolio.
2. Develop a systematic methodology to screen and aggregate data retrieved from BUILDER and NexGen IT.
3. Design a framework to evaluate the relationship between preventive maintenance and corrective maintenance.

To begin, literature review uncovered a gap in the knowledge base with respect to the quantifiable benefits preventive maintenance produces in corrective maintenance reductions. While many claims exist advocating the benefits of preventive maintenance, few studies have been completed analyzing the benefits for built infrastructure systems. To address this gap, this study focused on chiller assets within the USAF portfolio. Utilizing NexGen IT data provided by AFCEC, linear regression models were completed for each installation. Through the regression analysis it was apparent that, on average, preventive maintenance only accounted for portions, most often small, of the variance experienced in corrective maintenance. The study was hampered by data availability and data quality; nevertheless, it appears that targeting preventive maintenance may not be the only key to reducing corrective maintenance. In fact, preventive and corrective

maintenance were found to have a positive relationship, though it is unsure whether this is a reduction from systems that do not receive preventive maintenance. In the end, this thesis accomplished the stated research objectives and provided the foundation for future research discussed below.

Research Significance

The USAF maintains thousands of built infrastructure assets across large campus areas worldwide. Asset managers often prioritize preventive maintenance over lower-level sustainment operations. This research highlighted the utilization of current databases to inform future decision making. It also provided insights into better data management practices that could improve asset manager quality of life.

Recommendations for Future Research

It is hard to quantify if preventive maintenance reduces the corrective maintenance burden without a control study. To tackle this challenge, a test location could be identified where chillers would be operated without a preventive maintenance plan, only repairing, or replacing, an asset as needed. Then, at the same location, chiller systems servicing similar floor plans and functions could operate while being serviced through a recurring preventive maintenance plan. Comparing the differences in corrective maintenance would identify whether preventive maintenance reduces corrective maintenance, and thereby, total maintenance costs. Unfortunately, with the data currently available, there is no control facility or installation in the USAF that allows for this level of comparison. Similar outcomes could be achieved using a non-destructive approach

with smart sensors; however, this would also incur higher costs for training and system upgrades.

Additionally, most of the variability in corrective maintenance is not explained by the amount of preventive maintenance completed. Therefore, future research should look at other variables such as asset age, condition, or installation specific rates of completion. This study assumed that all installations completed the preventive maintenance required, which could have been incorrect. Much of this additional data already exists within the USAF asset manager's toolbox. Unfortunately, it is not communicative with maintenance data. It is recommended that work be completed to repair data collection inadequacies. AFCEC currently provides installations with data entry standards; however, it is apparent from this research that not all installations follow those data entry requirements. The reason for lack of standardization could vary by installation, but a focus on improved data collection could provide noticeable benefits. Further work to improve the tools provided to asset managers, such as creating a more user-friendly, data entry experience within NexGen IT itself, or enabling technicians to enter data on-site through information technology upgrades such as a mobile application, could have drastic improvements on data quality. These corrections may be time-consuming and costly at first, but the expected benefits of data quality and worker satisfaction far outweigh the cost.

The original inspiration for this study came from AFCEC's investigation of category management models to give back time and money to help Airmen accomplish their mission. Without a control study as discussed above, it is hard to say whether the Air Force is focusing too much or too little on corrective maintenance. However, based on the review of the literature, it is clear that preventive maintenance provides benefits,

many of which may be second- or third-order effects (e.g., reduced energy costs due to more efficient systems). This steers the category management discussion toward a more holistic viewpoint, where all costs and benefits are explored and analyzed in a total cost of ownership model to further inform decision making. While AFCEC is currently working on a total cost of ownership model, future research and improved data quality is needed to better quantify components of the existing model using U.S. Air Force assets, e.g., the relationship between preventive and corrective maintenance, or system efficiency and energy costs.

