



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

THESIS

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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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Captain, USAF

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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.

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Jacob A. Franke

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INVESTIGATING THE RELATIONSHIP OF PREVENTIVE AND CORRECTIVE MAINTENANCE 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 (Dotzlaaf, 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).

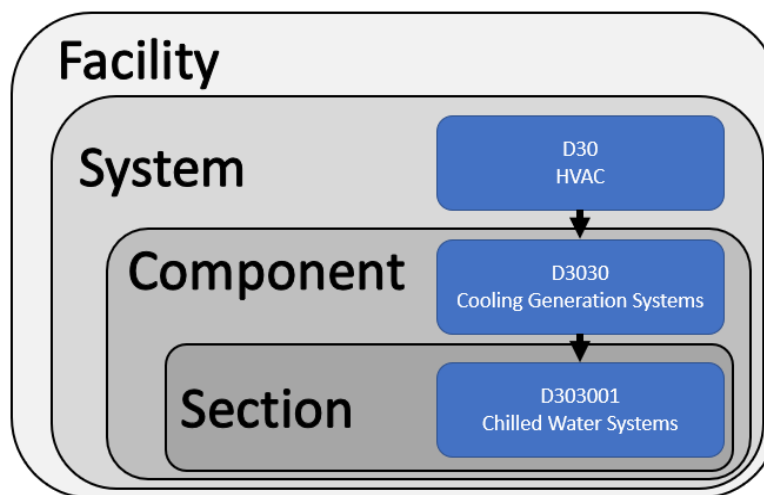


Figure 1: BUILDER Hierarchy for Chiller Assets

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).

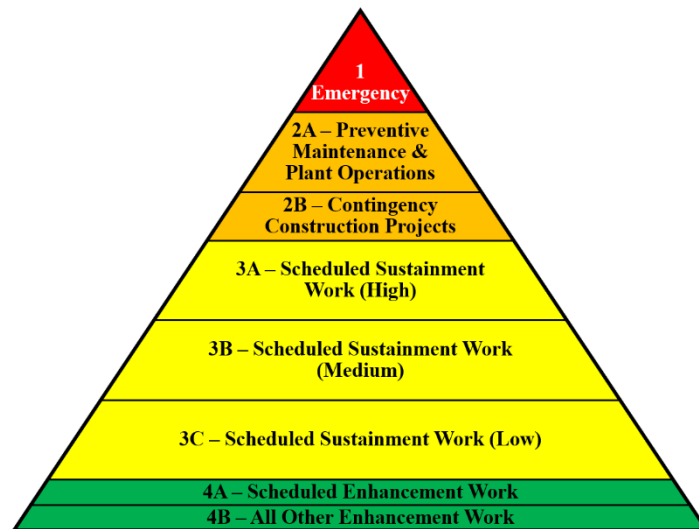


Figure 2: Air Force Work Task Priorities

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.

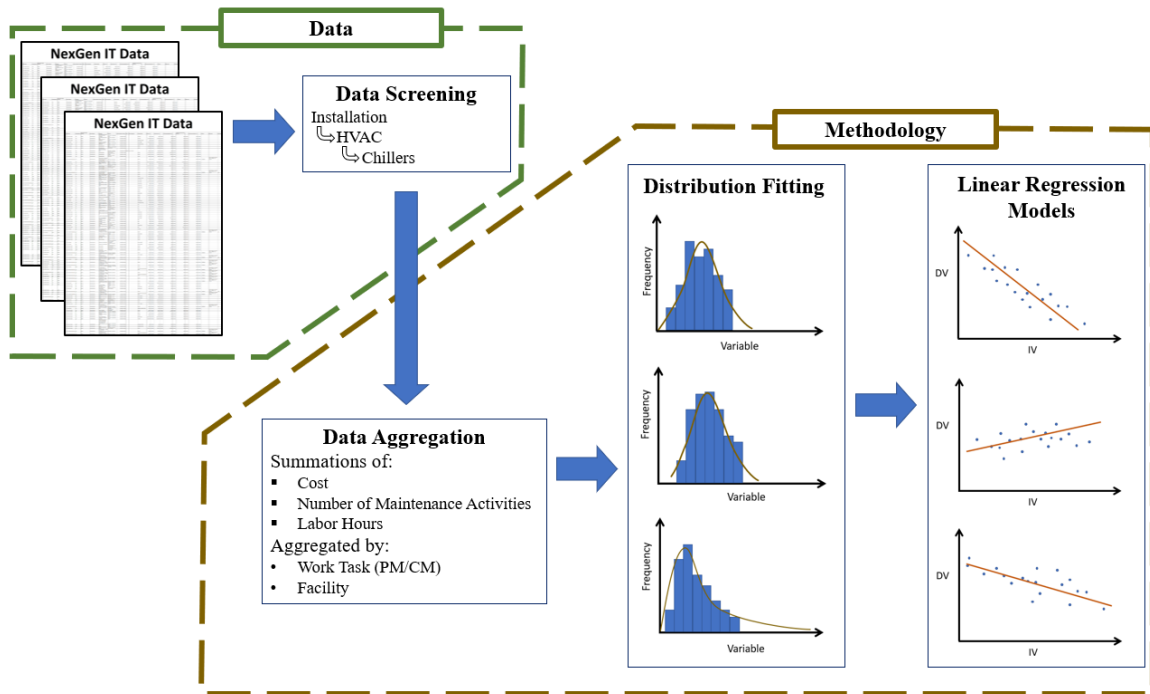


Figure 4: Systematic Methodology

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 activities* 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).

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

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 aggregations were based on the same categories as the main dataset: *total cost of the activities 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 identifying 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 activities. 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:

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

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 determined 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