Appendix A: Model Input Distributions

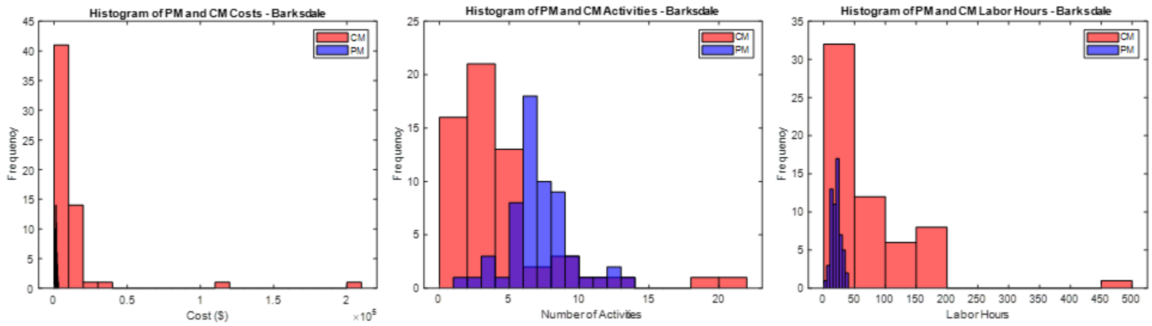


Figure A1: Model Input Distributions - Barksdale AFB

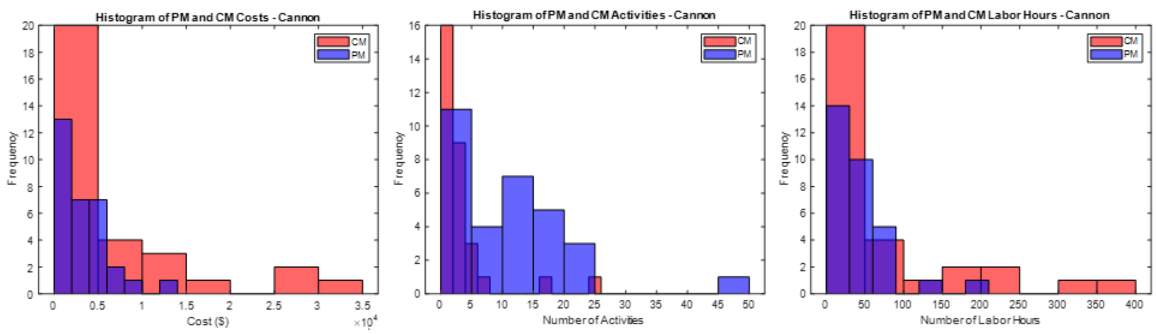


Figure A2: Model Input Distributions - Cannon AFB

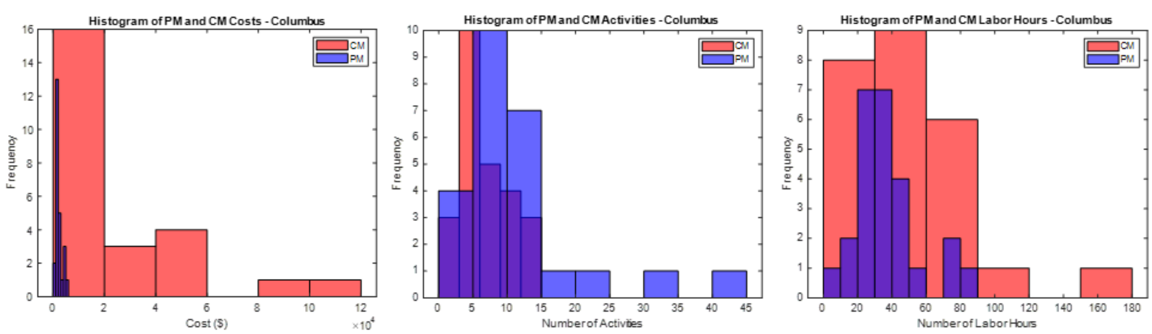


Figure A3: Model Input Distributions - Columbus AFB

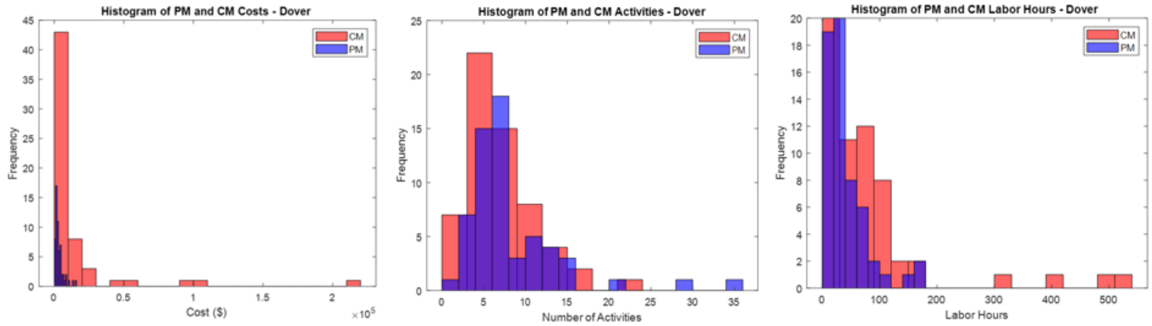


Figure A4: Model Input Distributions - Dover AFB

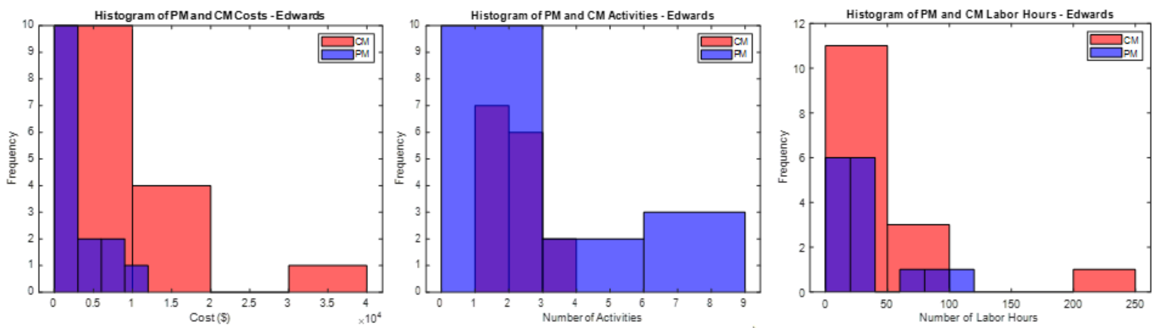


Figure A5: Model Input Distributions - Edwards AFB

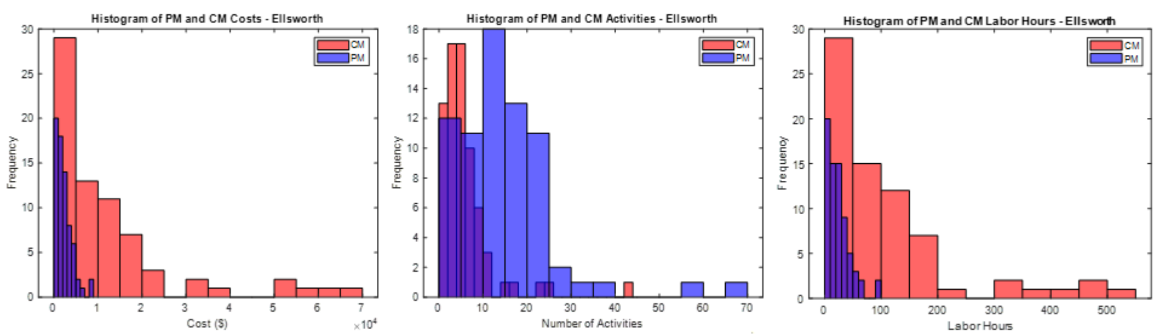


Figure A6: Model Input Distributions - Ellsworth AFB

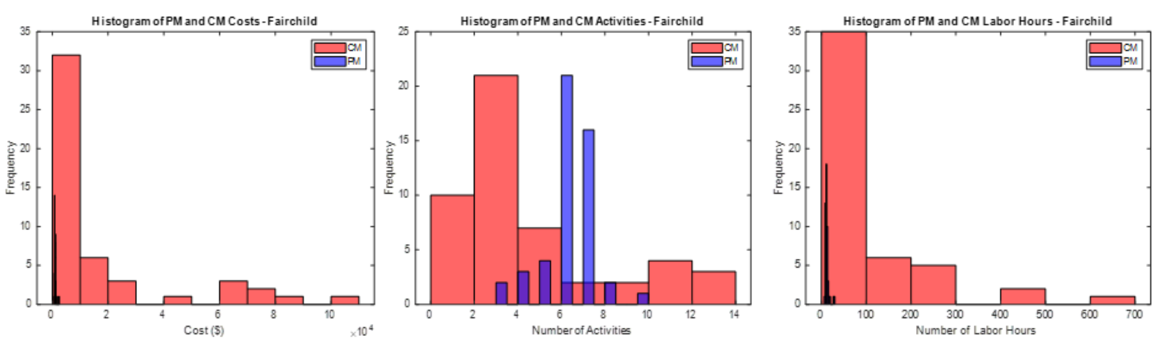


Figure A7: Model Input Distributions - Fairchild AFB

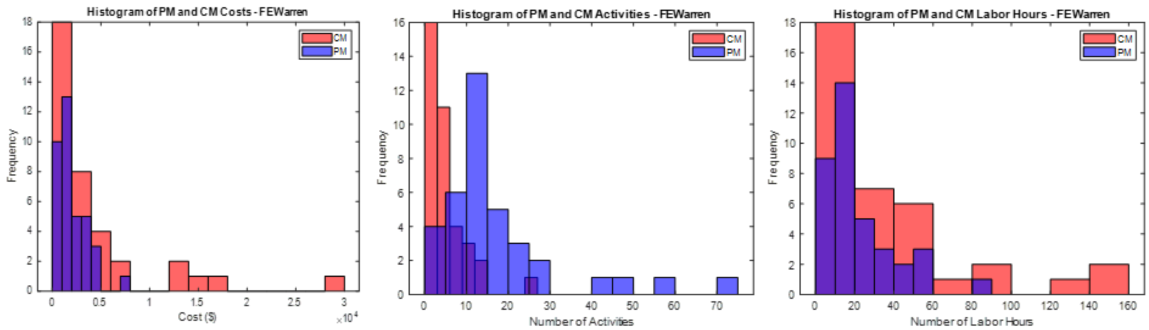


Figure A8: Model Input Distributions - F.E. Warren AFB

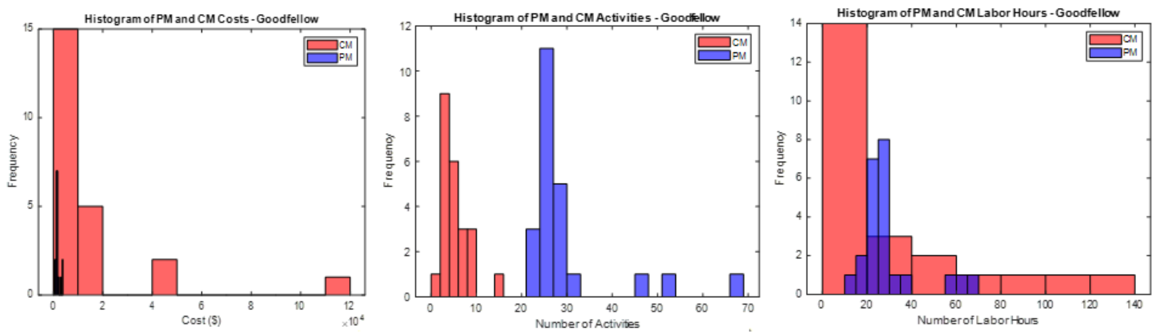


Figure A9: Model Input Distributions - Goodfellow AFB

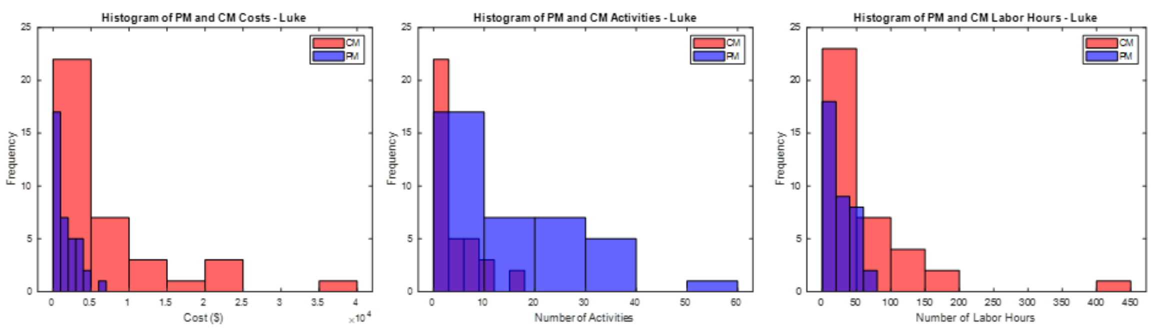


Figure A10: Model Input Distributions - Luke AFB

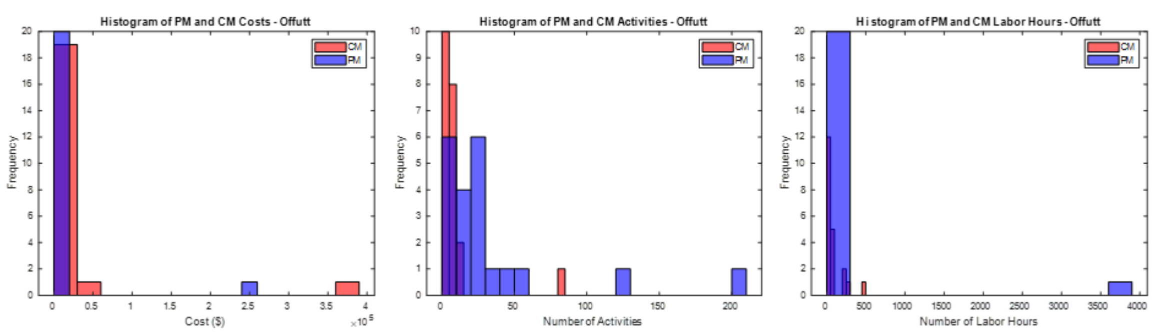


Figure A11: Model Input Distributions - Offutt AFB

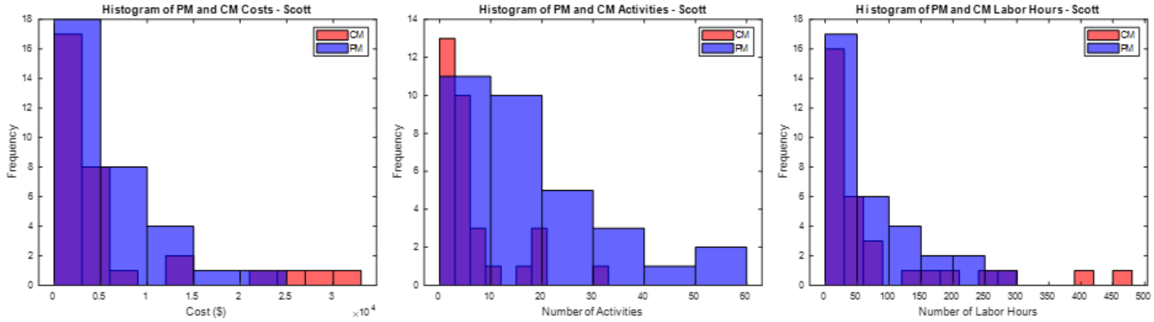


Figure A12: Model Input Distributions - Scott AFB

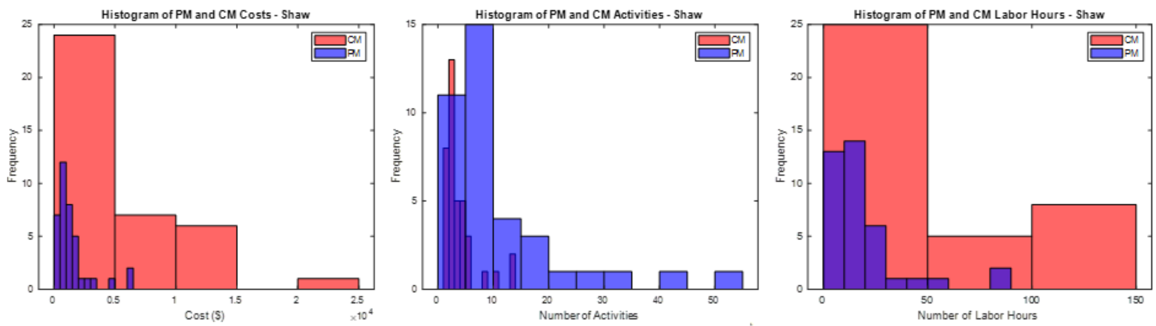


Figure A13: Model Input Distributions - Shaw AFB

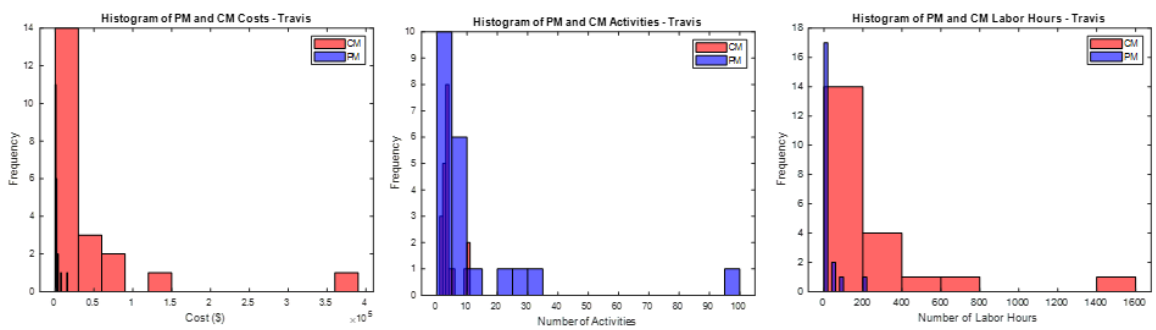


Figure A14: Model Input Distributions - Travis AFB

Appendix B: Single Linear Regression

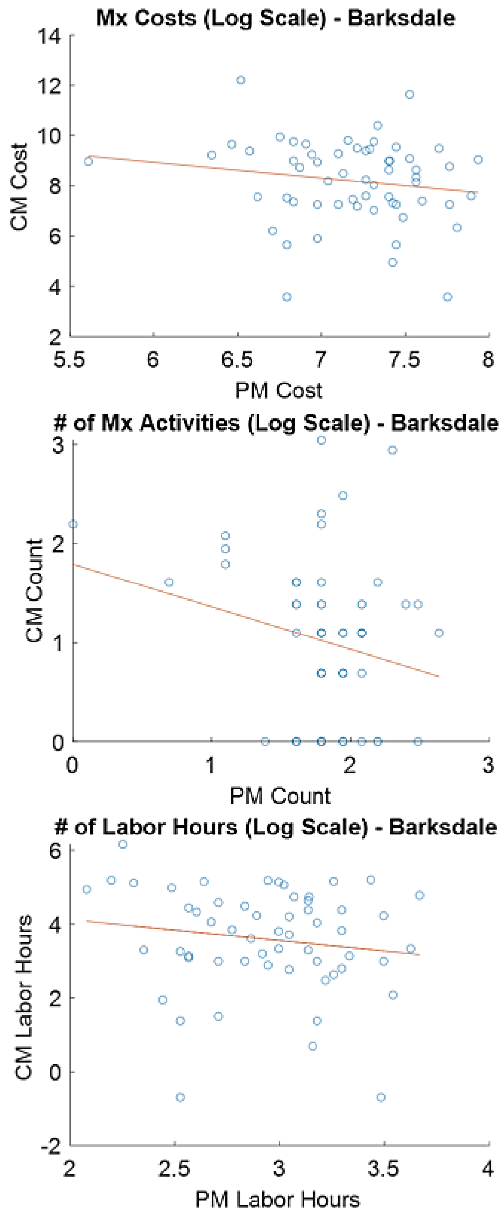
Results in Tables B1 and B2 are highlighted based on ranges of confidence for each model. Models which provide 95% confidence in results (i.e., $\alpha \leq 0.05$) are highlighted green, those with slightly less significant results which provide an 85-95% confidence (i.e., $0.05 < p\text{-}value \leq 0.15$) are highlighted yellow, and all others are highlighted red.

Table B1: Single Linear Regression Summary

Significance	Model Statistics	Cost	Activities	Labor Hrs	All Models
p-value $\leq$ 0.05	Number of Models	8	8	7	23
	Median Adj R^2	0.14	0.14	0.19	0.15
	Min Adj. R^2	0.07	0.08	0.11	0.07
	Max Adj. R^2	0.48	0.46	0.51	0.51
0.05 < p-value $\leq$ 0.15	Number of Models	1	2	2	5
	Median Adj. R^2	0.04	0.03	0.07	0.04
	Min Adj. R^2		0.03	0.05	0.03
	Max Adj. R^2		0.03	0.08	0.08
p-value > 0.15	Number of Models	5	4	5	14
	Median Adj. R^2	-0.004	-0.006	-0.008	-0.006
	Min Adj. R^2	-0.04	-0.05	-0.06	-0.06
	Max Adj. R^2	0.03	0.009	0.02	0.083

Table B2: Installation Specific Summary

Installation	Number of Facilities	Model Statistics	Single Linear Regression Model		
			Cost	Activities	Labor Hrs
Barksdale	59	Adj. R^2	0.0094	0.0326	0.0061
		p-value	0.2180	0.0912	0.2510
Cannon	31	Adj. R^2	0.2170	0.0088	0.1880
		p-value	0.0048	0.2700	0.0085
Columbus	25	Adj. R^2	0.1300	0.2350	0.0821
		p-value	0.0429	0.0081	0.0893
Dover	59	Adj. R^2	-0.0173	0.0285	-0.0085
		p-value	0.9070	0.1060	0.4770
Edwards	15	Adj. R^2	-0.0424	0.4630	-0.0638
		p-value	0.5230	0.0032	0.6950
Ellsworth	71	Adj. R^2	0.0967	0.1260	0.1300
		p-value	0.0048	0.0014	0.0012
Fairchild	49	Adj. R^2	0.0721	-0.0130	0.1110
		p-value	0.0347	0.5390	0.0112
FE Warren	37	Adj. R^2	0.1680	0.1160	0.1660
		p-value	0.0069	0.0220	0.0072
Goodfellow	23	Adj. R^2	0.1390	0.1500	0.2020
		p-value	0.0448	0.0386	0.0182
Luke	37	Adj. R^2	0.0261	-0.0001	0.0195
		p-value	0.1700	0.3250	0.1990
Offutt	21	Adj. R^2	0.1460	0.3650	0.2380
		p-value	0.0489	0.0022	0.0145
Scott	32	Adj. R^2	0.4830	0.0997	0.5080
		p-value	0.0000	0.0437	0.0000
Shaw	38	Adj. R^2	0.0360	0.0845	0.0493
		p-value	0.1310	0.0427	0.0962
Travis	21	Adj. R^2	-0.0038	-0.0513	-0.0419
		p-value	0.3490	0.8800	0.6630




```
BarksdaleCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    __________

    (Intercept)     12.693      3.6084     3.5176    0.00086245
    x1             -0.6246     0.50146    -1.2456       0.21802


Number of observations: 59, Error degrees of freedom: 57
Root Mean Squared Error: 1.64
R-squared: 0.0265,  Adjusted R-Squared: 0.00942
F-statistic vs. constant model: 1.55, p-value = 0.218
```

```
BarksdaleCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    __________

    (Intercept)     1.7915     0.46675     3.8383    0.00031288
    x1            -0.42901     0.24969    -1.7182      0.091191


Number of observations: 59, Error degrees of freedom: 57
Root Mean Squared Error: 0.79
R-squared: 0.0492,  Adjusted R-Squared: 0.0326
F-statistic vs. constant model: 2.95, p-value = 0.0912
```

```
BarksdaleCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    __________

    (Intercept)     5.2704      1.4606     3.6084    0.00066586
    x1            -0.57159     0.49277      -1.16       0.25108


Number of observations: 57, Error degrees of freedom: 55
Root Mean Squared Error: 1.41
R-squared: 0.0239,  Adjusted R-Squared: 0.00613
F-statistic vs. constant model: 1.35, p-value = 0.251
```

Figure B1.1: Barksdale AFB Single Linear Regressions

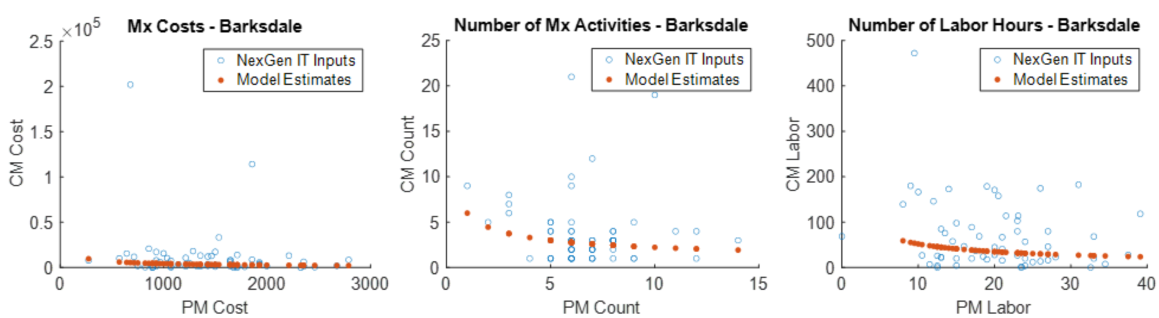
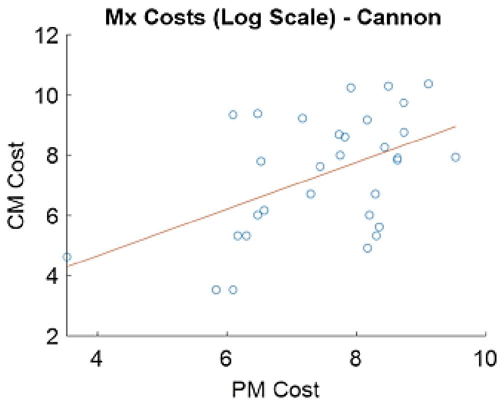


Figure B1.2: Barksdale AFB Model Framework



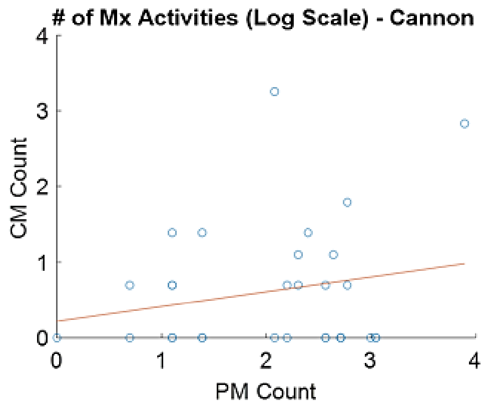

```
CannonCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    _________

    (Intercept)     1.5522      1.9358    0.80184      0.42917
    x1              0.7762     0.25409     3.0549    0.0047935


Number of observations: 31, Error degrees of freedom: 29
Root Mean Squared Error: 1.76
R-squared: 0.243,  Adjusted R-Squared: 0.217
F-statistic vs. constant model: 9.33, p-value = 0.00479
```



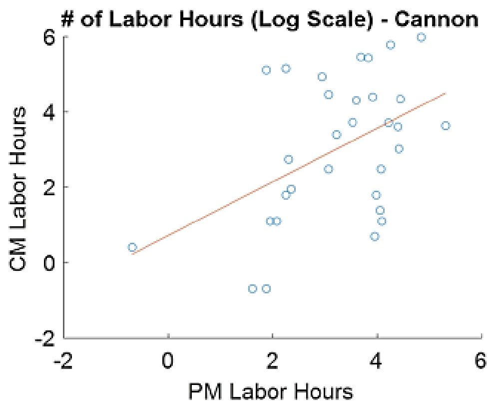

```
CannonCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______     _______    _______

    (Intercept)     0.21586    0.38669     0.55823    0.58097
    x1              0.19504    0.17341      1.1247    0.26992


Number of observations: 31, Error degrees of freedom: 29
Root Mean Squared Error: 0.846
R-squared: 0.0418,  Adjusted R-Squared: 0.00876
F-statistic vs. constant model: 1.27, p-value = 0.27
```




```
CannonCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    _________

    (Intercept)     0.71982    0.87685    0.82091      0.41839
    x1              0.71331    0.25278     2.8219    0.0085324


Number of observations: 31, Error degrees of freedom: 29
Root Mean Squared Error: 1.71
R-squared: 0.215,  Adjusted R-Squared: 0.188
F-statistic vs. constant model: 7.96, p-value = 0.00853
```

Figure B2.1: Cannon AFB Single Linear Regressions

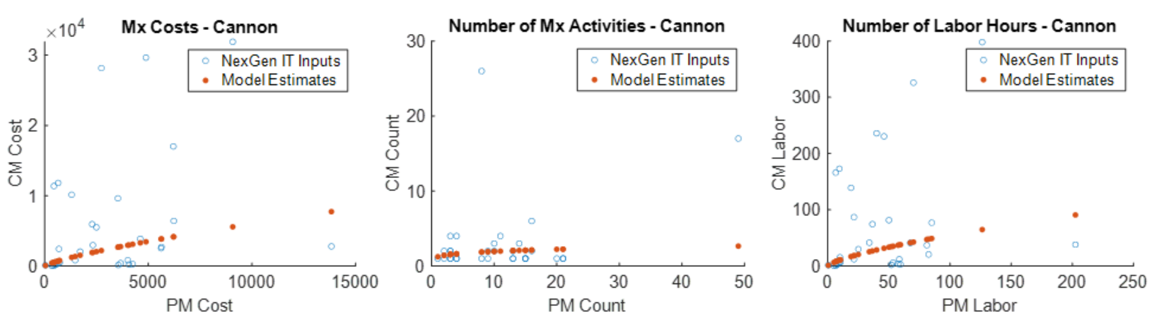
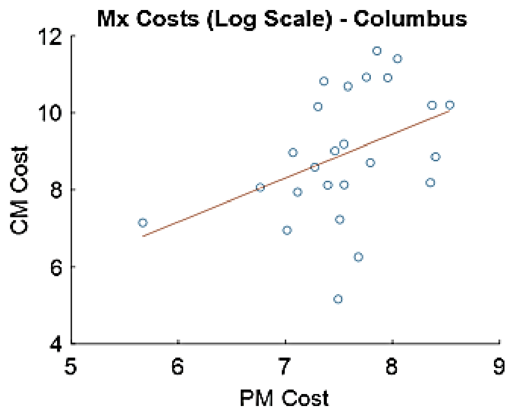


Figure B2.2: Cannon AFB Model Framework



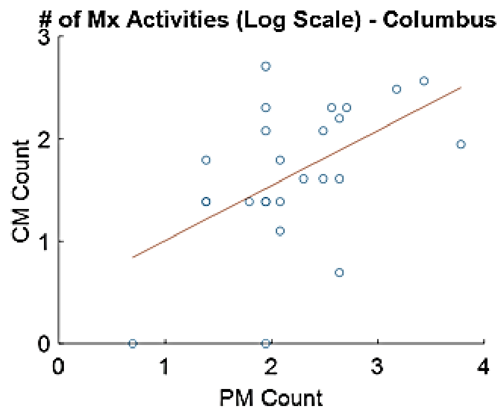

```
ColumbusCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ________    ________

    (Intercept)    0.34506     4.0213     0.085809    0.93236
    x1              1.1371     0.53067      2.1427    0.042949


Number of observations: 25, Error degrees of freedom: 23
Root Mean Squared Error: 1.57
R-squared: 0.166,  Adjusted R-Squared: 0.13
F-statistic vs. constant model: 4.59, p-value = 0.0429
```



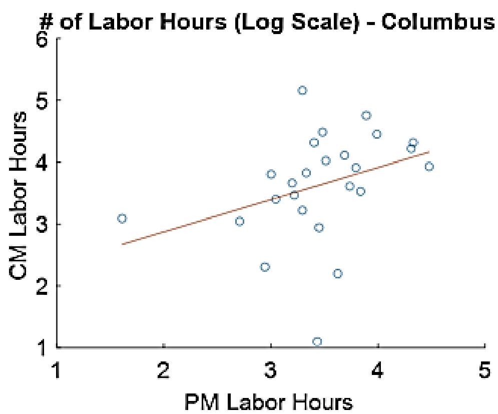

```
ColumbusCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _________

    (Intercept)    0.47088     0.42832    1.0994      0.28298
    x1             0.53625     0.18513    2.8966    0.0081357


Number of observations: 25, Error degrees of freedom: 23
Root Mean Squared Error: 0.613
R-squared: 0.267,  Adjusted R-Squared: 0.235
F-statistic vs. constant model: 8.39, p-value = 0.00814
```




```
ColumbusCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    ________

    (Intercept)     1.8335        1.03    1.7801    0.088274
    x1             0.52023     0.29328    1.7739    0.089327


Number of observations: 25, Error degrees of freedom: 23
Root Mean Squared Error: 0.842
R-squared: 0.12,  Adjusted R-Squared: 0.0821
F-statistic vs. constant model: 3.15, p-value = 0.0893
```