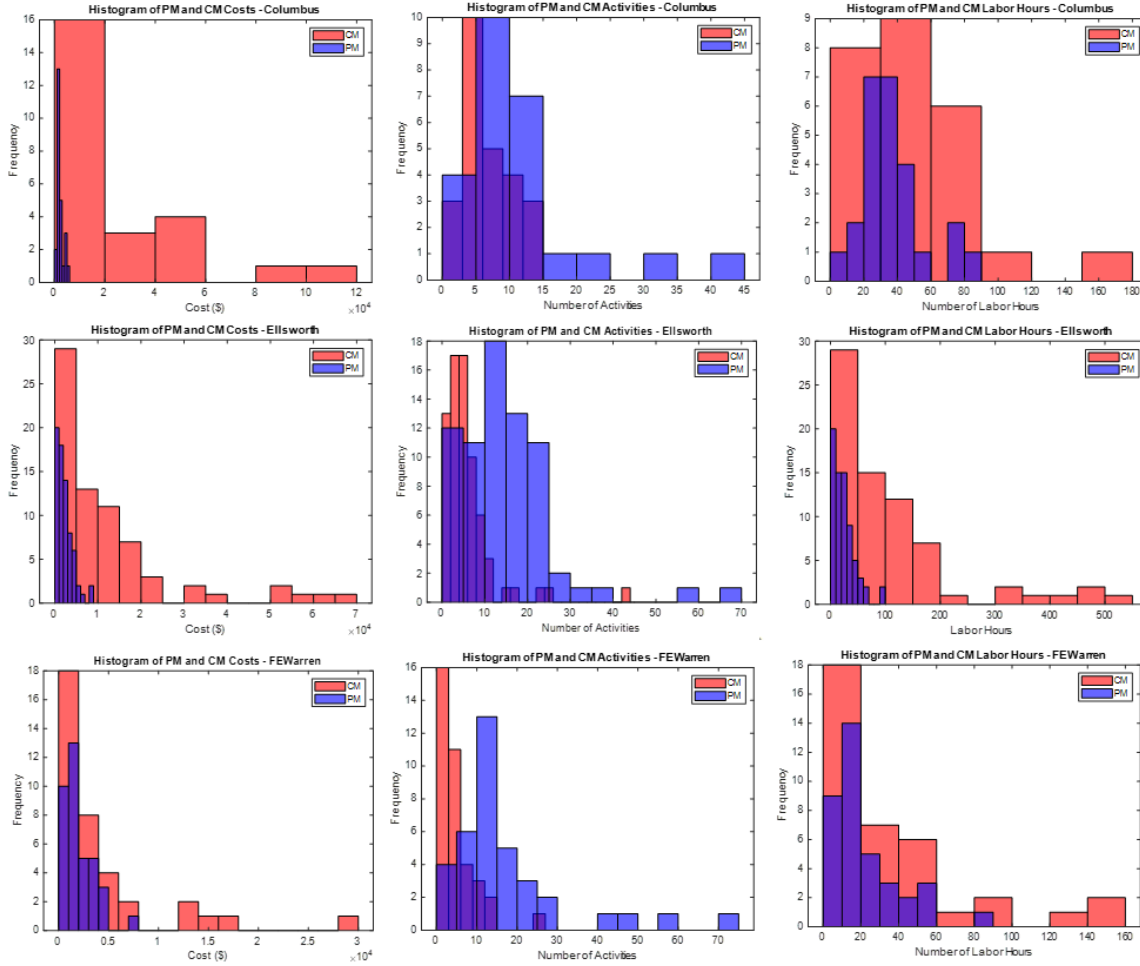


Figure 7: Model Input Distribution Sample. Each row contains a different installation: (top) Columbus AFB, (middle) Ellsworth AFB, (bottom) FE Warren AFB. The columns illustrate aggregated PM and CM comparisons: (left) costs, (middle) activities, (right) labor hours.

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).

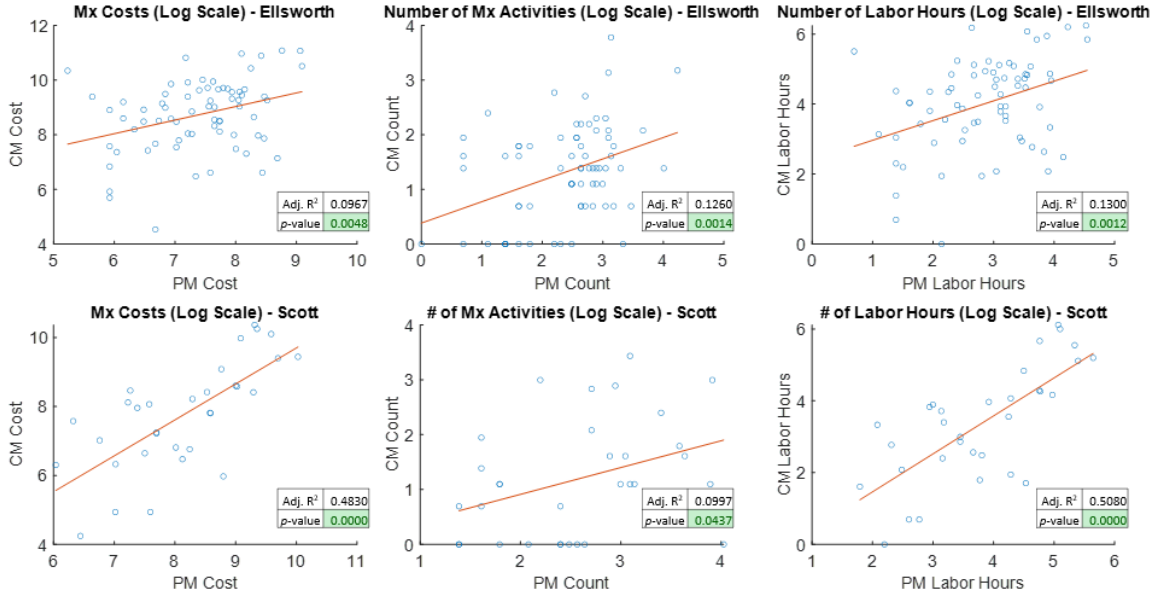


Figure 8: Sample of Single Linear Regression Relationships in Logarithmic Space

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).

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

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,

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

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.

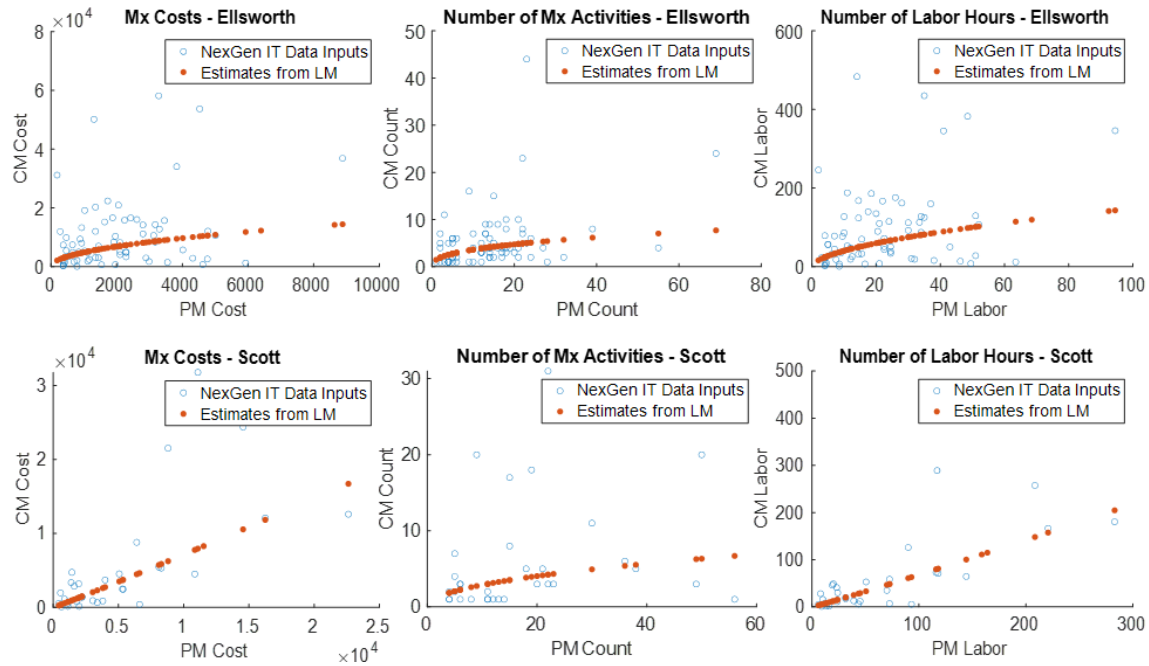


Figure 9: Example of Model Framework

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.

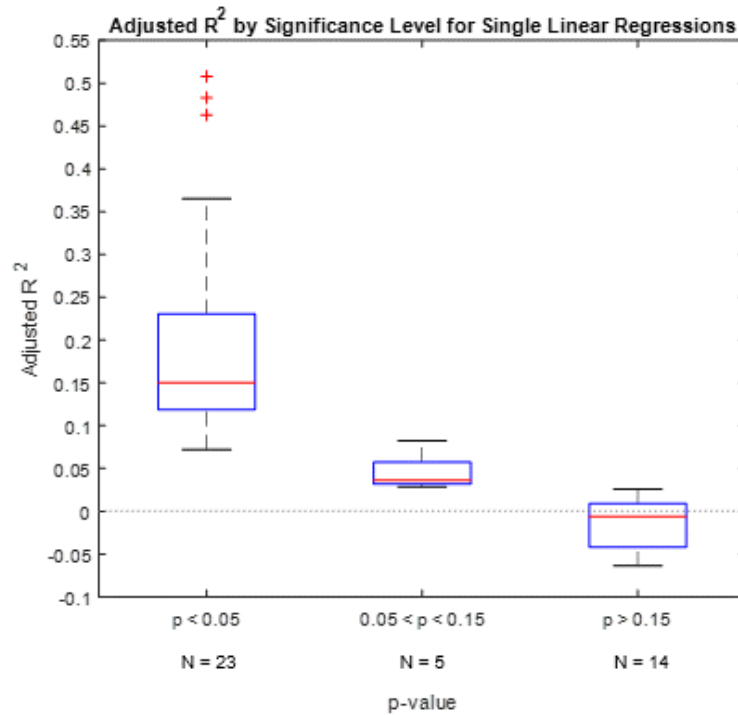


Figure 10: Boxplot of All Single Linear Regression Models

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 R^2 , 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.

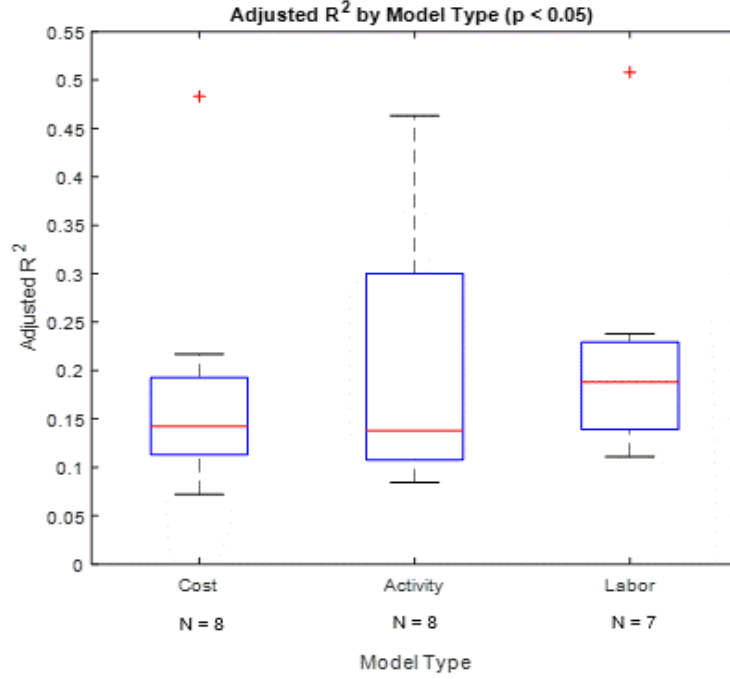


Figure 11 Boxplot of Significant Single Linear Regression Models ($p \leq 0.05$)

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 .

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

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*).

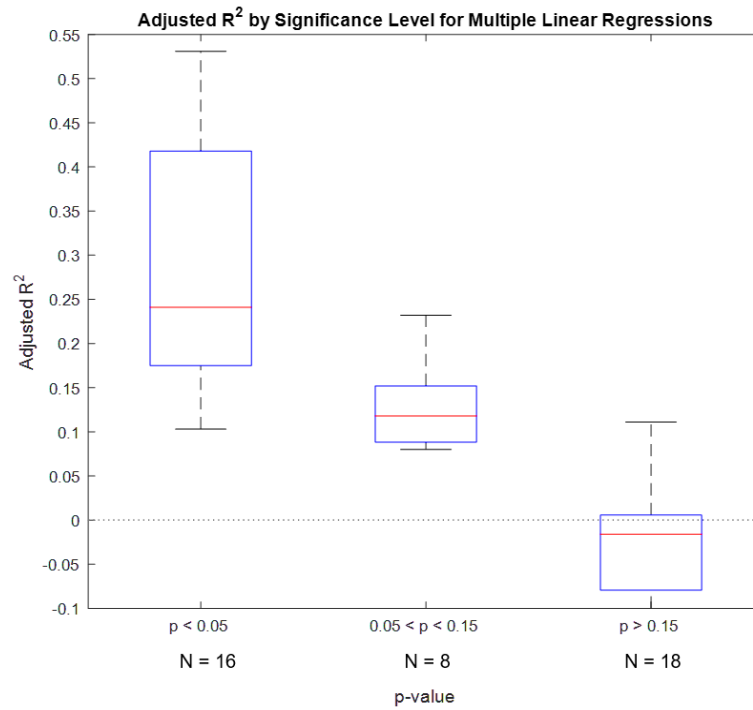


Figure 12: Boxplot of All Multiple Linear Regression Models

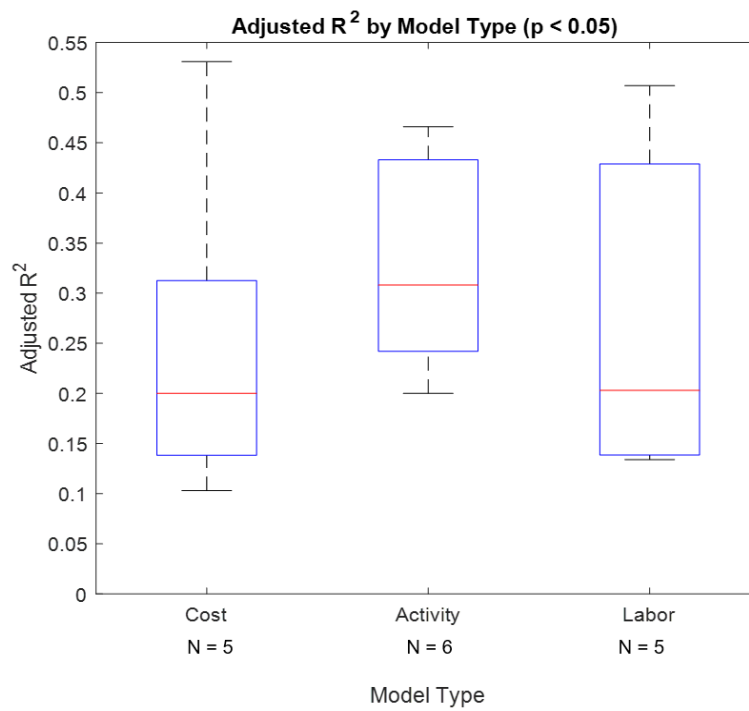


Figure 13: Boxplot of Significant Multiple Linear Regression Models ($p \leq 0.05$)