Figure B3.1: Columbus AFB Single Linear Regressions

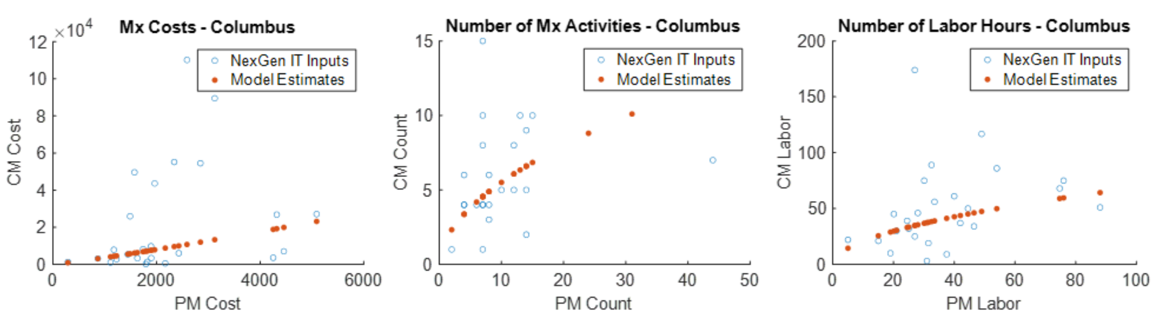
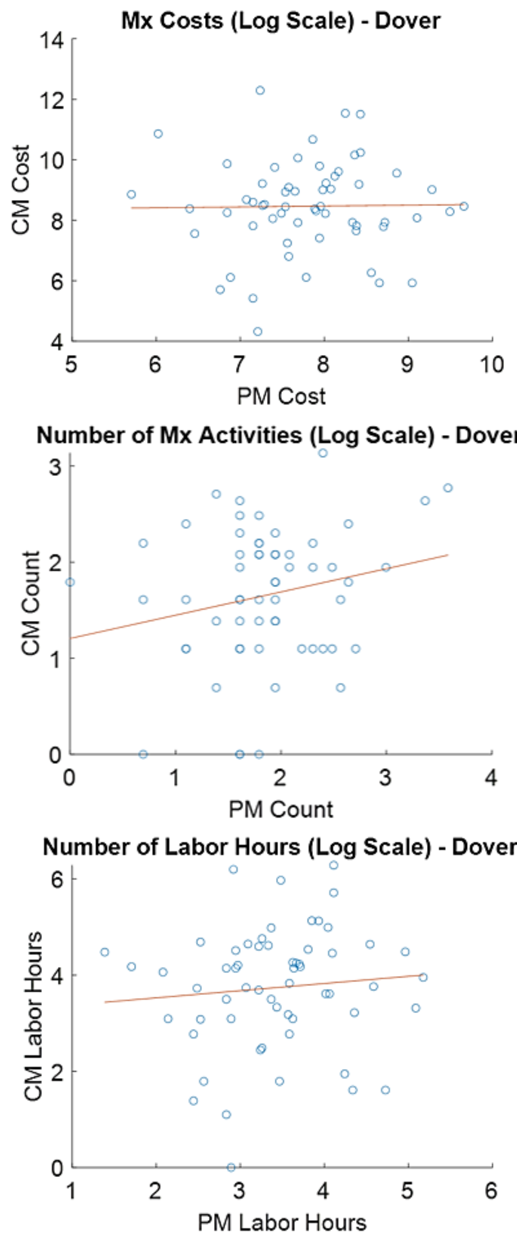


Figure B3.2: Columbus AFB Model Framework




```
DoverCostLog =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    __________

    (Intercept)       8.234     1.9731     4.1732    0.00010375
    x1              0.02949    0.25147    0.11727       0.90706


Number of observations: 59, Error degrees of freedom: 57
Root Mean Squared Error: 1.55
R-squared: 0.000241,  Adjusted R-Squared: -0.0173
F-statistic vs. constant model: 0.0138, p-value = 0.907
```

```
DoverCountLog =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ______    __________

    (Intercept)     1.2059     0.28863    4.1782    0.00010203
    x1             0.24199     0.14718    1.6442       0.10564


Number of observations: 59, Error degrees of freedom: 57
Root Mean Squared Error: 0.706
R-squared: 0.0453,  Adjusted R-Squared: 0.0285
F-statistic vs. constant model: 2.7, p-value = 0.106
```

```
DoverLaborLog =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat        pValue
                   ________    _______    _______    __________

    (Intercept)     3.2286     0.73139     4.4143    4.5709e-05
    x1             0.14904     0.20821    0.71582       0.47702


Number of observations: 59, Error degrees of freedom: 57
Root Mean Squared Error: 1.27
R-squared: 0.00891,  Adjusted R-Squared: -0.00848
F-statistic vs. constant model: 0.512, p-value = 0.477
```

Figure B4.1: Dover AFB Single Linear Regressions

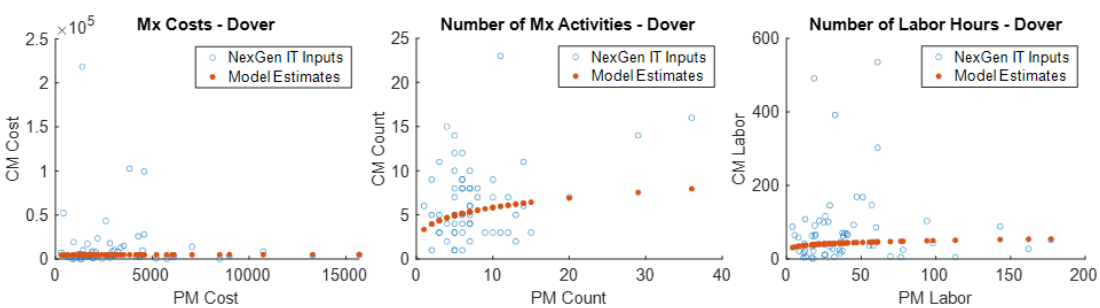
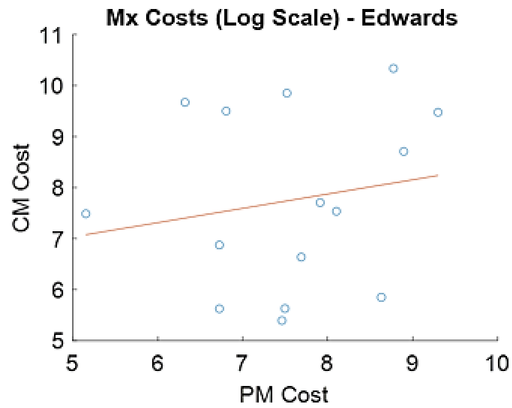


Figure B4.2: Dover AFB Model Framework



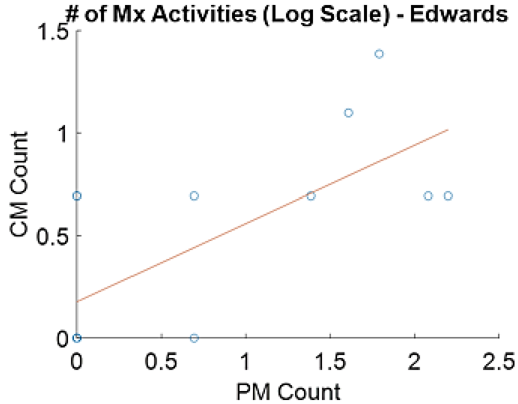

```
EdwardsCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _______

    (Intercept)     5.6318     3.2652     1.7248    0.10825
    x1             0.28021    0.42721     0.6559    0.52333


Number of observations: 15, Error degrees of freedom: 13
Root Mean Squared Error: 1.77
R-squared: 0.032,  Adjusted R-Squared: -0.0424
F-statistic vs. constant model: 0.43, p-value = 0.523
```



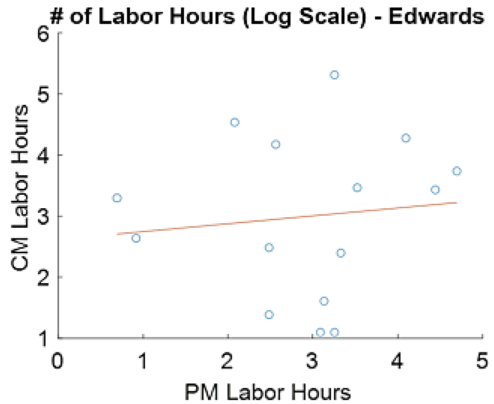

```
EdwardsCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _________

    (Intercept)    0.17696    0.11517     1.5365       0.1484
    x1             0.38174    0.10562     3.6141    0.0031457


Number of observations: 15, Error degrees of freedom: 13
Root Mean Squared Error: 0.343
R-squared: 0.501,  Adjusted R-Squared: 0.463
F-statistic vs. constant model: 13.1, p-value = 0.00315
```




```
EdwardsCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    _______    ________

    (Intercept)     2.6187     1.0069      2.6007    0.021976
    x1             0.12871    0.32133     0.40054     0.69527


Number of observations: 15, Error degrees of freedom: 13
Root Mean Squared Error: 1.36
R-squared: 0.0122,  Adjusted R-Squared: -0.0638
F-statistic vs. constant model: 0.16, p-value = 0.695
```

Figure B5.1: Edwards AFB Single Linear Regressions

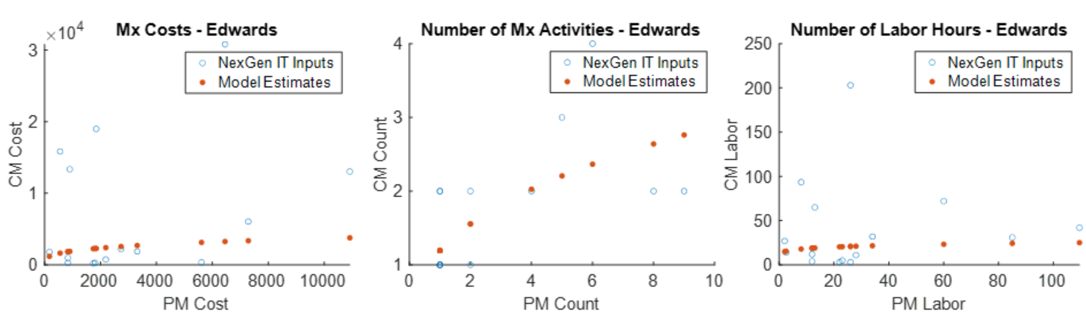
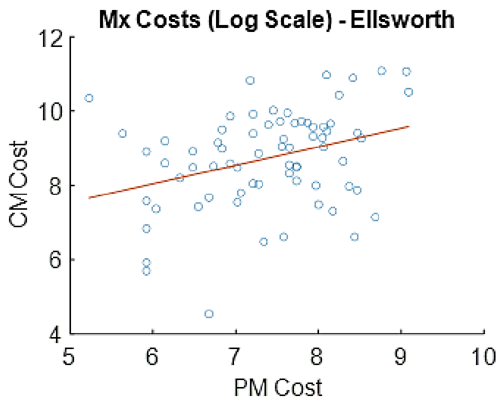


Figure B5.2: Edwards AFB Model Framework



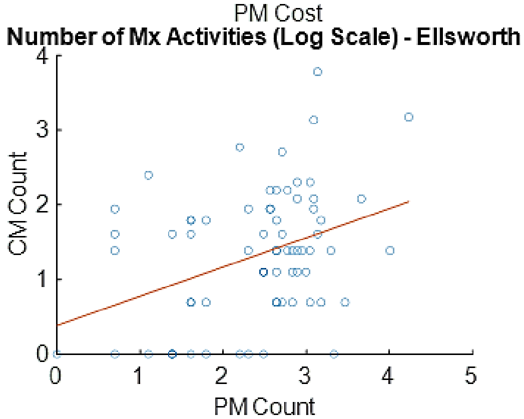

```
EllsworthCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE      tStat      pValue
                   ________    _______    _____    __________

    (Intercept)     5.0588      1.2685    3.988    0.00016349
    x1             0.49709     0.17052   2.9151     0.0047915


Number of observations: 71, Error degrees of freedom: 69
Root Mean Squared Error: 1.25
R-squared: 0.11,  Adjusted R-Squared: 0.0967
F-statistic vs. constant model: 8.5, p-value = 0.00479
```



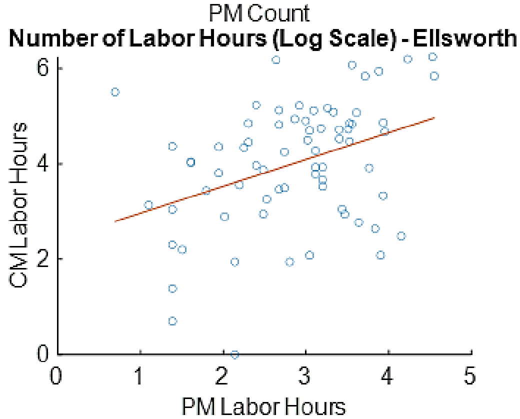

```
EllsworthLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE      tStat       pValue
                   ________    _______    ______    __________

    (Intercept)      2.402     0.49682    4.8347    7.7919e-06
    x1             0.56358     0.16669    3.3809     0.0011928


Number of observations: 71, Error degrees of freedom: 69
Root Mean Squared Error: 1.22
R-squared: 0.142,  Adjusted R-Squared: 0.13
F-statistic vs. constant model: 11.4, p-value = 0.00119
```




```
EllsworthCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _________

    (Intercept)    0.38435     0.29666    1.2956      0.19944
    x1             0.39131     0.11728    3.3365    0.0013693


Number of observations: 71, Error degrees of freedom: 69
Root Mean Squared Error: 0.825
R-squared: 0.139,  Adjusted R-Squared: 0.126
F-statistic vs. constant model: 11.1, p-value = 0.00137
```

Figure B6.1: Ellsworth AFB Single Linear Regressions

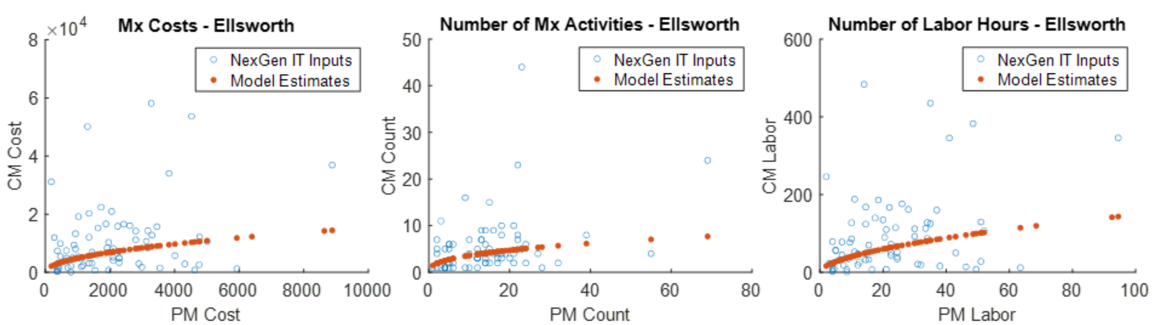
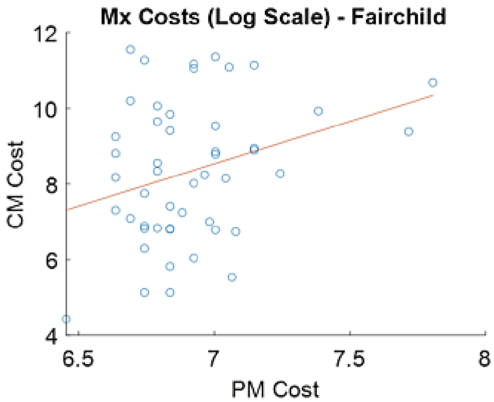


Figure B6.2: Ellsworth AFB Model Framework



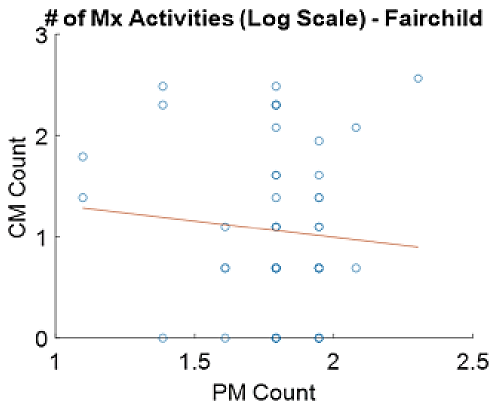

```
FairchildCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    ______    _______    ________

    (Intercept)    -7.1243     7.1145    -1.0014     0.32177
    x1              2.2371     1.0286     2.1748    0.034709


Number of observations: 49, Error degrees of freedom: 47
Root Mean Squared Error: 1.79
R-squared: 0.0914,  Adjusted R-Squared: 0.0721
F-statistic vs. constant model: 4.73, p-value = 0.0347
```



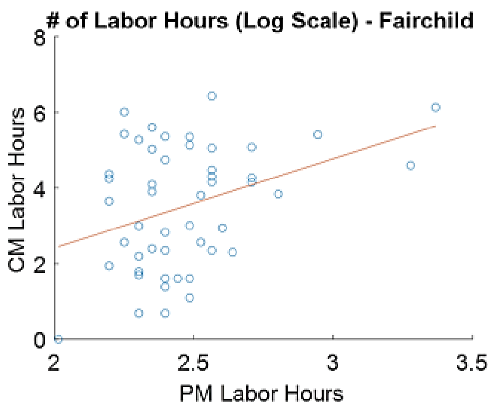

```
FairchildCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)     1.6379     0.93862       1.745    0.087514
    x1            -0.32101     0.51863    -0.61896     0.53893


Number of observations: 49, Error degrees of freedom: 47
Root Mean Squared Error: 0.802
R-squared: 0.00809,  Adjusted R-Squared: -0.013
F-statistic vs. constant model: 0.383, p-value = 0.539
```




```
FairchildCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    _______    ________

    (Intercept)    -2.3022      2.2155    -1.0391     0.30407
    x1              2.3587     0.89289     2.6417    0.011168


Number of observations: 49, Error degrees of freedom: 47
Root Mean Squared Error: 1.55
R-squared: 0.129,  Adjusted R-Squared: 0.111
F-statistic vs. constant model: 6.98, p-value = 0.0112
```

Figure B7.1: Fairchild AFB Single Linear Regressions

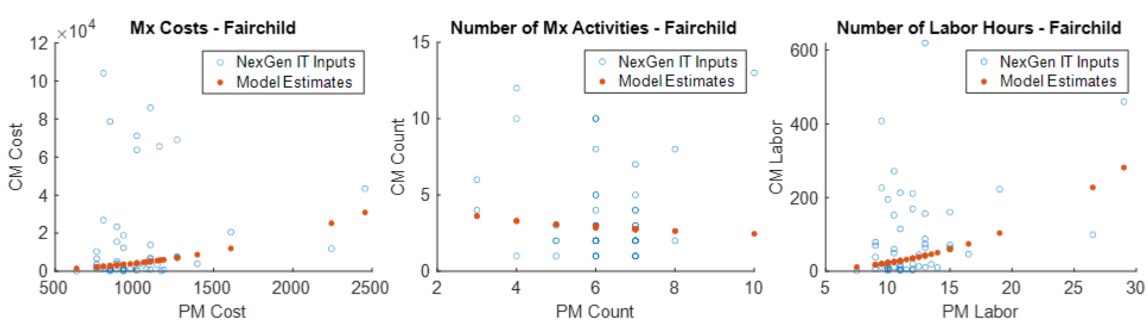
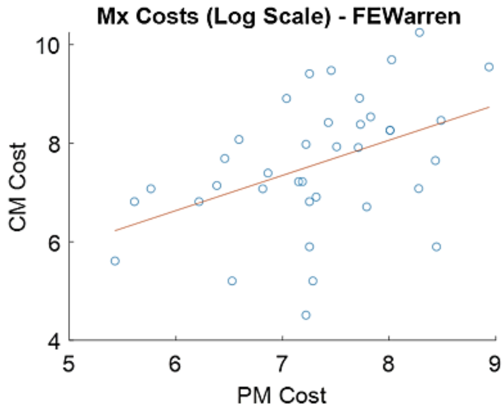


Figure B7.2: Fairchild AFB Model Framework



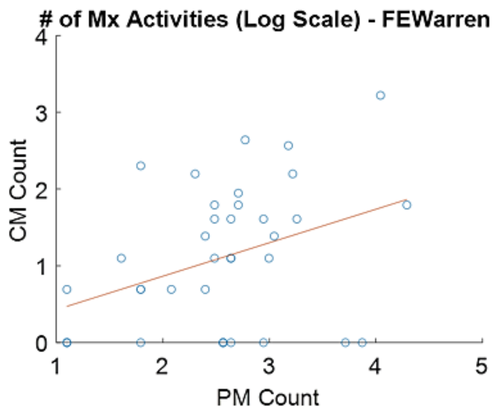

```
FEWarrenCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ______    _________

    (Intercept)     2.3482      1.8311    1.2824      0.20813
    x1             0.71421     0.24857    2.8733    0.0068604


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 1.23
R-squared: 0.191,  Adjusted R-Squared: 0.168
F-statistic vs. constant model: 8.26, p-value = 0.00686
```



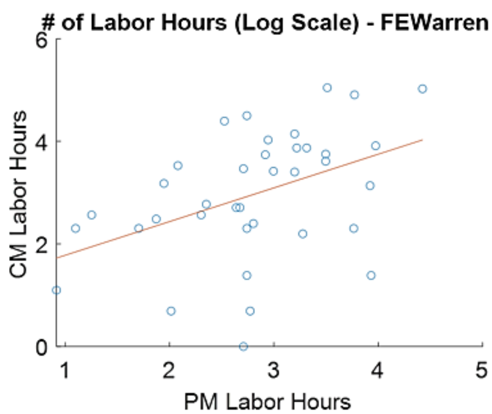

```
FEWarrenCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                    Estimate        SE        tStat       pValue
                   __________    _______    _________    ________

    (Intercept)    -0.0067546    0.48203    -0.014013      0.9889
    x1                0.43586    0.18182       2.3972    0.021995


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 0.863
R-squared: 0.141,  Adjusted R-Squared: 0.116
F-statistic vs. constant model: 5.75, p-value = 0.022
```




```
FEWarrenCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    ________

    (Intercept)      1.123     0.67172    1.6719     0.10347
    x1             0.65632     0.22971    2.8572    0.007148


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 1.13
R-squared: 0.189,  Adjusted R-Squared: 0.166
F-statistic vs. constant model: 8.16, p-value = 0.00715
```

Figure B8.1: F.E. Warren AFB Single Linear Regressions

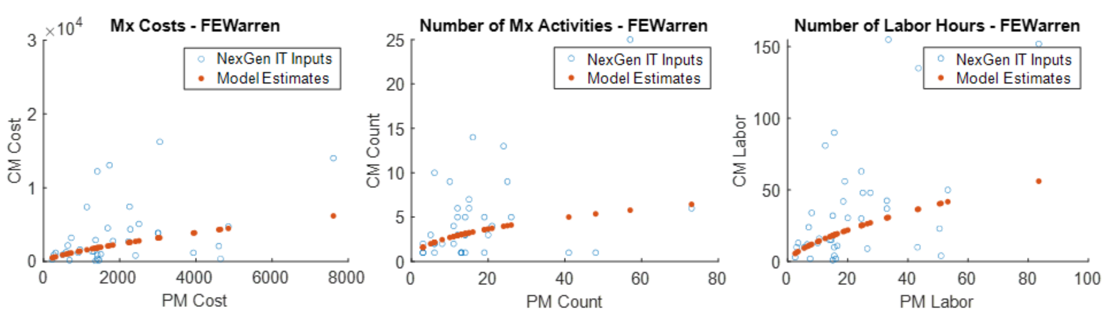
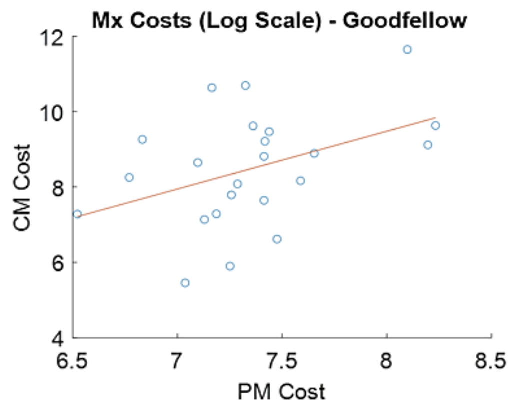


Figure B8.2: F.E. Warren AFB Model Framework



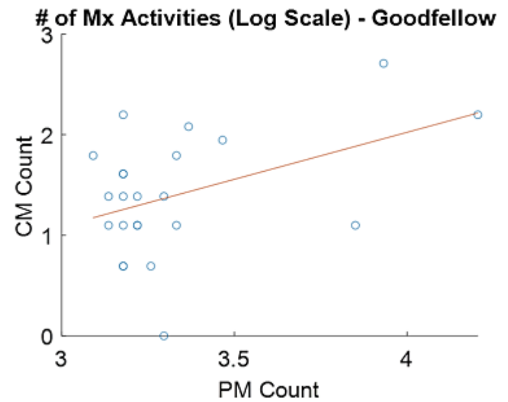

```
GoodfellowCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE        tStat      pValue  
                   ________    _______    ________    ________

    (Intercept)    -2.7901      5.2933    -0.52709     0.60366
    x1              1.5337     0.71866      2.1341    0.044786


Number of observations: 23, Error degrees of freedom: 21
Root Mean Squared Error: 1.41
R-squared: 0.178,  Adjusted R-Squared: 0.139
F-statistic vs. constant model: 4.55, p-value = 0.0448
```



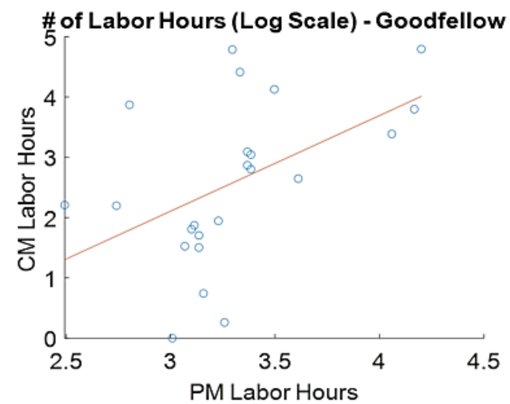

```
GoodfellowCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE        tStat      pValue  
                   ________    _______    ______    ________

    (Intercept)    -1.7129      1.4145    -1.211     0.23936
    x1               0.934     0.42327    2.2066    0.038609


Number of observations: 23, Error degrees of freedom: 21
Root Mean Squared Error: 0.561
R-squared: 0.188,  Adjusted R-Squared: 0.15
F-statistic vs. constant model: 4.87, p-value = 0.0386
```




```
GoodfellowCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE        tStat      pValue  
                   ________    _______    _______    ________

    (Intercept)    -2.6527      2.0588    -1.2885      0.2116
    x1              1.5864     0.61914     2.5622    0.018155


Number of observations: 23, Error degrees of freedom: 21
Root Mean Squared Error: 1.21
R-squared: 0.238,  Adjusted R-Squared: 0.202
F-statistic vs. constant model: 6.56, p-value = 0.0182
```

Figure B9.1: Goodfellow AFB Single Linear Regressions

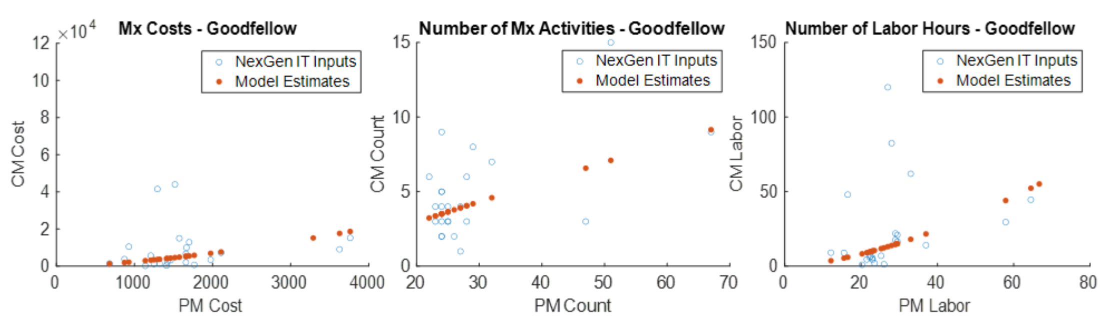
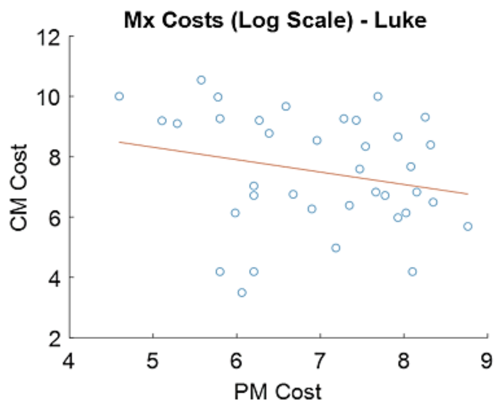


Figure B9.2: Goodfellow AFB Model Framework



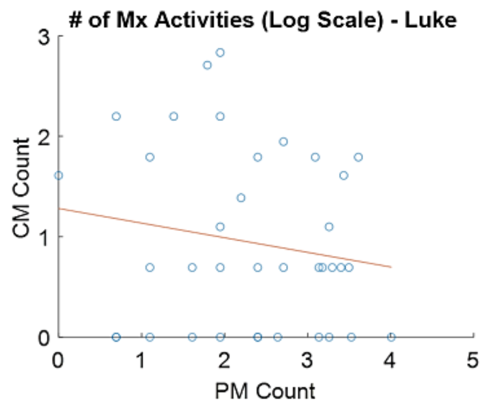

```
LukeCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE       tStat       pValue
                   ________    _______    _______    __________

    (Intercept)     10.373       2.068      5.016    1.5285e-05
    x1             -0.41181    0.29365    -1.4024       0.16961


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 1.88
R-squared: 0.0532,  Adjusted R-Squared: 0.0261
F-statistic vs. constant model: 1.97, p-value = 0.17
```



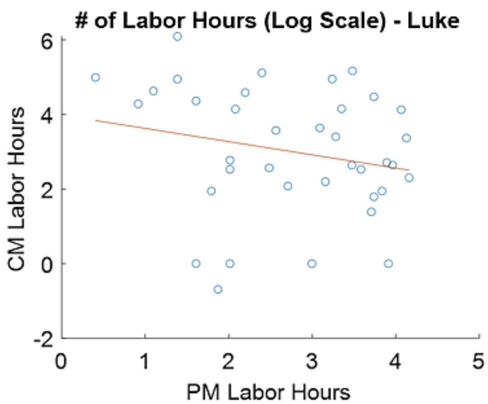

```
LukeCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _________

    (Intercept)     1.2805     0.36535       3.505    0.0012711
    x1             -0.14559    0.14581    -0.99848       0.3249


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 0.878
R-squared: 0.0277,  Adjusted R-Squared: -8.44e-05
F-statistic vs. constant model: 0.997, p-value = 0.325
```




```
LukeCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE       tStat       pValue
                   ________    _______    _______    _________

    (Intercept)      3.981     0.79256     5.0229    1.497e-05
    x1             -0.35494    0.27099    -1.3098      0.19881


Number of observations: 37, Error degrees of freedom: 35
Root Mean Squared Error: 1.69
R-squared: 0.0467,  Adjusted R-Squared: 0.0195
F-statistic vs. constant model: 1.72, p-value = 0.199
```

Figure B10.1: Luke AFB Single Linear Regressions

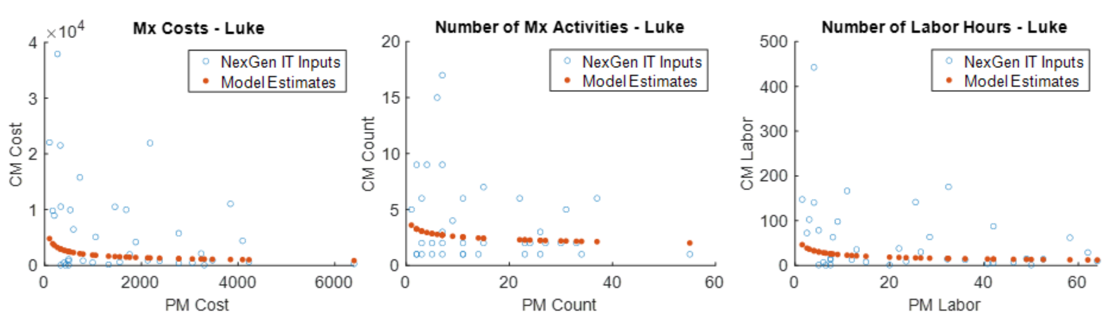
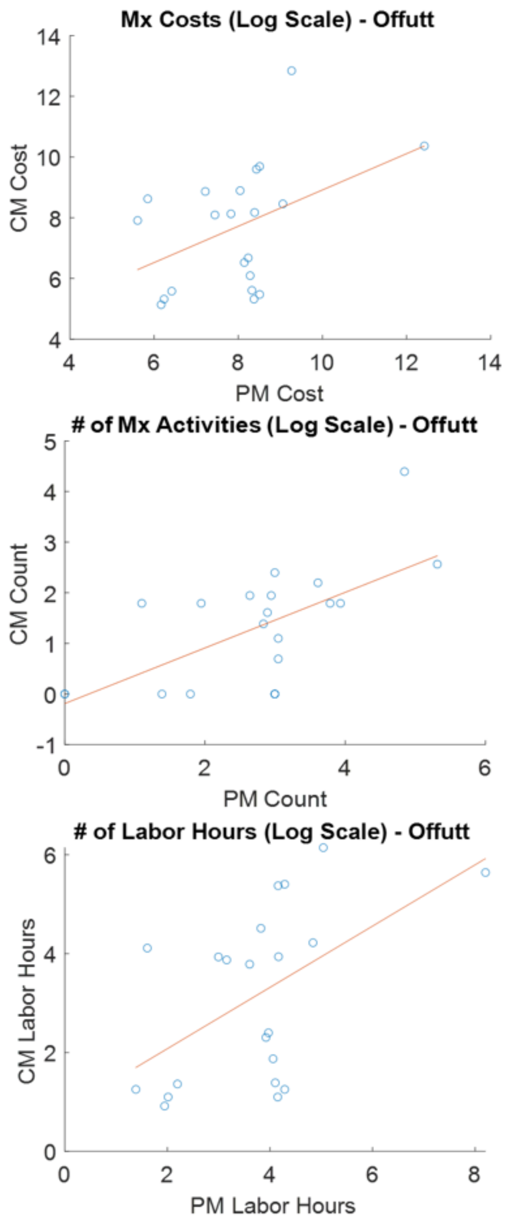


Figure B10.2: Luke AFB Model Framework




```
OffuttCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat     pValue
                   ________    _______    ______    _______

    (Intercept)     2.9401      2.2912    1.2832    0.21485
    x1             0.59743     0.28387    2.1046    0.04887


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 1.88
R-squared: 0.189,  Adjusted R-Squared: 0.146
F-statistic vs. constant model: 4.43, p-value = 0.0489
```

```
OffuttCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _________

    (Intercept)    -0.18851    0.46899    -0.40195      0.69221
    x1              0.54934    0.15547      3.5333    0.0022208


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 0.932
R-squared: 0.397,  Adjusted R-Squared: 0.365
F-statistic vs. constant model: 12.5, p-value = 0.00222
```

```
OffuttCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    _______    ________

    (Intercept)    0.83587     0.91798    0.91055     0.37394
    x1             0.61997     0.23056      2.689    0.014529


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 1.53
R-squared: 0.276,  Adjusted R-Squared: 0.238
F-statistic vs. constant model: 7.23, p-value = 0.0145
```