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.

$$y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_4x_1x_2 + \beta_5x_1x_3 + \beta_6x_2x_3 \quad (\text{Eq. 6})$$

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 $\beta_1 + \beta_4x_2 + \beta_5x_3$ 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*).

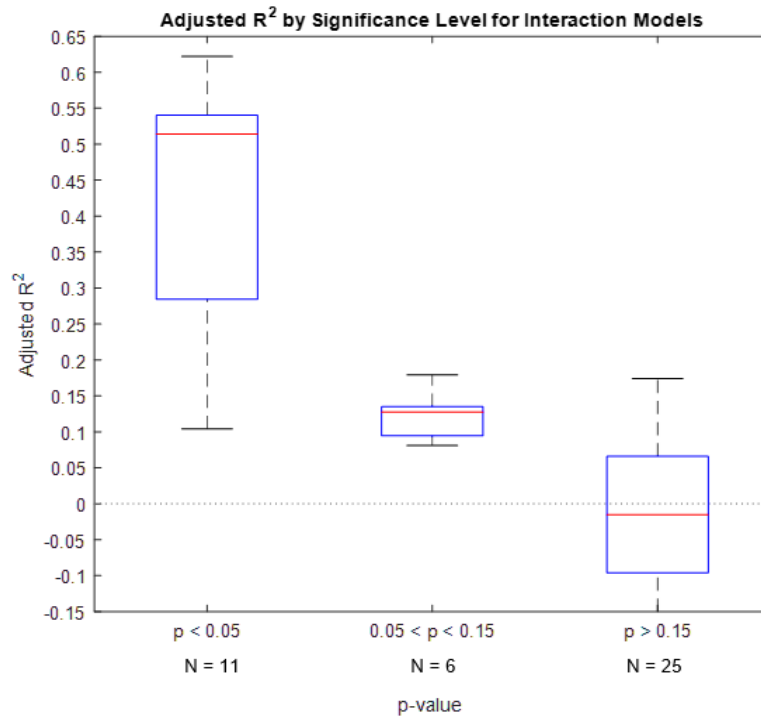


Figure 14: Boxplot of All Interaction Regression Models

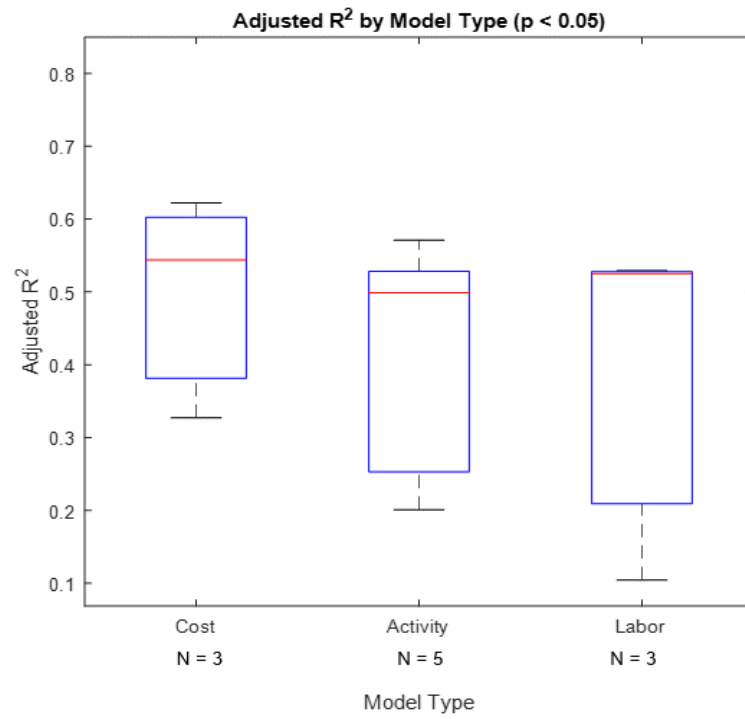


Figure 15: Boxplot of Significant Interaction Regression Models ($p \leq 0.05$)

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.

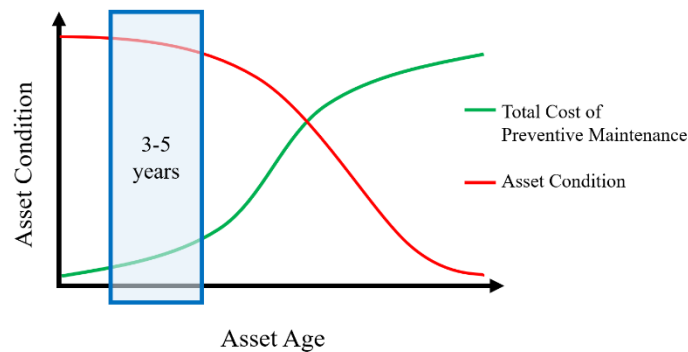


Figure 17: Theoretical Relationship Between Preventive Maintenance Cost and Asset Condition

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.