Figure B11.1: Offutt AFB Single Linear Regressions

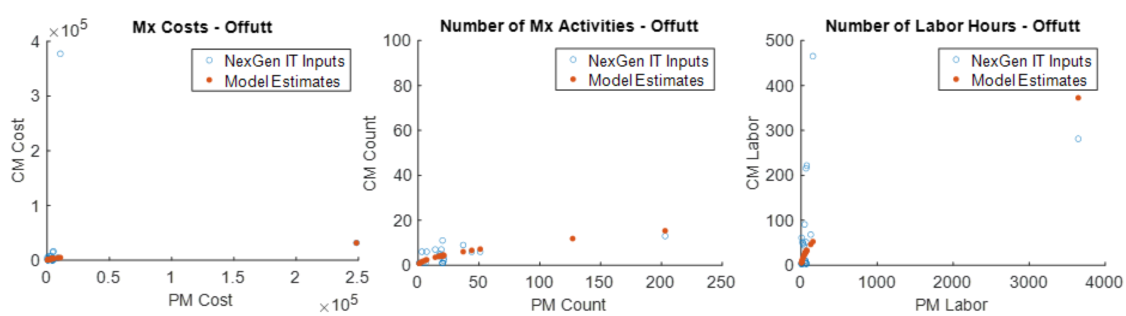
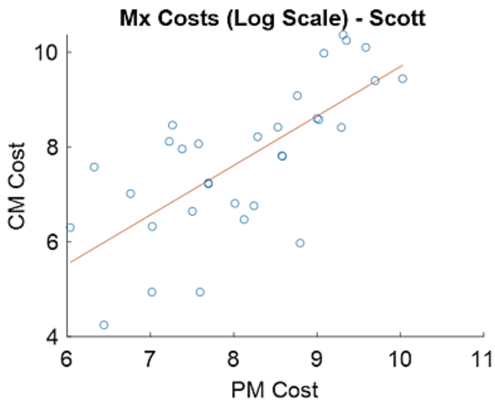


Figure B11.2: Offutt AFB Model Framework



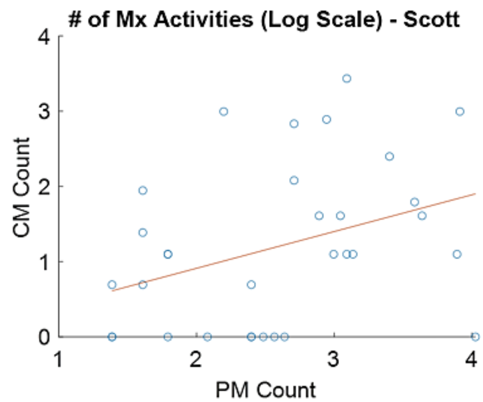

```
ScottCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ________    __________

    (Intercept)    -0.73095     1.5609    -0.46829       0.64296
    x1               1.0427    0.19067      5.4685    6.2056e-06


Number of observations: 32, Error degrees of freedom: 30
Root Mean Squared Error: 1.12
R-squared: 0.499,  Adjusted R-Squared: 0.483
F-statistic vs. constant model: 29.9, p-value = 6.21e-06
```



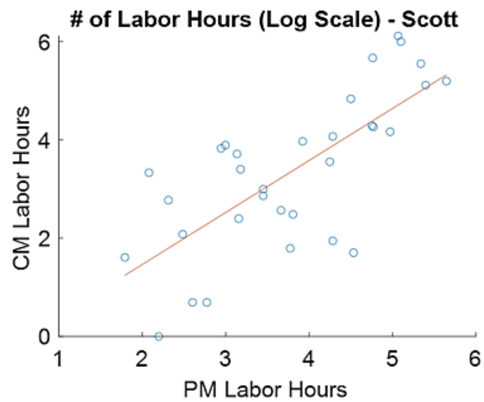

```
ScottCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   _________    _______    ________    _______

    (Intercept)    -0.065497    0.62534    -0.10474    0.91728
    x1               0.48855    0.23202      2.1057    0.04371


Number of observations: 32, Error degrees of freedom: 30
Root Mean Squared Error: 1.02
R-squared: 0.129,  Adjusted R-Squared: 0.0997
F-statistic vs. constant model: 4.43, p-value = 0.0437
```




```
ScottCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ________    __________

    (Intercept)    -0.65227    0.72505    -0.89961       0.37549
    x1               1.0582    0.18403      5.7498    2.8113e-06


Number of observations: 32, Error degrees of freedom: 30
Root Mean Squared Error: 1.11
R-squared: 0.524,  Adjusted R-Squared: 0.508
F-statistic vs. constant model: 33.1, p-value = 2.81e-06
```

Figure B12.1: Scott AFB Single Linear Regressions

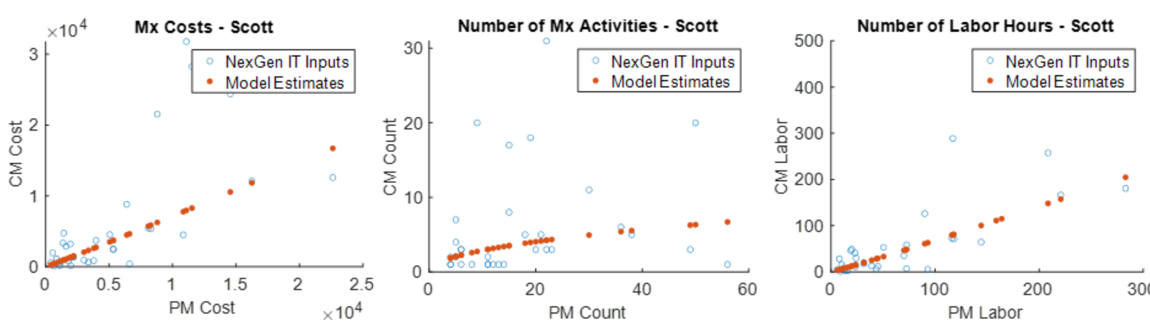
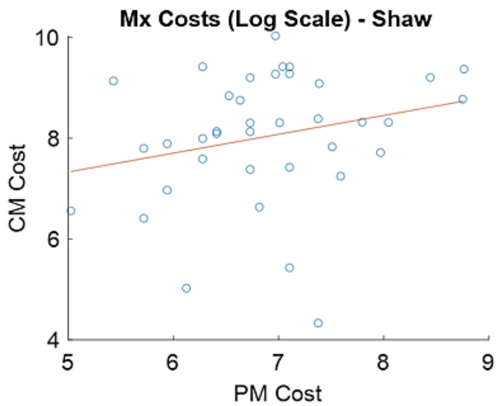


Figure B12.2: Scott AFB Model Framework



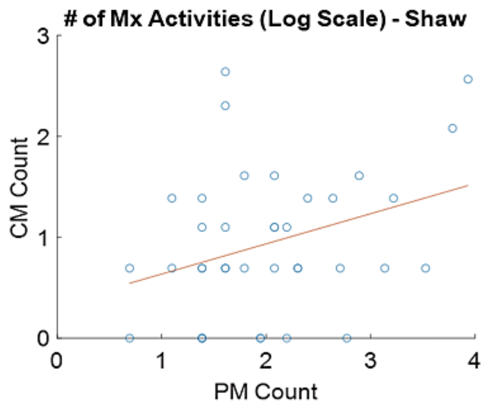

```
ShawCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _________

    (Intercept)     5.4618      1.6815    3.2481    0.0025176
    x1             0.37383     0.24219    1.5435      0.13145


Number of observations: 38, Error degrees of freedom: 36
Root Mean Squared Error: 1.26
R-squared: 0.0621,  Adjusted R-Squared: 0.036
F-statistic vs. constant model: 2.38, p-value = 0.131
```



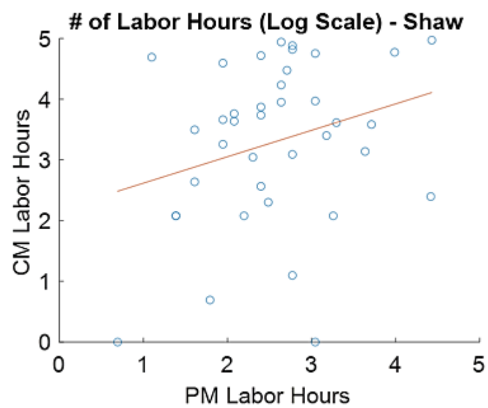

```
ShawCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    ________

    (Intercept)    0.33693     0.30932    1.0893     0.28328
    x1             0.29879     0.14219    2.1013    0.042676


Number of observations: 38, Error degrees of freedom: 36
Root Mean Squared Error: 0.686
R-squared: 0.109,  Adjusted R-Squared: 0.0845
F-statistic vs. constant model: 4.42, p-value = 0.0427
```




```
ShawCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    ______    _________

    (Intercept)     2.1826     0.68336     3.194    0.0029141
    x1             0.43497     0.25463    1.7083     0.096198


Number of observations: 38, Error degrees of freedom: 36
Root Mean Squared Error: 1.31
R-squared: 0.075,  Adjusted R-Squared: 0.0493
F-statistic vs. constant model: 2.92, p-value = 0.0962
```

Figure B13.1: Shaw AFB Single Linear Regressions

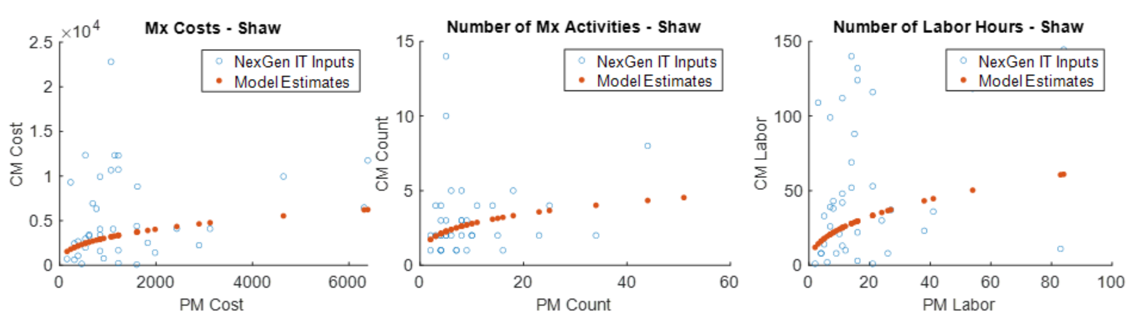
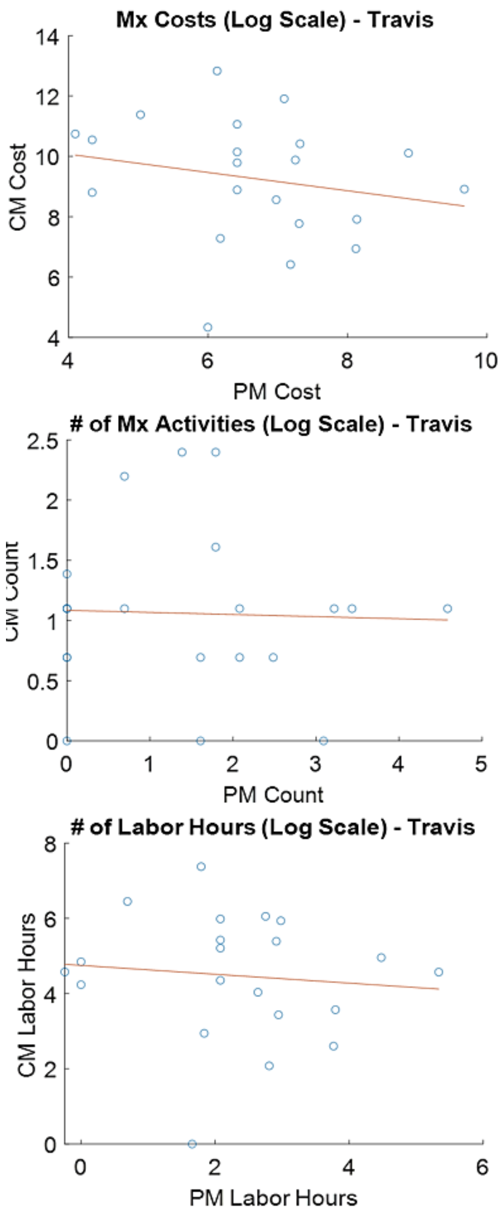


Figure B13.2: Shaw AFB Model Framework




```
TravisCMCostLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ________    __________

    (Intercept)     11.281      2.1398      5.2719    4.3468e-05
    x1            -0.30252     0.31473    -0.96122       0.34852


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 2.02
R-squared: 0.0464,  Adjusted R-Squared: -0.00382
F-statistic vs. constant model: 0.924, p-value = 0.349
```

```
TravisCMCountLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   _________    _______    ________    __________

    (Intercept)      1.0846     0.22582      4.8032    0.00012358
    x1            -0.017489     0.11425    -0.15307       0.87995


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 0.701
R-squared: 0.00123,  Adjusted R-Squared: -0.0513
F-statistic vs. constant model: 0.0234, p-value = 0.88
```

```
TravisCMLaborLM =


Linear regression model:
    y ~ 1 + x1

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    _______    ________    __________

    (Intercept)     4.7483     0.71792       6.614    2.4988e-06
    x1            -0.11783     0.26615    -0.44273       0.66296


Number of observations: 21, Error degrees of freedom: 19
Root Mean Squared Error: 1.7
R-squared: 0.0102,  Adjusted R-Squared: -0.0419
F-statistic vs. constant model: 0.196, p-value = 0.663
```

Figure B14.1: Travis AFB Single Linear Regressions

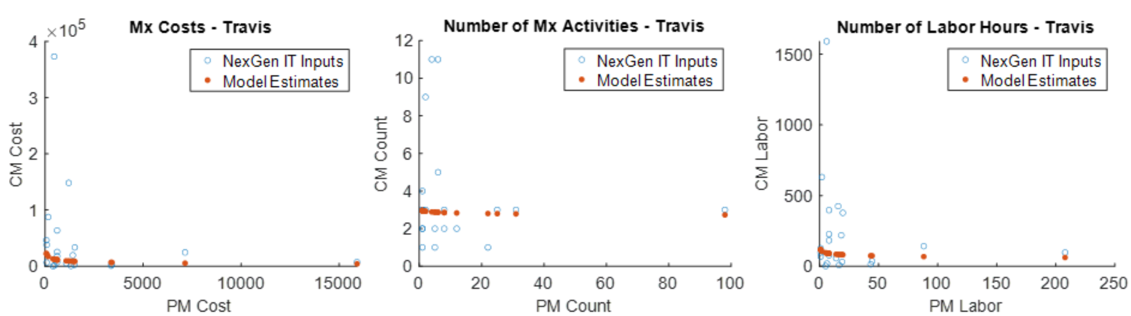


Figure B14.2: Travis AFB Model Framework

Appendix C: Multiple Linear Regression

Results in Tables C1 and C2 are highlighted based on ranges of confidence for each model. Models which provide 95% confidence in results (i.e., $\alpha \leq 0.05$) are highlighted green, those with slightly less significant results which provide an 85-95% confidence (i.e., $0.05 < p\text{-}value \leq 0.15$) are highlighted yellow, and all others are highlighted red.

Table C1: Multiple Linear Regression Summary

Significance	Model Statistics	Cost	Activities	Labor Hrs	All Models
p-value $\leq$ 0.05	Number of Models	5	6	5	16
	Median Adj R^2	0.20	0.31	0.20	0.24
	Min Adj. R^2	0.10	0.20	0.13	0.10
	Max Adj. R^2	0.53	0.47	0.51	0.53
0.05 < p-value $\leq$ 0.15	Number of Models	3	3	2	8
	Median Adj. R^2	0.11	0.13	0.12	0.12
	Min Adj. R^2	0.08	0.08	0.10	0.08
	Max Adj. R^2	0.23	0.16	0.15	0.23
p-value > 0.15	Number of Models	6	5	7	18
	Median Adj. R^2	-0.007	0.01	-0.02	-0.02
	Min Adj. R^2	-0.13	-0.13	-0.23	-0.23
	Max Adj. R^2	0.20	0.03	0.11	0.20

Table C2: Installation Specific Summary

Installation	Number of Facilities	Model Statistics	Multiple Linear Regression Model		
			Cost	Activities	Labor Hrs
Barksdale	59	Adj. R^2	-0.0065	0.0103	-0.0117
		p-value	0.4480	0.2820	0.5120
Cannon	31	Adj. R^2	0.2000	0.0125	0.2030
		p-value	0.0290	0.3560	0.0275
Columbus	25	Adj. R^2	0.1100	0.2710	0.1111
		p-value	0.1460	0.0216	0.3750
Dover	59	Adj. R^2	-0.0468	0.0269	-0.0201
		p-value	0.9390	0.2160	0.6050
Edwards	15	Adj. R^2	-0.1340	0.4660	-0.2250
		p-value	0.7230	0.0191	0.9330
Ellsworth	71	Adj. R^2	0.1030	0.2420	0.1340
		p-value	0.0165	0.0001	0.0055
Fairchild	49	Adj. R^2	0.0799	0.0804	0.0961
		p-value	0.0812	0.0804	0.0567
FE Warren	37	Adj. R^2	0.1500	0.2000	0.1400
		p-value	0.0395	0.0155	0.0465
Goodfellow	23	Adj. R^2	0.2400	0.1550	0.1490
		p-value	0.0420	0.1060	0.1110
Luke	37	Adj. R^2	0.0014	-0.0590	-0.0228
		p-value	0.3980	0.8020	0.5400
Offutt	21	Adj. R^2	0.2320	0.3450	0.4030
		p-value	0.0587	0.0168	0.0079
Scott	32	Adj. R^2	0.5310	0.4330	0.5070
		p-value	0.0000	0.0003	0.0000
Shaw	38	Adj. R^2	0.0010	0.1260	0.0056
		p-value	0.3990	0.0558	0.3750
Travis	21	Adj. R^2	-0.0794	-0.1270	-0.0905
		p-value	0.6810	0.8610	0.7230

The multiple linear regression results are provided for each installation. The number of activities model is listed as "InstallationCMCountMLM" as it counts the number of activities. The independent variables for all models are defined below.

x_1 = Preventive maintenance cost

x_2 = Number of preventive maintenance activities

x_3= Labor hours spent conducting preventive maintenance

```
BarksdaleCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat        pValue
                   ________    _______    ________    __________

    (Intercept)           0          0         NaN           NaN
    x1               2.3966    0.40567      5.9078    2.3958e-07
    x2             -0.47842    0.84596    -0.56554       0.57405
    x3              -2.7858     1.0857     -2.5658      0.013102


Number of observations: 58, Error degrees of freedom: 55
Root Mean Squared Error: 1.67
R-squared: 0.0288,  Adjusted R-Squared: -0.00654
F-statistic vs. constant model: 0.815, p-value = 0.448

BarksdaleCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    _______    _______    _______

    (Intercept)           0          0        NaN        NaN
    x1              0.20004     0.1923     1.0402    0.30287
    x2             -0.63519    0.40102    -1.5839    0.11905
    x3              0.24617    0.51467    0.47831    0.63436


Number of observations: 58, Error degrees of freedom: 55
Root Mean Squared Error: 0.791
R-squared: 0.045,  Adjusted R-Squared: 0.0103
F-statistic vs. constant model: 1.3, p-value = 0.282

BarksdaleCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat        pValue
                   ________    _______    ________    __________

    (Intercept)           0          0         NaN           NaN
    x1               1.2404    0.34654      3.5793    0.00074696
    x2              -0.1311    0.72565    -0.18067       0.85732
    x3               -1.737    0.92551     -1.8767      0.066063


Number of observations: 57, Error degrees of freedom: 54
Root Mean Squared Error: 1.42
R-squared: 0.0245,  Adjusted R-Squared: -0.0117
F-statistic vs. constant model: 0.677, p-value = 0.512
```

Figure C1: Barksdale AFB Multiple Linear Regression Results

```
CannonCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -8.3936     9.7399    -0.86177     0.3964
    x1               3.1495     2.2954      1.3721    0.18133
    x2             -0.36673    0.83821    -0.43752    0.66522
    x3              -2.1989     2.4483    -0.89812    0.37706


Number of observations: 31, Error degrees of freedom: 27
Root Mean Squared Error: 1.78
R-squared: 0.28,  Adjusted R-Squared: 0.2
F-statistic vs. constant model: 3.5, p-value = 0.029

CannonCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -4.6409     4.6296     -1.0024    0.32503
    x1               1.1015     1.0911      1.0096    0.32167
    x2             -0.14206    0.39842    -0.35656     0.7242
    x3             -0.84102     1.1637    -0.72269    0.47609


Number of observations: 31, Error degrees of freedom: 27
Root Mean Squared Error: 0.844
R-squared: 0.111,  Adjusted R-Squared: 0.0125
F-statistic vs. constant model: 1.13, p-value = 0.356

CannonCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -13.405     9.3125     -1.4395     0.1615
    x1               3.3388     2.1947      1.5213    0.13981
    x2             -0.27528    0.80143    -0.34349    0.73389
    x3               -2.491     2.3409     -1.0641     0.2967


Number of observations: 31, Error degrees of freedom: 27
Root Mean Squared Error: 1.7
R-squared: 0.283,  Adjusted R-Squared: 0.203
F-statistic vs. constant model: 3.55, p-value = 0.0275
```

Figure C2: Cannon AFB Multiple Linear Regression Results

```
ColumbusCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    ______    ________    _______

    (Intercept)     16.529     14.136      1.1693    0.25538
    x1             -2.7306     3.3875    -0.80608    0.42923
    x2             0.63789     1.1555     0.55205    0.58674
    x3              3.3541     3.5237     0.95188    0.35199


Number of observations: 25, Error degrees of freedom: 21
Root Mean Squared Error: 1.58
R-squared: 0.222,  Adjusted R-Squared: 0.11
F-statistic vs. constant model: 1.99, p-value = 0.146

ColumbusCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     0.67768     5.3409     0.12689    0.90024
    x1             -0.41427     1.2799    -0.32367    0.74939
    x2             -0.12739    0.43658    -0.29179    0.77331
    x3               1.2682     1.3314     0.95255    0.35166


Number of observations: 25, Error degrees of freedom: 21
Root Mean Squared Error: 0.599
R-squared: 0.363,  Adjusted R-Squared: 0.271
F-statistic vs. constant model: 3.98, p-value = 0.0216

ColumbusCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     5.6524      7.7957     0.72507    0.47641
    x1             -0.8481      1.8682    -0.45397    0.65451
    x2             0.27914     0.63725     0.43805    0.66582
    x3              1.0886      1.9433     0.56021    0.58127


Number of observations: 25, Error degrees of freedom: 21
Root Mean Squared Error: 0.874
R-squared: 0.135,  Adjusted R-Squared: 0.0111
F-statistic vs. constant model: 1.09, p-value = 0.375
```

Figure C3: Columbus AFB Multiple Linear Regression Results

```
DoverCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)       10.42     4.7211      2.2072    0.031491
    x1             -0.51128      1.038    -0.49254      0.6243
    x2             -0.19793    0.66256    -0.29873     0.76627
    x3              0.70196     1.1304     0.62099     0.53717


Number of observations: 59, Error degrees of freedom: 55
Root Mean Squared Error: 1.58
R-squared: 0.00731,  Adjusted R-Squared: -0.0468
F-statistic vs. constant model: 0.135, p-value = 0.939

DoverCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate        SE        tStat       pValue
                   _________    _______    ________    _______

    (Intercept)       2.5237     2.1167      1.1923    0.23828
    x1              -0.37662    0.46542    -0.80921    0.42188
    x2             -0.037098    0.29707    -0.12488    0.90107
    x3               0.62551    0.50682      1.2342    0.22239


Number of observations: 59, Error degrees of freedom: 55
Root Mean Squared Error: 0.707
R-squared: 0.0773,  Adjusted R-Squared: 0.0269
F-statistic vs. constant model: 1.54, p-value = 0.216

DoverCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)      6.9153      3.821      1.8098    0.075793
    x1             -0.85994    0.84015     -1.0236     0.31053
    x2             -0.27423    0.53625    -0.51139     0.61112
    x3                1.182    0.91489      1.2919     0.20179


Number of observations: 59, Error degrees of freedom: 55
Root Mean Squared Error: 1.28
R-squared: 0.0327,  Adjusted R-Squared: -0.0201
F-statistic vs. constant model: 0.619, p-value = 0.605
```

Figure C4: Dover AFB Multiple Linear Regression Results

```
EdwardsCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	6.4819	3.7873	1.7115	0.115
x1	0.049014	0.64496	0.075995	0.94079
x2	0.47678	0.63367	0.75241	0.4676
x3	0.19315	0.68001	0.28405	0.78165

```
Number of observations: 15, Error degrees of freedom: 11
Root Mean Squared Error: 1.85
R-squared: 0.109,  Adjusted R-Squared: -0.134
F-statistic vs. constant model: 0.449, p-value = 0.723
```

```
EdwardsCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	-0.72686	0.70244	-1.0348	0.32299
x1	0.1713	0.11962	1.432	0.17993
x2	0.4081	0.11753	3.4724	0.0052182
x3	-0.13991	0.12612	-1.1093	0.29095

```
Number of observations: 15, Error degrees of freedom: 11
Root Mean Squared Error: 0.342
R-squared: 0.58,  Adjusted R-Squared: 0.466
F-statistic vs. constant model: 5.07, p-value = 0.0191
```

```
EdwardsCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
```

	Estimate	SE	tStat	pValue
(Intercept)	2.0568	2.9927	0.68727	0.50615
x1	0.115	0.50964	0.22565	0.82561
x2	0.25459	0.50073	0.50845	0.62118
x3	-0.036699	0.53734	-0.068297	0.94677

```
Number of observations: 15, Error degrees of freedom: 11
Root Mean Squared Error: 1.46
R-squared: 0.0373,  Adjusted R-Squared: -0.225
F-statistic vs. constant model: 0.142, p-value = 0.933
```

Figure C5: Edwards AFB Multiple Linear Regression Results

```
EllsworthCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      -120.9     176.96    -0.68319    0.49684
    x1               28.267     39.028     0.72427    0.47142
    x2             -0.60768    0.41453     -1.4659    0.14734
    x3              -27.275     39.031    -0.69881    0.48709


Number of observations: 71, Error degrees of freedom: 67
Root Mean Squared Error: 1.25
R-squared: 0.141,  Adjusted R-Squared: 0.103
F-statistic vs. constant model: 3.66, p-value = 0.0165

EllsworthCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    _______    _______

    (Intercept)      -119.5     108.95    -1.0968    0.27666
    x1               26.332      24.03     1.0958    0.27709
    x2             -0.41054    0.25523    -1.6085    0.11243
    x3              -25.515     24.031    -1.0617    0.29216


Number of observations: 71, Error degrees of freedom: 67
Root Mean Squared Error: 0.769
R-squared: 0.274,  Adjusted R-Squared: 0.242
F-statistic vs. constant model: 8.44, p-value = 7.75e-05

EllsworthCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      -127.3     172.96    -0.73598    0.46431
    x1               28.596     38.147     0.74963     0.4561
    x2             -0.56735    0.40517     -1.4003    0.16604
    x3              -27.573     38.149    -0.72277    0.47234


Number of observations: 71, Error degrees of freedom: 67
Root Mean Squared Error: 1.22
R-squared: 0.171,  Adjusted R-Squared: 0.134
F-statistic vs. constant model: 4.6, p-value = 0.00551
```

Figure C6: Ellsworth AFB Multiple Linear Regression Results

```
FairchildCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    ______    _______    _______

    (Intercept)      70.407    54.559     1.2905    0.20348
    x1               -14.91    12.218    -1.2203    0.22871
    x2             -0.93448    1.1614    -0.8046    0.42528
    x3               17.281    12.291     1.4061    0.16658


Number of observations: 49, Error degrees of freedom: 45
Root Mean Squared Error: 1.78
R-squared: 0.137,  Adjusted R-Squared: 0.0799
F-statistic vs. constant model: 2.39, p-value = 0.0812


FairchildCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)      37.336     23.382      1.5968     0.11731
    x1                -8.52     5.2363     -1.6271      0.1107
    x2             -0.38238    0.49774    -0.76824     0.44636
    x3                9.438     5.2673      1.7918    0.079888


Number of observations: 49, Error degrees of freedom: 45
Root Mean Squared Error: 0.764
R-squared: 0.138,  Adjusted R-Squared: 0.0804
F-statistic vs. constant model: 2.4, p-value = 0.0804


FairchildCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    _______

    (Intercept)      48.474     47.65      1.0173    0.31445
    x1               -11.24    10.671     -1.0533    0.29781
    x2             -0.48705    1.0143    -0.48016    0.63344
    x3               13.615    10.734      1.2684    0.21118


Number of observations: 49, Error degrees of freedom: 45
Root Mean Squared Error: 1.56
R-squared: 0.153,  Adjusted R-Squared: 0.0961
F-statistic vs. constant model: 2.7, p-value = 0.0567
```

Figure C7: Fairchild AFB Multiple Linear Regression Results

```
FEWarrenCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)     -373.65     486.57    -0.76794    0.44798
    x1                84.06     107.84     0.77948    0.44125
    x2             -0.44091    0.61686    -0.71478    0.47977
    x3              -82.978     107.93    -0.76884    0.44745


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 1.24
R-squared: 0.221,  Adjusted R-Squared: 0.15
F-statistic vs. constant model: 3.11, p-value = 0.0395
```

```
FEWarrenCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)      536.86     322.31      1.6656    0.10525
    x1              -119.05     71.436     -1.6666    0.10507
    x2             -0.26823    0.40862    -0.65643     0.5161
    x3               119.81     71.493      1.6758    0.10323


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 0.821
R-squared: 0.267,  Adjusted R-Squared: 0.2
F-statistic vs. constant model: 4.01, p-value = 0.0155
```

```
FEWarrenCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)     -335.27     451.55    -0.74249    0.46305
    x1               74.563     100.08     0.74504    0.46152
    x2             -0.30962    0.57246    -0.54086    0.59224
    x3              -73.651     100.16    -0.73535    0.46732


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 1.15
R-squared: 0.212,  Adjusted R-Squared: 0.14
F-statistic vs. constant model: 2.96, p-value = 0.0465
```

Figure C8: F.E. Warren AFB Multiple Linear Regression Results

```
GoodfellowCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat      pValue
                   ________    ______    _______    _______

    (Intercept)     28.998     17.806     1.6285    0.11988
    x1             -6.8076     4.1979    -1.6217    0.12135
    x2              1.0165     1.6782    0.60568    0.55189
    x3              7.9299     4.4124     1.7972    0.08822


Number of observations: 23, Error degrees of freedom: 19
Root Mean Squared Error: 1.32
R-squared: 0.344,  Adjusted R-Squared: 0.24
F-statistic vs. constant model: 3.32, p-value = 0.042


GoodfellowCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    ______    ________    _______

    (Intercept)      1.7165    7.5451      0.2275    0.82247
    x1             -0.72251    1.7788    -0.40618    0.68915
    x2              0.10691    0.7111     0.15034    0.88208
    x3               1.4055    1.8697     0.75175    0.46141


Number of observations: 23, Error degrees of freedom: 19
Root Mean Squared Error: 0.559
R-squared: 0.27,  Adjusted R-Squared: 0.155
F-statistic vs. constant model: 2.34, p-value = 0.106


GoodfellowCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    ______    ________    _______

    (Intercept)     2.9593     16.812     0.17602    0.86214
    x1             -1.7605     3.9636    -0.44417    0.66193
    x2              1.0355     1.5845     0.65352    0.52125
    x3              2.7641     4.1661     0.66347      0.515


Number of observations: 23, Error degrees of freedom: 19
Root Mean Squared Error: 1.25
R-squared: 0.265,  Adjusted R-Squared: 0.149
F-statistic vs. constant model: 2.29, p-value = 0.111
```

Figure C9: Goodfellow AFB Multiple Linear Regression Results

```
LukeCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      11.876     9.0498      1.3123    0.19848
    x1             -0.81027     2.1515    -0.37661    0.70888
    x2             -0.91356    0.87005       -1.05    0.30134
    x3               1.2322     2.3484     0.52471    0.60329


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 1.9
R-squared: 0.0846,  Adjusted R-Squared: 0.00138
F-statistic vs. constant model: 1.02, p-value = 0.398


LukeCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                    Estimate        SE         tStat       pValue
                   __________    _______    __________    _______

    (Intercept)        1.6823     4.3012       0.39111    0.69823
    x1              -0.085355     1.0226     -0.083472    0.93398
    x2              -0.062616    0.41352      -0.15142    0.88056
    x3             0.00060732     1.1161    0.00054413    0.99957


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 0.903
R-squared: 0.0293,  Adjusted R-Squared: -0.059
F-statistic vs. constant model: 0.332, p-value = 0.802


LukeCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      7.6153      8.227     0.92566    0.36135
    x1             -0.88611     1.9559    -0.45305    0.65348
    x2             -0.47196    0.79094     -0.5967    0.55478
    x3              0.96771     2.1349     0.45329     0.6533


Number of observations: 37, Error degrees of freedom: 33
Root Mean Squared Error: 1.73
R-squared: 0.0624,  Adjusted R-Squared: -0.0228
F-statistic vs. constant model: 0.733, p-value = 0.54
```

Figure C10: Luke AFB Multiple Linear Regression Results

```
OffuttCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue  
                   ________    _______    ________    ________

    (Intercept)    -61.097      85.748    -0.71251     0.48581
    x1              15.838       20.25     0.78214     0.44489
    x2              1.3331     0.73258      1.8198    0.086447
    x3             -16.337      20.199     -0.8088     0.42981


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 1.78
R-squared: 0.347,  Adjusted R-Squared: 0.232
F-statistic vs. constant model: 3.02, p-value = 0.0587


OffuttCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue  
                   ________    _______    ________    ________

    (Intercept)    -23.263      45.573    -0.51046      0.6163
    x1              5.5359      10.762     0.51437     0.61361
    x2             0.91357     0.38934      2.3464    0.031334
    x3             -5.8959      10.735    -0.54921        0.59


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 0.946
R-squared: 0.443,  Adjusted R-Squared: 0.345
F-statistic vs. constant model: 4.51, p-value = 0.0168


OffuttCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue  
                   ________    _______    ________    ________

    (Intercept)    -87.759      64.995     -1.3502     0.19465
    x1              21.031      15.349      1.3701     0.18847
    x2              1.2256     0.55528      2.2072    0.041332
    x3             -21.411       15.31     -1.3984     0.17996


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 1.35
R-squared: 0.493,  Adjusted R-Squared: 0.403
F-statistic vs. constant model: 5.51, p-value = 0.00789
```

Figure C11: Offutt AFB Multiple Linear Regression Results

```
ScottCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   _________    _______    ________    ________

    (Intercept)       13.022     6.3213        2.06    0.048805
    x1               -2.0936     1.4207     -1.4737     0.15172
    x2             0.0052561    0.35037    0.015002     0.98814
    x3                3.0848     1.3636      2.2623    0.031631


Number of observations: 32, Error degrees of freedom: 28
Root Mean Squared Error: 1.07
R-squared: 0.577,  Adjusted R-Squared: 0.531
F-statistic vs. constant model: 12.7, p-value = 1.99e-05


ScottCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -1.3669     4.7924    -0.28522    0.77758
    x1             0.048983     1.0771    0.045478    0.96405
    x2              -0.3322    0.26563     -1.2506    0.22142
    x3               0.7967     1.0338     0.77067    0.44735


Number of observations: 32, Error degrees of freedom: 28
Root Mean Squared Error: 0.81
R-squared: 0.488,  Adjusted R-Squared: 0.433
F-statistic vs. constant model: 8.9, p-value = 0.000266


ScottCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)      7.3646     6.5763      1.1199     0.27229
    x1              -1.7788      1.478     -1.2036     0.23884
    x2             -0.16505    0.36451    -0.45279     0.65419
    x3               2.8649     1.4186      2.0196    0.053094


Number of observations: 32, Error degrees of freedom: 28
Root Mean Squared Error: 1.11
R-squared: 0.555,  Adjusted R-Squared: 0.507
F-statistic vs. constant model: 11.6, p-value = 3.96e-05
```

Figure C12: Scott AFB Multiple Linear Regression Results

```
ShawCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -10.174     29.575    -0.34399    0.73297
    x1               3.9807     6.8512     0.58103    0.56505
    x2             -0.56036    0.70411    -0.79584    0.43165
    x3              -3.1691     6.7962    -0.46631    0.64397


Number of observations: 38, Error degrees of freedom: 34
Root Mean Squared Error: 1.28
R-squared: 0.082,  Adjusted R-Squared: 0.000989
F-statistic vs. constant model: 1.01, p-value = 0.399


ShawCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -21.239     15.423     -1.3772    0.17746
    x1               4.9419     3.5727      1.3833     0.1756
    x2             -0.27557    0.36717    -0.75053     0.4581
    x3              -4.4359      3.544     -1.2517    0.21924


Number of observations: 38, Error degrees of freedom: 34
Root Mean Squared Error: 0.67
R-squared: 0.197,  Adjusted R-Squared: 0.126
F-statistic vs. constant model: 2.78, p-value = 0.0558


ShawCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      -10.85     30.856    -0.35164    0.72728
    x1               3.0333      7.148     0.42436    0.67398
    x2              0.26054    0.73461     0.35467    0.72503
    x3              -2.8582     7.0906    -0.40309     0.6894


Number of observations: 38, Error degrees of freedom: 34
Root Mean Squared Error: 1.34
R-squared: 0.0862,  Adjusted R-Squared: 0.0056
F-statistic vs. constant model: 1.07, p-value = 0.375
```

Figure C13: Shaw AFB Multiple Linear Regression Results

```
TravisCMCostMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)      61.231     162.22     0.37745    0.71051
    x1              -11.841     37.416    -0.31646    0.75551
    x2             -0.32668    0.54176      -0.603    0.55447
    x3                11.82     37.444     0.31568    0.75609


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 2.1
R-squared: 0.0825,  Adjusted R-Squared: -0.0794
F-statistic vs. constant model: 0.51, p-value = 0.681


TravisCMCountMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate        SE        tStat      pValue
                   _________    _______    ________    _______

    (Intercept)        32.56     56.141     0.57997    0.56954
    x1               -7.2891     12.949    -0.56292    0.58084
    x2             -0.063543    0.18749    -0.33892    0.73882
    x3                7.4012     12.958     0.57116    0.57536


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 0.725
R-squared: 0.042,  Adjusted R-Squared: -0.127
F-statistic vs. constant model: 0.248, p-value = 0.861


TravisCMLaborMLM =


Linear regression model:
    y ~ 1 + x1 + x2 + x3

Estimated Coefficients:
                   Estimate       SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)      83.031     134.77      0.6161    0.54599
    x1              -18.072     31.084    -0.58139    0.56861
    x2             -0.28959    0.45008    -0.64343    0.52853
    x3               18.236     31.107     0.58623    0.56542


Number of observations: 21, Error degrees of freedom: 17
Root Mean Squared Error: 1.74
R-squared: 0.073,  Adjusted R-Squared: -0.0905
F-statistic vs. constant model: 0.446, p-value = 0.723
```

Figure C14: Travis AFB Multiple Linear Regression Results

Appendix D: Multiple Linear Regression with Interactions

Results in Tables D1 and D2 are highlighted based on ranges of confidence for each model. Models which provide 95% confidence in results (i.e., $\alpha \leq 0.05$) are highlighted green, those with slightly less significant results which provide an 85-95% confidence (i.e., $0.05 < p\text{-}value \leq 0.15$) are highlighted yellow, and all others are highlighted red.