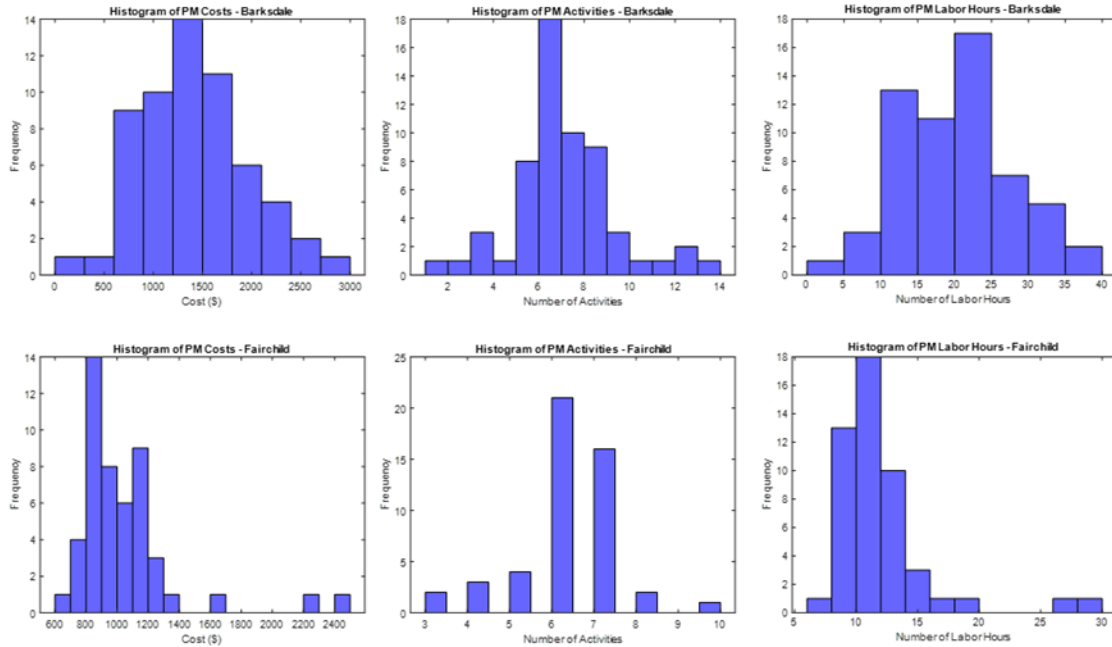


Figure 18: Model Input Distributions for Barksdale and Fairchild

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.

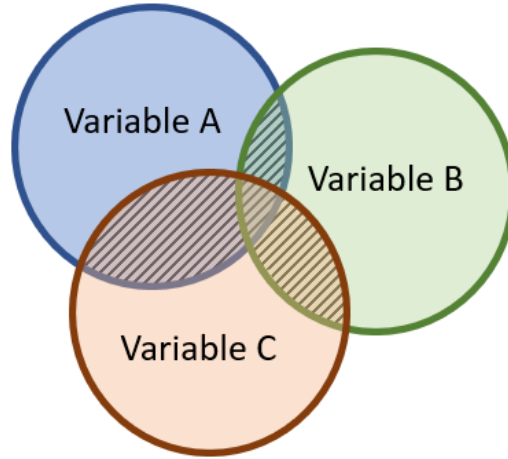


Figure 19: Example of Multicollinearity

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.