Table D1: Multiple Linear Regression Interaction Analysis Summary

<table>
<tr><th>Significance</th><th>Model Statistics</th><th>Cost</th><th>Activities</th><th>Labor Hrs</th><th>All Models</th></tr>
<tr><td rowspan="4">p-value $\leq$ 0.05</td><td>Number of Models</td><td>3</td><td>5</td><td>3</td><td>11</td></tr>
<tr><td>Median Adj. R^2</td><td>0.54</td><td>0.50</td><td>0.53</td><td>0.51</td></tr>
<tr><td>Min Adj. R^2</td><td>0.33</td><td>0.20</td><td>0.10</td><td>0.10</td></tr>
<tr><td>Max Adj. R^2</td><td>0.62</td><td>0.57</td><td>0.53</td><td>0.62</td></tr>
<tr><td rowspan="4">0.05 < p-value $\leq$ 0.15</td><td>Number of Models</td><td>3</td><td>1</td><td>2</td><td>6</td></tr>
<tr><td>Median Adj. R^2</td><td>0.10</td><td rowspan="3">0.18</td><td>0.13</td><td>0.12</td></tr>
<tr><td>Min Adj. R^2</td><td>0.08</td><td>0.12</td><td>0.08</td></tr>
<tr><td>Max Adj. R^2</td><td>0.13</td><td>0.14</td><td>0.14</td></tr>
<tr><td rowspan="4">p-value > 0.15</td><td>Number of Models</td><td>8</td><td>8</td><td>9</td><td>25</td></tr>
<tr><td>Median Adj. R^2</td><td>-0.05</td><td>-0.006</td><td>-0.06</td><td>-0.04</td></tr>
<tr><td>Min Adj. R^2</td><td>-0.47</td><td>-0.21</td><td>-0.47</td><td>-0.47</td></tr>
<tr><td>Max Adj. R^2</td><td>0.11</td><td>0.17</td><td>0.17</td><td>0.17</td></tr>
</table>

Table D2: Installation Specific Summary

Installation	Number of Facilities	Model Statistics	Interactions Model		
			Cost	Activities	Labor Hrs
Barksdale	59	Adj. R^2	-0.0359	0.0339	-0.0405
		p-value	0.7310	0.2160	0.7680
Cannon	31	Adj. R^2	0.1080	-0.0578	0.1100
		p-value	0.1880	0.6320	0.1850
Columbus	25	Adj. R^2	0.0935	0.1670	-0.1270
		p-value	0.2640	0.1550	0.7650
Dover	59	Adj. R^2	-0.4680	0.0269	-0.0201
		p-value	0.9390	0.2160	0.6050
Edwards	15	Adj. R^2	0.0413	0.5710	-0.4670
		p-value	0.4370	0.0351	0.9420
Ellsworth	71	Adj. R^2	0.0810	0.2700	0.1040
		p-value	0.0747	0.0002	0.0409
Fairchild	49	Adj. R^2	0.0945	0.0474	0.1350
		p-value	0.1150	0.2380	0.0565
FE Warren	37	Adj. R^2	0.1330	0.2010	0.1220
		p-value	0.0908	0.0333	0.1070
Goodfellow	23	Adj. R^2	0.3270	0.0655	0.1740
		p-value	0.0478	0.3300	0.1690
Luke	37	Adj. R^2	0.0668	-0.1220	-0.0034
		p-value	0.2360	0.9060	0.4560
Offutt	21	Adj. R^2	0.6220	0.5140	0.5290
		p-value	0.0019	0.0094	0.0077
Scott	32	Adj. R^2	0.5440	0.4990	0.5250
		p-value	0.0002	0.0005	0.0003
Shaw	38	Adj. R^2	-0.0747	0.1790	-0.0151
		p-value	0.7500	0.0558	0.5020
Travis	21	Adj. R^2	-0.0909	-0.2070	-0.1110
		p-value	0.6390	0.8480	0.6770

The results from the multiple linear regression interactions analysis are provided for each installation. The second model is listed as "InstallationCMCountInteractions" as the model counts the number of maintenance activities. The independent variables for all models are defined below.

x_1 = Preventive maintenance cost

x_2 = Number of preventive maintenance activities

x_3= Labor hours spent conducting preventive maintenance

```
BarksdaleCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    _________    _______

    (Intercept)           0         0          NaN        NaN
    x1                3.093    2.7598       1.1207    0.26766
    x2                    0         0          NaN        NaN
    x3              -0.9692    18.738    -0.051725    0.95895
    x1:x2           -1.0603    1.5128     -0.70088    0.48657
    x1:x3          -0.50017    1.8483     -0.27061    0.78778
    x2:x3            2.4717    3.7163      0.66511    0.50898


Number of observations: 58, Error degrees of freedom: 53
Root Mean Squared Error: 1.69
R-squared: 0.0368,  Adjusted R-Squared: -0.0359
F-statistic vs. constant model: 0.507, p-value = 0.731


BarksdaleCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE         tStat       pValue
                   _________    _______    _________    _______

    (Intercept)            0          0          NaN        NaN
    x1                1.8357     1.2742       1.4407    0.15577
    x2                     0          0          NaN        NaN
    x3               -3.6575     8.6508     -0.42279    0.67423
    x1:x2            -1.1051    0.69841      -1.5823    0.11976
    x1:x3          -0.034907    0.85332    -0.040907    0.96753
    x2:x3             2.5506     1.7157       1.4866    0.14327


Number of observations: 58, Error degrees of freedom: 53
Root Mean Squared Error: 0.781
R-squared: 0.102,  Adjusted R-Squared: 0.0339
F-statistic vs. constant model: 1.5, p-value = 0.216


BarksdaleCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    _______

    (Intercept)           0         0         NaN        NaN
    x1               2.6354    2.3536      1.1197    0.26819
    x2                    0         0         NaN        NaN
    x3              -6.8463    16.014    -0.42752    0.67083
    x1:x2          -0.56944    1.2929    -0.44044    0.66152
    x1:x3           0.21846    1.5815     0.13814    0.89069
    x2:x3            1.3954    3.1784     0.43903    0.66253


Number of observations: 57, Error degrees of freedom: 52
Root Mean Squared Error: 1.44
R-squared: 0.0338,  Adjusted R-Squared: -0.0405
F-statistic vs. constant model: 0.455, p-value = 0.768
```

Figure D1: Barksdale AFB Interactions Analysis Results

```
CannonCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -2.9643     36.023   -0.082288     0.9351
    x1               1.9384     8.5071     0.22786    0.82169
    x2              -5.2234      16.89    -0.30926    0.75979
    x3              0.45691      9.364    0.048794    0.96149
    x1:x2           0.80243     3.7188     0.21578    0.83099
    x1:x3          -0.18474    0.40515    -0.45599    0.65249
    x2:x3          -0.43961     3.7029    -0.11872    0.90648


Number of observations: 31, Error degrees of freedom: 24
Root Mean Squared Error: 1.87
R-squared: 0.287,  Adjusted R-Squared: 0.108
F-statistic vs. constant model: 1.61, p-value = 0.188


CannonCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   _________    _______    _________    _______

    (Intercept)      -6.5399     16.788     -0.38956     0.7003
    x1                1.6804     3.9647      0.42384    0.67546
    x2               -1.5421     7.8714     -0.19591    0.84633
    x3              -0.30233      4.364    -0.069277    0.94534
    x1:x2          -0.031978     1.7331    -0.018451    0.98543
    x1:x3           -0.15744    0.18882     -0.83385    0.41259
    x2:x3            0.42955     1.7257      0.24891    0.80555


Number of observations: 31, Error degrees of freedom: 24
Root Mean Squared Error: 0.873
R-squared: 0.154,  Adjusted R-Squared: -0.0578
F-statistic vs. constant model: 0.727, p-value = 0.632


CannonCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     -10.781     34.483    -0.31263    0.75726
    x1                2.773     8.1435     0.34052    0.73642
    x2              -3.4871     16.168    -0.21568    0.83106
    x3              -0.6868     8.9638   -0.076619    0.93956
    x1:x2           0.47563     3.5599     0.13361    0.89483
    x1:x3          -0.15955    0.38783     -0.4114    0.68443
    x2:x3          -0.17093     3.5446   -0.048222    0.96194


Number of observations: 31, Error degrees of freedom: 24
Root Mean Squared Error: 1.79
R-squared: 0.288,  Adjusted R-Squared: 0.11
F-statistic vs. constant model: 1.62, p-value = 0.185
```

Figure D2: Cannon AFB Interactions Analysis Results

```
ColumbusCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    ______    ________    _______

    (Intercept)     -599.69    438.83     -1.3666    0.18859
    x1               152.07    109.19      1.3927    0.18067
    x2               270.93    179.95      1.5056    0.14952
    x3              -179.87    120.44     -1.4935    0.15264
    x1:x2            -64.06    43.443     -1.4746     0.1576
    x1:x3             3.323    2.5632      1.2965    0.21119
    x2:x3            61.031    42.458      1.4374    0.16775


Number of observations: 25, Error degrees of freedom: 18
Root Mean Squared Error: 1.6
R-squared: 0.32,  Adjusted R-Squared: 0.0935
F-statistic vs. constant model: 1.41, p-value = 0.264


ColumbusCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    _________    _______

    (Intercept)     -60.317    175.63     -0.34344    0.73525
    x1               14.336    43.699      0.32805    0.74666
    x2               20.686    72.019      0.28723    0.77722
    x3              -11.346    48.202     -0.23538    0.81657
    x1:x2           -5.2881    17.387     -0.30414    0.76451
    x1:x3          -0.24681    1.0258     -0.24059    0.81259
    x2:x3            5.4953    16.993      0.32339    0.75013


Number of observations: 25, Error degrees of freedom: 18
Root Mean Squared Error: 0.64
R-squared: 0.375,  Adjusted R-Squared: 0.167
F-statistic vs. constant model: 1.8, p-value = 0.155

ColumbusCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    _________    _______

    (Intercept)     -100.76    255.97     -0.39364    0.69847
    x1               26.254    63.689      0.41222    0.68504
    x2               49.649    104.96      0.47301    0.64189
    x3              -33.484    70.252     -0.47663    0.63936
    x1:x2           -11.597     25.34     -0.45767    0.65267
    x1:x3            0.8659    1.4951      0.57916    0.56966
    x2:x3            10.887    24.766      0.43961    0.66545


Number of observations: 25, Error degrees of freedom: 18
Root Mean Squared Error: 0.933
R-squared: 0.154,  Adjusted R-Squared: -0.127
F-statistic vs. constant model: 0.548, p-value = 0.765
```

Figure D3: Columbus AFB Interactions Analysis Results

```
DoverCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    _______

    (Intercept)      2.3719    14.941     0.15875    0.87448
    x1               1.1045    3.2598     0.33884     0.7361
    x2               1.0021    11.111    0.090187    0.92849
    x3               1.5133      5.99     0.25263    0.80155
    x1:x2          -0.57432    2.2928    -0.25049    0.80319
    x1:x3          -0.26645   0.57346    -0.46463    0.64414
    x2:x3           0.92588    2.1646     0.42775     0.6706


Number of observations: 59, Error degrees of freedom: 52
Root Mean Squared Error: 1.61
R-squared: 0.0161,  Adjusted R-Squared: -0.0974
F-statistic vs. constant model: 0.142, p-value = 0.99


DoverCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)    -0.98852     6.6385    -0.14891     0.8822
    x1              0.36787     1.4484     0.25399     0.8005
    x2              -0.5592     4.9368    -0.11327    0.91025
    x3               1.4186     2.6614     0.53304    0.59627
    x1:x2          -0.14324     1.0187    -0.14061    0.88872
    x1:x3          -0.18346    0.25479    -0.72004    0.47473
    x2:x3             0.458    0.96173     0.47622    0.63591


Number of observations: 59, Error degrees of freedom: 52
Root Mean Squared Error: 0.717
R-squared: 0.102,  Adjusted R-Squared: -0.00173
F-statistic vs. constant model: 0.983, p-value = 0.446


DoverCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)     0.70067     12.047    0.058162    0.95384
    x1              0.13977     2.6283     0.05318    0.95779
    x2              -2.6165     8.9587    -0.29206     0.7714
    x3               3.9773     4.8296     0.82352    0.41397
    x1:x2           0.13632     1.8486    0.073744     0.9415
    x1:x3          -0.40665    0.46237    -0.87949    0.38318
    x2:x3            0.3353     1.7452     0.19212     0.8484


Number of observations: 59, Error degrees of freedom: 52
Root Mean Squared Error: 1.3
R-squared: 0.0485,  Adjusted R-Squared: -0.0613
F-statistic vs. constant model: 0.442, p-value = 0.847
```

Figure D4: Dover AFB Interactions Analysis Results

```
EdwardsCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    _______    ________

    (Intercept)     18.196       7.379     2.4659    0.038959
    x1              -1.344     0.99781    -1.3469     0.21492
    x2              30.386      22.172     1.3705     0.20776
    x3             -3.9857        2.92     -1.365     0.20941
    x1:x2          -8.0642      5.3042    -1.5203     0.16692
    x1:x3          0.48208     0.35659     1.3519     0.21337
    x2:x3           9.5813      5.7064      1.679     0.13166


Number of observations: 15, Error degrees of freedom: 8
Root Mean Squared Error: 1.7
R-squared: 0.452,  Adjusted R-Squared: 0.0413
F-statistic vs. constant model: 1.1, p-value = 0.437


EdwardsCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE         tStat       pValue
                   ________    ________    ________    ________

    (Intercept)     1.9073       1.3336      1.4302     0.19053
    x1            -0.14517      0.18033      -0.805     0.44409
    x2               3.571        4.007     0.89118     0.39884
    x3             -1.0638      0.52772     -2.0159    0.078555
    x1:x2         -0.93996      0.95861    -0.98054     0.35554
    x1:x3           0.1076     0.064444      1.6697     0.13353
    x2:x3           1.2068       1.0313      1.1702     0.27559


Number of observations: 15, Error degrees of freedom: 8
Root Mean Squared Error: 0.307
R-squared: 0.755,  Adjusted R-Squared: 0.571
F-statistic vs. constant model: 4.11, p-value = 0.0351


EdwardsCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      6.724      6.9377      0.9692    0.36083
    x1            -0.44453     0.93814    -0.47384    0.64827
    x2              18.235      20.846     0.87477    0.40719
    x3             -1.9254      2.7454    -0.70134    0.50298
    x1:x2          -4.5901       4.987     -0.9204    0.38428
    x1:x3          0.22229     0.33526     0.66303    0.52595
    x2:x3           5.1796      5.3652     0.96541    0.36261


Number of observations: 15, Error degrees of freedom: 8
Root Mean Squared Error: 1.6
R-squared: 0.162,  Adjusted R-Squared: -0.467
F-statistic vs. constant model: 0.258, p-value = 0.942
```

Figure D5: Edwards AFB Interactions Analysis Results

```
EllsworthCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    ________

    (Intercept)     -591.32    2094.9    -0.28227     0.77865
    x1               132.14    461.86     0.28611     0.77571
    x2               130.01    588.67     0.22085     0.82591
    x3              -134.73    461.75    -0.29178      0.7714
    x1:x2           -28.544    129.81    -0.21988     0.82666
    x1:x3           0.44488    0.3922      1.1343      0.2609
    x2:x3            28.141    129.92     0.21659     0.82921


Number of observations: 71, Error degrees of freedom: 64
Root Mean Squared Error: 1.26
R-squared: 0.16,  Adjusted R-Squared: 0.081
F-statistic vs. constant model: 2.03, p-value = 0.0747


EllsworthCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    ________

    (Intercept)     -379.09    1250.9    -0.30305     0.76284
    x1               83.812    275.79      0.3039     0.76219
    x2               74.382    351.51     0.21161     0.83309
    x3              -87.227    275.72    -0.31636     0.75276
    x1:x2           -16.225    77.516    -0.20932     0.83486
    x1:x3           0.51225    0.2342      2.1873    0.032382
    x2:x3            15.808    77.581     0.20376     0.83918


Number of observations: 71, Error degrees of freedom: 64
Root Mean Squared Error: 0.754
R-squared: 0.332,  Adjusted R-Squared: 0.27
F-statistic vs. constant model: 5.31, p-value = 0.00017


EllsworthCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE         tStat       pValue
                   ________    _______    ________    ________

    (Intercept)     -460.45     2057.9    -0.22375     0.82367
    x1               102.09      453.7     0.22501     0.82269
    x2               87.329     578.27     0.15102     0.88044
    x3              -103.43     453.59    -0.22803     0.82035
    x1:x2           -19.167     127.52     -0.1503       0.881
    x1:x3           0.31506    0.38527     0.81777     0.41653
    x2:x3            18.816     127.63     0.14743     0.88326


Number of observations: 71, Error degrees of freedom: 64
Root Mean Squared Error: 1.24
R-squared: 0.181,  Adjusted R-Squared: 0.104
F-statistic vs. constant model: 2.35, p-value = 0.0409
```