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

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

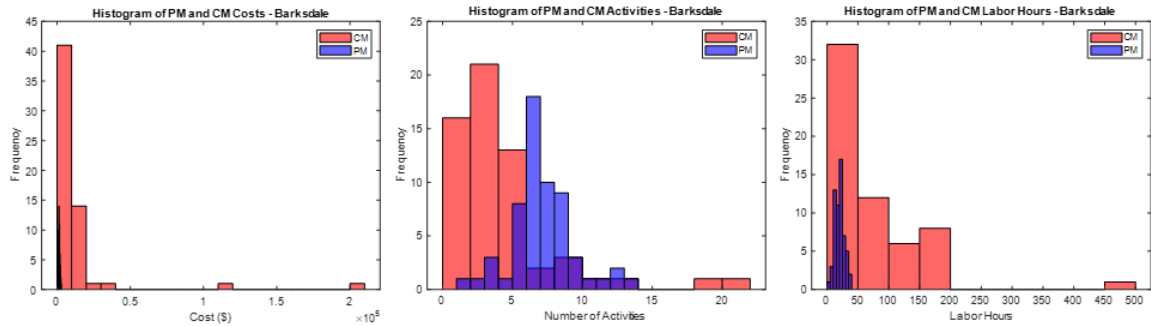


Figure A1: Model Input Distributions - Barksdale AFB

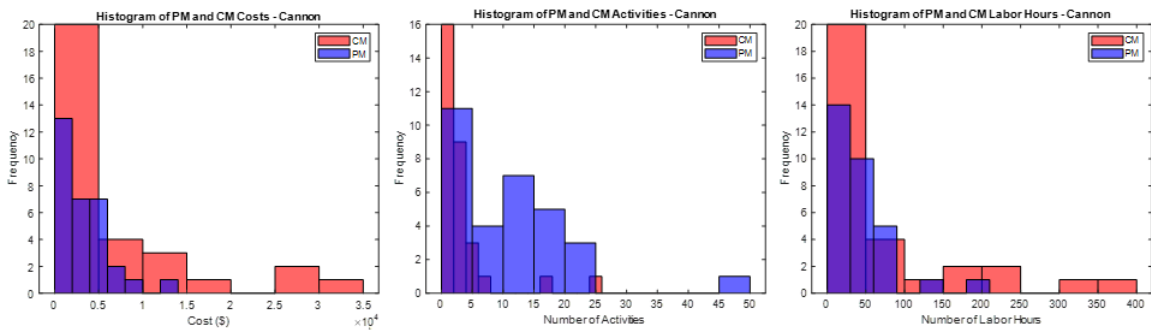


Figure A2: Model Input Distributions - Cannon AFB

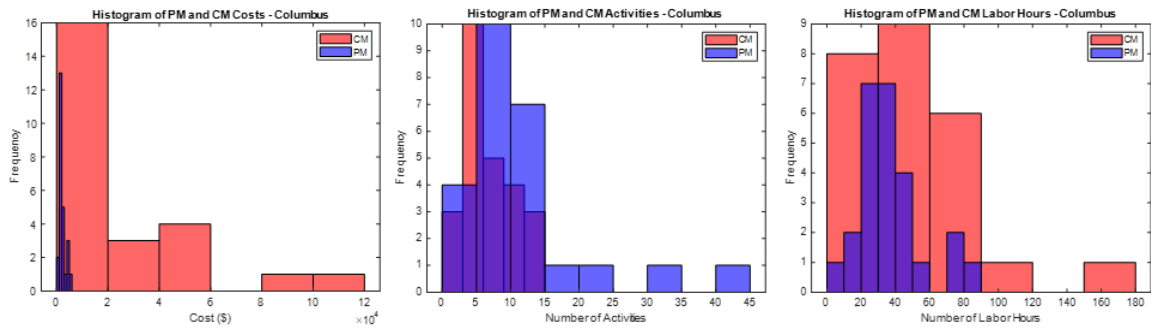


Figure A3: Model Input Distributions - Columbus AFB

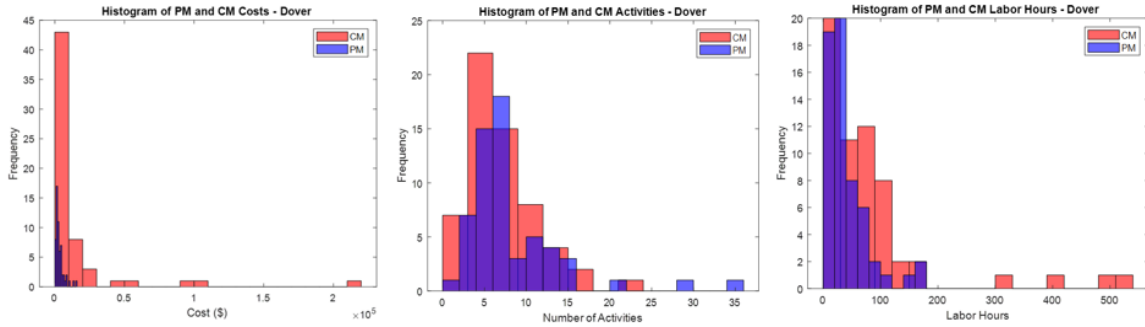


Figure A4: Model Input Distributions - Dover AFB

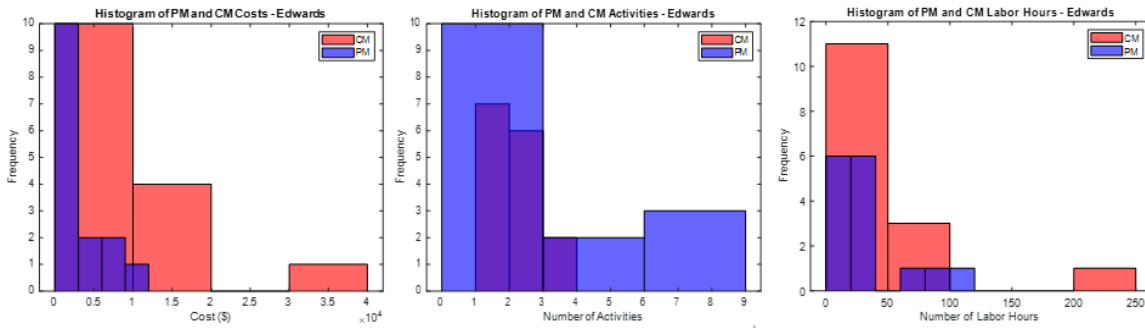


Figure A5: Model Input Distributions - Edwards AFB

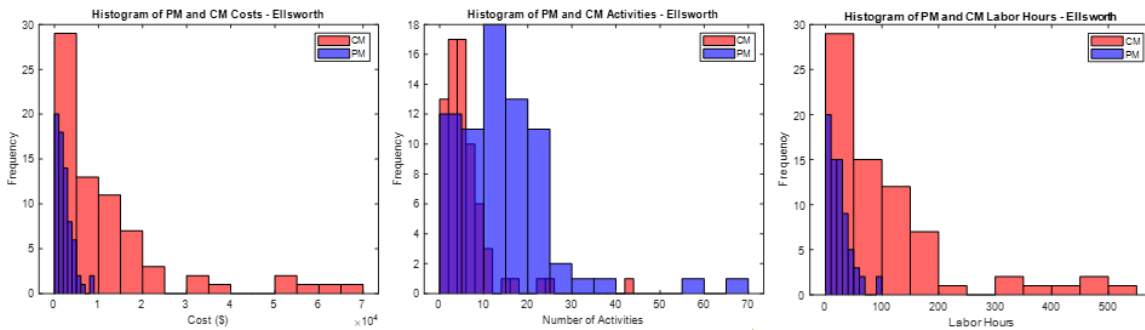


Figure A6: Model Input Distributions - Ellsworth AFB

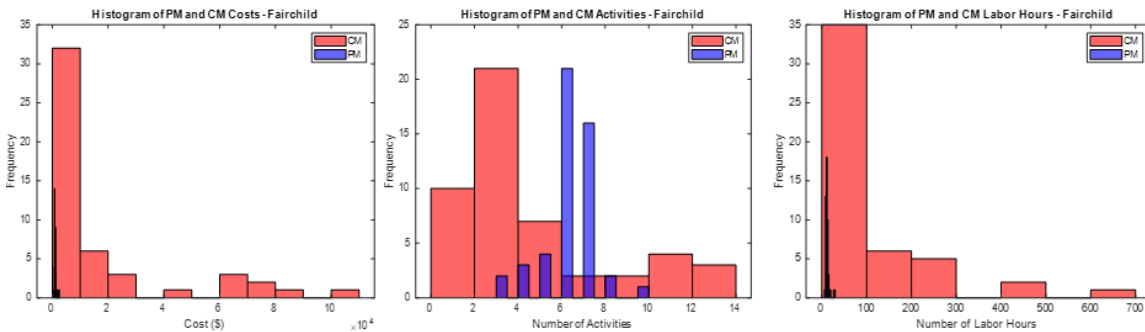


Figure A7: Model Input Distributions - Fairchild AFB

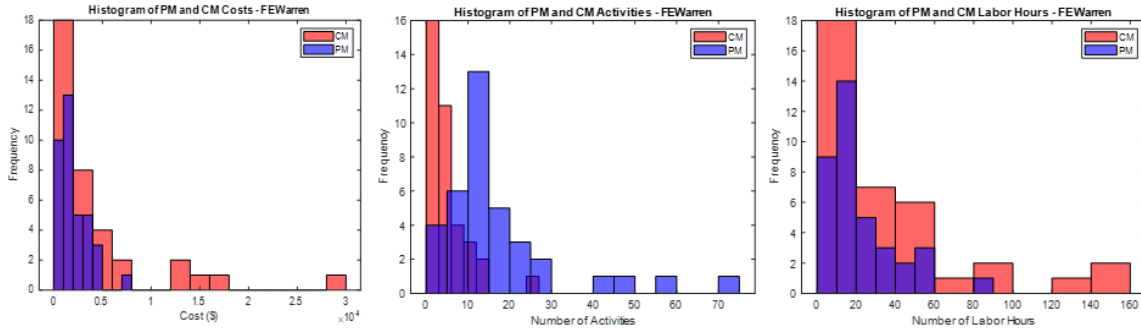


Figure A8: Model Input Distributions - F.E. Warren AFB

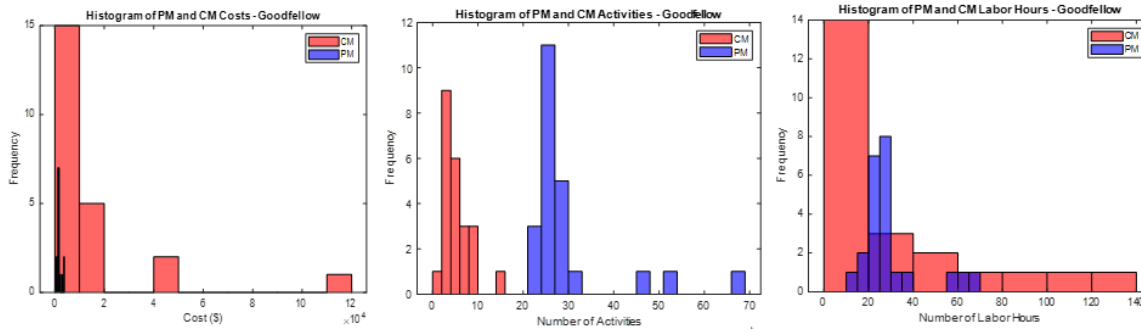


Figure A9: Model Input Distributions - Goodfellow AFB

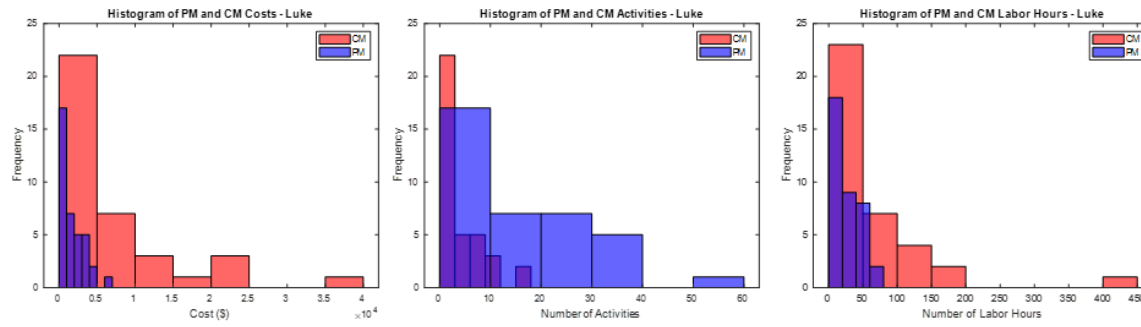


Figure A10: Model Input Distributions - Luke AFB

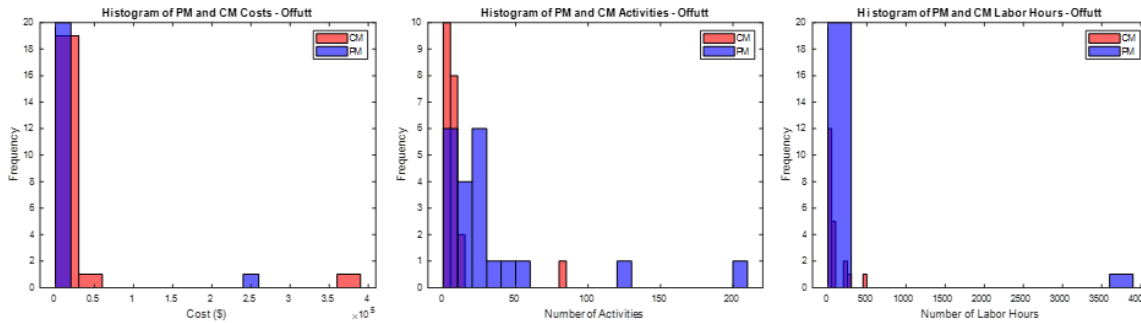


Figure A11: Model Input Distributions - Offutt AFB

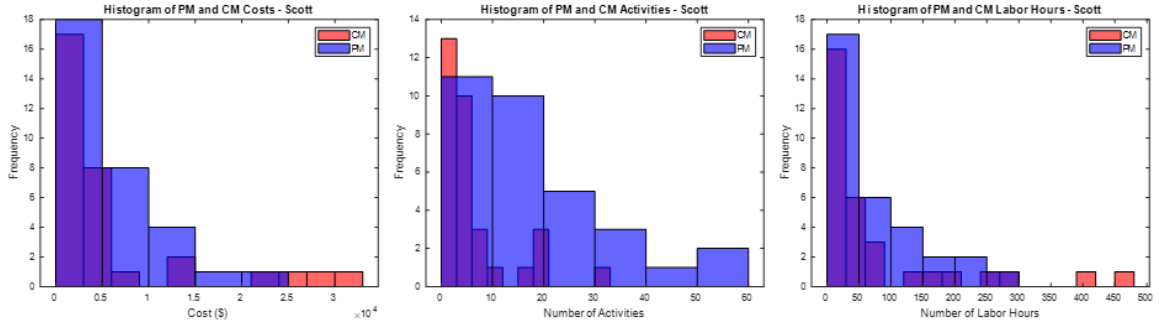


Figure A12: Model Input Distributions - Scott AFB

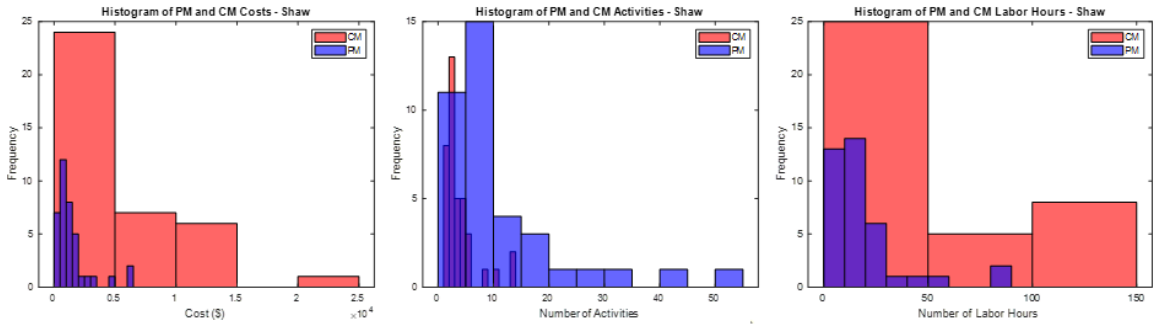


Figure A13: Model Input Distributions - Shaw AFB

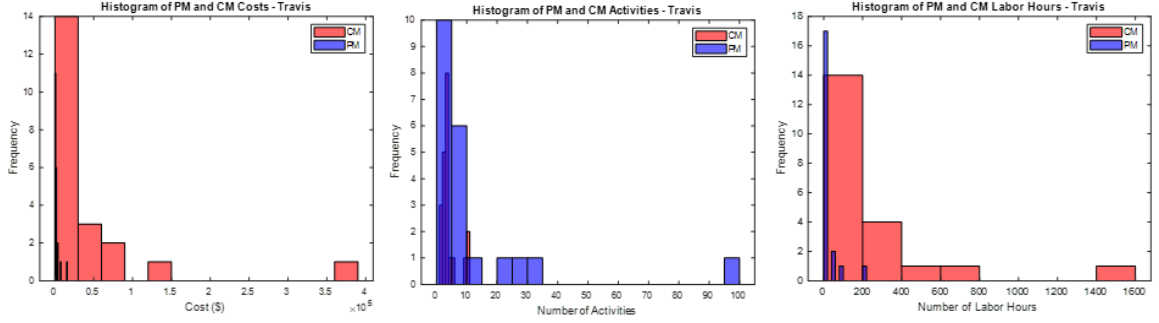


Figure A14: Model Input Distributions - Travis AFB

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
$p\text{-value} \leq 0.05$	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
$0.05 < p\text{-value} \leq 0.15$	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
$p\text{-value} > 0.15$	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
		<i>p</i> -value	0.2180	0.0912	0.2510
Cannon	31	Adj. R ²	0.2170	0.0088	0.1880
		<i>p</i> -value	0.0048	0.2700	0.0085
Columbus	25	Adj. R ²	0.1300	0.2350	0.0821
		<i>p</i> -value	0.0429	0.0081	0.0893
Dover	59	Adj. R ²	-0.0173	0.0285	-0.0085
		<i>p</i> -value	0.9070	0.1060	0.4770