Figure D6: Ellsworth AFB Interactions Analysis Results

```
FairchildCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue 
                   ________    ______    ________    ________

    (Intercept)      2334.8    1447.8      1.6126     0.11431
    x1              -520.98    325.48     -1.6007     0.11695
    x2              -1398.5    883.33     -1.5832     0.12087
    x3                  527    322.63      1.6334     0.10985
    x1:x2            311.53    198.97      1.5657     0.12492
    x1:x3           -1.4975    2.8955    -0.51719     0.60774
    x2:x3           -305.89    199.05     -1.5367     0.13186


Number of observations: 49, Error degrees of freedom: 42
Root Mean Squared Error: 1.77
R-squared: 0.208,  Adjusted R-Squared: 0.0945
F-statistic vs. constant model: 1.83, p-value = 0.115


FairchildCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue 
                   ________    ______    ________    ________

    (Intercept)      132.19    636.57     0.20766      0.8365
    x1              -27.893     143.1    -0.19491      0.8464
    x2              -44.784    388.38    -0.11531     0.90875
    x3               15.368    141.85     0.10834     0.91424
    x1:x2            10.152     87.48     0.11604     0.90817
    x1:x3            1.4413    1.2731      1.1322     0.26398
    x2:x3           -10.496    87.517    -0.11993     0.90511


Number of observations: 49, Error degrees of freedom: 42
Root Mean Squared Error: 0.778
R-squared: 0.166,  Adjusted R-Squared: 0.0474
F-statistic vs. constant model: 1.4, p-value = 0.238


FairchildCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE       tStat       pValue  
                   ________    ______    ________    ________

    (Intercept)      2442.4    1246.6      1.9593    0.056738
    x1              -546.04    280.24     -1.9485    0.058061
    x2              -1471.9    760.56     -1.9353    0.059703
    x3               546.96    277.79       1.969    0.055573
    x1:x2            328.44    171.31      1.9172    0.062033
    x1:x3          -0.87981    2.4931    -0.35291     0.72592
    x2:x3           -323.29    171.38     -1.8863    0.066177


Number of observations: 49, Error degrees of freedom: 42
Root Mean Squared Error: 1.52
R-squared: 0.243,  Adjusted R-Squared: 0.135
F-statistic vs. constant model: 2.25, p-value = 0.0565
```

Figure D7: Fairchild AFB Interactions Analysis Results

```
FEWarrenCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _________

    (Intercept)          0          0         NaN          NaN
    x1              1.2921    0.38861      3.3248    0.0023427
    x2             -125.54     187.05    -0.67116      0.50725
    x3             -7.6525     6.4672     -1.1833      0.24599
    x1:x2           28.385     41.421     0.68528      0.49843
    x1:x3          0.98969    0.84125      1.1765      0.24867
    x2:x3          -29.403     41.361    -0.71089      0.48264


Number of observations: 37, Error degrees of freedom: 31
Root Mean Squared Error: 1.25
R-squared: 0.254,  Adjusted R-Squared: 0.133
F-statistic vs. constant model: 2.11, p-value = 0.0908


FEWarrenCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)          0          0         NaN         NaN
    x1            -0.06136    0.25497    -0.24066     0.81146
    x2              217.23     122.72      1.7701    0.086879
    x3             -5.0013     4.2431     -1.1787     0.24778
    x1:x2          -47.669     27.176     -1.7541    0.089623
    x1:x3          0.77913    0.55194      1.4116     0.16835
    x2:x3           46.847     27.136      1.7264    0.094571


Number of observations: 37, Error degrees of freedom: 31
Root Mean Squared Error: 0.821
R-squared: 0.312,  Adjusted R-Squared: 0.201
F-statistic vs. constant model: 2.81, p-value = 0.0333


FEWarrenCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)          0          0         NaN         NaN
    x1             0.32148    0.36112     0.89023     0.38042
    x2             -113.42     173.82    -0.65252     0.51903
    x3             -6.1339     6.0096     -1.0207     0.31556
    x1:x2           25.648      38.49     0.66636     0.51028
    x1:x3          0.88983    0.78173      1.1383     0.26401
    x2:x3          -26.547     38.434     -0.6907     0.49506


Number of observations: 37, Error degrees of freedom: 31
Root Mean Squared Error: 1.16
R-squared: 0.244,  Adjusted R-Squared: 0.122
F-statistic vs. constant model: 2, p-value = 0.107
```

Figure D8: F.E. Warren AFB Interactions Analysis Results

```
GoodfellowCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE       tStat       pValue
                   ________    ______    ________    ________

    (Intercept)     2315.8     1949.6      1.1878     0.25223
    x1             -589.55     476.41     -1.2375     0.23376
    x2             -699.92     611.12     -1.1453     0.26893
    x3              595.51     474.55      1.2549     0.22754
    x1:x2           179.82     148.79      1.2085     0.24441
    x1:x3           1.5189     2.5544     0.59462     0.56041
    x2:x3          -186.17     146.05     -1.2747     0.22062


Number of observations: 23, Error degrees of freedom: 16
Root Mean Squared Error: 1.24
R-squared: 0.51,  Adjusted R-Squared: 0.327
F-statistic vs. constant model: 2.78, p-value = 0.0478


GoodfellowCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    ________

    (Intercept)     632.45     922.66     0.68547     0.50286
    x1              -150.9     225.47    -0.66929     0.51285
    x2             -203.13     289.22    -0.70235     0.49256
    x3              152.86     224.59     0.68061     0.50585
    x1:x2           47.677     70.418     0.67705     0.50804
    x1:x3          -1.0548     1.2089    -0.87247     0.39586
    x2:x3          -44.703      69.12    -0.64675     0.52696


Number of observations: 23, Error degrees of freedom: 16
Root Mean Squared Error: 0.588
R-squared: 0.32,  Adjusted R-Squared: 0.0655
F-statistic vs. constant model: 1.26, p-value = 0.33


GoodfellowCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    ________    ________

    (Intercept)    -1877.8     1927.5    -0.97421     0.34445
    x1              444.12     471.03     0.94288     0.35976
    x2              614.46     604.22      1.0169     0.32431
    x3              -452.8     469.19    -0.96507     0.34887
    x1:x2          -142.57     147.11    -0.96911     0.34691
    x1:x3           4.2501     2.5256      1.6828     0.11181
    x2:x3              132      144.4      0.9141     0.37423


Number of observations: 23, Error degrees of freedom: 16
Root Mean Squared Error: 1.23
R-squared: 0.399,  Adjusted R-Squared: 0.174
F-statistic vs. constant model: 1.77, p-value = 0.169
```

Figure D9: Goodfellow AFB Interactions Analysis Results

```
LukeCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    _______    ________

    (Intercept)    -72.896      61.477    -1.1857     0.24503
    x1              20.059       14.61     1.3729     0.17995
    x2              37.104      20.423     1.8168    0.079257
    x3             -29.615      15.349    -1.9295     0.06318
    x1:x2          -8.5219      4.8077    -1.7725    0.086461
    x1:x3           1.2795     0.92627     1.3814     0.17736
    x2:x3           7.6437      4.8405     1.5791      0.1248


Number of observations: 37, Error degrees of freedom: 30
Root Mean Squared Error: 1.84
R-squared: 0.222,  Adjusted R-Squared: 0.0668
F-statistic vs. constant model: 1.43, p-value = 0.236


LukeCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)    -7.6056      31.111    -0.24446    0.80854
    x1              2.0693      7.3936     0.27987     0.7815
    x2              5.2398      10.336     0.50696    0.61589
    x3             -3.7746      7.7675    -0.48595    0.63053
    x1:x2          -1.0371       2.433    -0.42626    0.67296
    x1:x3          0.25589     0.46876     0.54588    0.58918
    x2:x3          0.67346      2.4496     0.27492    0.78526


Number of observations: 37, Error degrees of freedom: 30
Root Mean Squared Error: 0.93
R-squared: 0.0651,  Adjusted R-Squared: -0.122
F-statistic vs. constant model: 0.348, p-value = 0.906


LukeCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    _______

    (Intercept)    -53.484      57.262    -0.93402    0.35775
    x1              14.207      13.608       1.044    0.30482
    x2              27.944      19.023       1.469    0.15225
    x3             -22.287      14.296     -1.5589     0.1295
    x1:x2          -6.3161      4.4781     -1.4105    0.16869
    x1:x3           1.0498     0.86276      1.2168    0.23318
    x2:x3           5.5764      4.5086      1.2368    0.22574


Number of observations: 37, Error degrees of freedom: 30
Root Mean Squared Error: 1.71
R-squared: 0.164,  Adjusted R-Squared: -0.00337
F-statistic vs. constant model: 0.98, p-value = 0.456
```

Figure D10: Luke AFB Interactions Analysis Results

```
OffuttCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    _______    ________

    (Intercept)     -351.58     216.13    -1.6267      0.1261
    x1               85.707     51.138      1.676     0.11592
    x2               93.254     78.292     1.1911     0.25342
    x3              -85.116     50.658    -1.6802     0.11508
    x1:x2           -22.402     18.595    -1.2047     0.24829
    x1:x3            -0.505    0.26094    -1.9353    0.073413
    x2:x3            23.632      18.71      1.263      0.2272


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 1.25
R-squared: 0.735,  Adjusted R-Squared: 0.622
F-statistic vs. constant model: 6.48, p-value = 0.00193


OffuttCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    _______    ________

    (Intercept)      -266.16     140.97     -1.888    0.079921
    x1                63.389     33.353     1.9005    0.078155
    x2                85.806     51.064     1.6803     0.11506
    x3               -62.736      33.04    -1.8988    0.078402
    x1:x2            -20.407     12.128    -1.6826     0.11462
    x1:x3           -0.26252    0.17019    -1.5425     0.14525
    x2:x3             20.963     12.203     1.7178     0.10785


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 0.815
R-squared: 0.66,  Adjusted R-Squared: 0.514
F-statistic vs. constant model: 4.53, p-value = 0.00939


OffuttCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate       SE         tStat       pValue
                   ________    _______    ________    _______

    (Intercept)      -311.58     207.42     -1.5022    0.15527
    x1                74.765     49.075      1.5235    0.14991
    x2                77.289     75.135      1.0287    0.32108
    x3               -75.613     48.615     -1.5553    0.14217
    x1:x2            -18.231     17.845     -1.0216    0.32429
    x1:x3           -0.17688    0.25042    -0.70637    0.49155
    x2:x3             18.799     17.956       1.047    0.31286


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 1.2
R-squared: 0.67,  Adjusted R-Squared: 0.529
F-statistic vs. constant model: 4.75, p-value = 0.00772
```

Figure D11: Offutt AFB Interactions Analysis Results

```
ScottCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    _______    _______

    (Intercept)     -43.333     42.419    -1.0215    0.31679
    x1                11.75     9.9744      1.178    0.24987
    x2                28.85      17.68     1.6318    0.11526
    x3              -15.245     10.463    -1.4571    0.15755
    x1:x2           -6.4336     4.0945    -1.5713    0.12869
    x1:x3           0.42772    0.42372     1.0094    0.32244
    x2:x3            6.1633     4.1565     1.4828    0.15062


Number of observations: 32, Error degrees of freedom: 25
Root Mean Squared Error: 1.05
R-squared: 0.632,  Adjusted R-Squared: 0.544
F-statistic vs. constant model: 7.16, p-value = 0.000159


ScottCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)     -8.1718     30.635    -0.26675     0.79185
    x1               2.4661     7.2035     0.34235     0.73495
    x2               10.672     12.769     0.83578     0.41119
    x3              -8.0685     7.5563     -1.0678     0.29582
    x1:x2           -2.0203      2.957    -0.68321     0.50076
    x1:x3            0.6396    0.30601      2.0902    0.046934
    x2:x3            1.4953     3.0018     0.49814     0.62274


Number of observations: 32, Error degrees of freedom: 25
Root Mean Squared Error: 0.761
R-squared: 0.596,  Adjusted R-Squared: 0.499
F-statistic vs. constant model: 6.15, p-value = 0.000459


ScottCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    _______    _______

    (Intercept)     -51.259     43.935    -1.1667    0.25434
    x1                12.64     10.331     1.2235    0.23255
    x2               30.397     18.312     1.6599    0.10942
    x3              -16.587     10.837    -1.5306    0.13843
    x1:x2           -6.7714     4.2408    -1.5967     0.1229
    x1:x3           0.48522    0.43886     1.1056    0.27941
    x2:x3            6.4396      4.305     1.4959    0.14721


Number of observations: 32, Error degrees of freedom: 25
Root Mean Squared Error: 1.09
R-squared: 0.617,  Adjusted R-Squared: 0.525
F-statistic vs. constant model: 6.7, p-value = 0.000255
```

Figure D12: Scott AFB Interactions Analysis Results

```
ShawCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE         tStat       pValue
                   ________    _______    _________    _______

    (Intercept)      17.588     205.09     0.085758    0.93221
    x1              -2.3491     47.401    -0.049557    0.96079
    x2              -12.182     63.978     -0.19041    0.85023
    x3               6.9813      46.14      0.15131    0.88071
    x1:x2            2.2313     14.951      0.14924    0.88233
    x1:x3           -0.5669    0.94211     -0.60173    0.55173
    x2:x3           -1.4971     15.352    -0.097519    0.92294


Number of observations: 38, Error degrees of freedom: 31
Root Mean Squared Error: 1.33
R-squared: 0.0996,  Adjusted R-Squared: -0.0747
F-statistic vs. constant model: 0.571, p-value = 0.75


ShawCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE         tStat       pValue
                   ________    _______    _________    _______

    (Intercept)     -39.452     99.976     -0.39461    0.69583
    x1                9.179     23.107      0.39724    0.69392
    x2              0.92215     31.188     0.029567     0.9766
    x3              -1.8848     22.492    -0.083797    0.93376
    x1:x2          -0.98976     7.2884      -0.1358    0.89286
    x1:x3          -0.99244    0.45926       -2.161    0.03854
    x2:x3            2.1926     7.4838      0.29298    0.77149


Number of observations: 38, Error degrees of freedom: 31
Root Mean Squared Error: 0.65
R-squared: 0.312,  Adjusted R-Squared: 0.179
F-statistic vs. constant model: 2.34, p-value = 0.0558


ShawCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    ______    _________    _______

    (Intercept)      48.289    208.44      0.23167    0.81832
    x1              -11.087    48.176     -0.23013     0.8195
    x2              -21.772    65.024     -0.33483    0.74001
    x3                16.86    46.894      0.35954    0.72163
    x1:x2            4.8934    15.196      0.32203    0.74959
    x1:x3          -0.72236    0.9575     -0.75441    0.45629
    x2:x3           -4.4367    15.603     -0.28436    0.77803


Number of observations: 38, Error degrees of freedom: 31
Root Mean Squared Error: 1.35
R-squared: 0.149,  Adjusted R-Squared: -0.0151
F-statistic vs. constant model: 0.908, p-value = 0.502
```

Figure D13: Shaw AFB Interactions Analysis Results

```
TravisCMCostInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)       1370      1056.2      1.2971    0.21558
    x1             -313.42      243.47     -1.2873    0.21887
    x2             -423.09      331.05      -1.278    0.22203
    x3              315.44      243.74      1.2942    0.21654
    x1:x2           97.116      76.333      1.2723    0.22401
    x1:x3          -0.3027     0.45304    -0.66815     0.5149
    x2:x3          -96.638      76.347     -1.2658    0.22625


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 2.11
R-squared: 0.236,  Adjusted R-Squared: -0.0909
F-statistic vs. constant model: 0.722, p-value = 0.639


TravisCMCountInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)     281.97      376.27     0.74938    0.46603
    x1             -64.825      86.736    -0.74738     0.4672
    x2             -81.653      117.94    -0.69235    0.50004
    x3              66.261       86.83     0.76312    0.45806
    x1:x2            18.73      27.193     0.68877    0.50222
    x1:x3         -0.17346     0.16139     -1.0748    0.30065
    x2:x3          -18.598      27.198     -0.6838    0.50526


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 0.751
R-squared: 0.155,  Adjusted R-Squared: -0.207
F-statistic vs. constant model: 0.428, p-value = 0.848


TravisCMLaborInteractions =


Linear regression model:
    y ~ 1 + x1*x2 + x1*x3 + x2*x3

Estimated Coefficients:
                   Estimate      SE        tStat      pValue
                   ________    _______    ________    _______

    (Intercept)     1126.4      880.82      1.2788    0.22178
    x1             -258.52      203.04     -1.2732    0.22368
    x2             -338.85      276.08     -1.2274    0.23992
    x3              261.07      203.26      1.2844    0.21984
    x1:x2           77.722      63.657      1.2209    0.24227
    x1:x3         -0.34201      0.3778    -0.90526    0.38064
    x2:x3          -77.256      63.669     -1.2134    0.24505


Number of observations: 21, Error degrees of freedom: 14
Root Mean Squared Error: 1.76
R-squared: 0.223,  Adjusted R-Squared: -0.111
F-statistic vs. constant model: 0.668, p-value = 0.677
```

Figure D14: Travis AFB Interactions Analysis Results

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

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1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From - To)*
25-03-2022	Master's Thesis	September 2020 - March 2022

4. TITLE AND SUBTITLE	**5a. CONTRACT NUMBER**
Investigating the Relationship of Preventive and Corrective Maintenance in Chiller Assets Using Linear Regression Analysis	
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Franke, Jacob A., Capt, USAF	
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/ENY) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865	AFIT-ENV-MS-22-M-195
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
Air Force Civil Engineering Center, Detachment 1 139 Barnes Dr, Suite 1 Tyndall AFB FL 32403-5319	AFCEC
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

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14. ABSTRACT

Asset managers must balance maintenance plans between preventive (PM) and corrective maintenance (CM). While PM plans have been a staple for decades, the benefits achieved have not been thoroughly examined at the asset specific level. This study focuses on the U.S. Air Force chiller portfolio to better understand the relationship between PM and CM, utilizing multiple stages of linear regression modeling and data from 14 US Air Force installations. PM and CM were found to be positively correlated, with PM accounting for relatively small portions of the variance experienced in CM. This study reveals the value of standardized data collection and suggests ways to improve data management in large built asset portfolios.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Lieutenant Colonel Justin D. Delorit, AFIT/ENV
					19b. TELEPHONE NUMBER *(Include area code)*
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