Edwards	15	Adj. R ²	-0.0424	0.4630	-0.0638
		<i>p</i> -value	0.5230	0.0032	0.6950
Ellsworth	71	Adj. R ²	0.0967	0.1260	0.1300
		<i>p</i> -value	0.0048	0.0014	0.0012
Fairchild	49	Adj. R ²	0.0721	-0.0130	0.1110
		<i>p</i> -value	0.0347	0.5390	0.0112
FE Warren	37	Adj. R ²	0.1680	0.1160	0.1660
		<i>p</i> -value	0.0069	0.0220	0.0072
Goodfellow	23	Adj. R ²	0.1390	0.1500	0.2020
		<i>p</i> -value	0.0448	0.0386	0.0182
Luke	37	Adj. R ²	0.0261	-0.0001	0.0195
		<i>p</i> -value	0.1700	0.3250	0.1990
Offutt	21	Adj. R ²	0.1460	0.3650	0.2380
		<i>p</i> -value	0.0489	0.0022	0.0145
Scott	32	Adj. R ²	0.4830	0.0997	0.5080
		<i>p</i> -value	0.0000	0.0437	0.0000
Shaw	38	Adj. R ²	0.0360	0.0845	0.0493
		<i>p</i> -value	0.1310	0.0427	0.0962
Travis	21	Adj. R ²	-0.0038	-0.0513	-0.0419
		<i>p</i> -value	0.3490	0.8800	0.6630

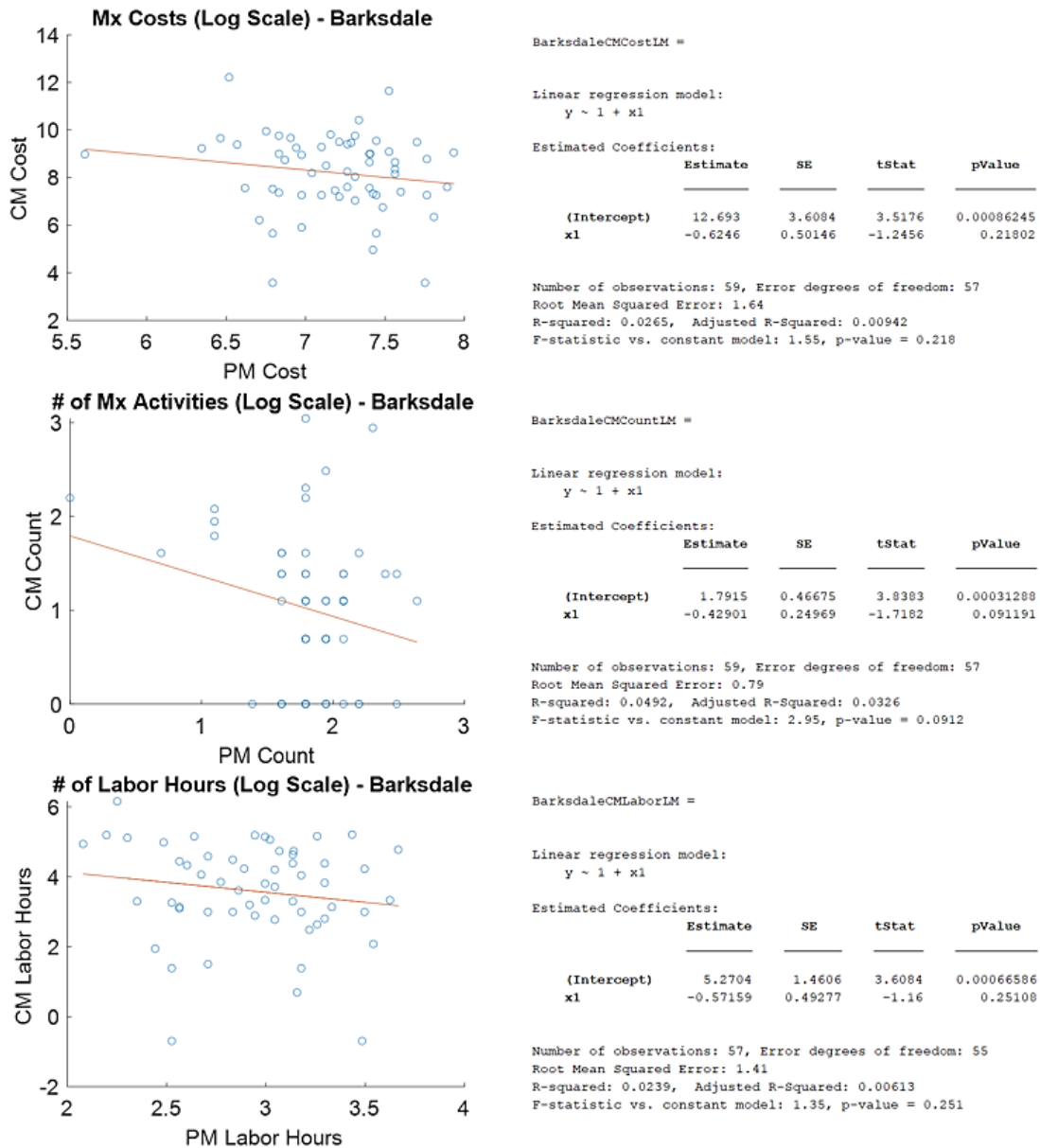


Figure B1.1: Barksdale AFB Single Linear Regressions

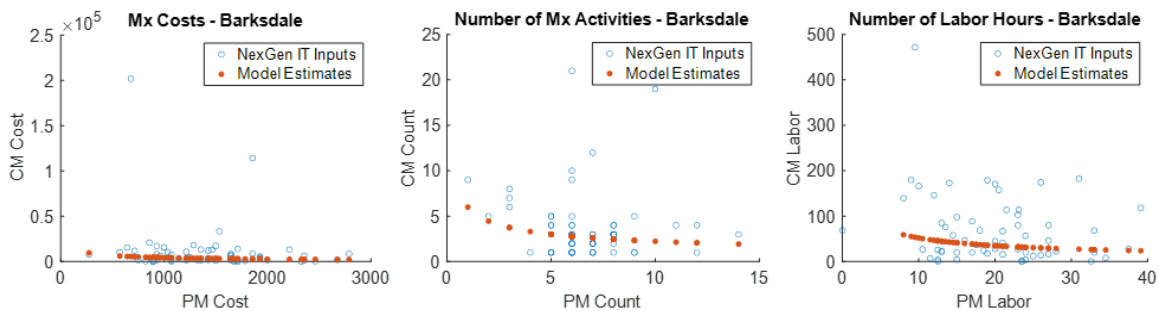


Figure B1.2: Barksdale AFB Model Framework

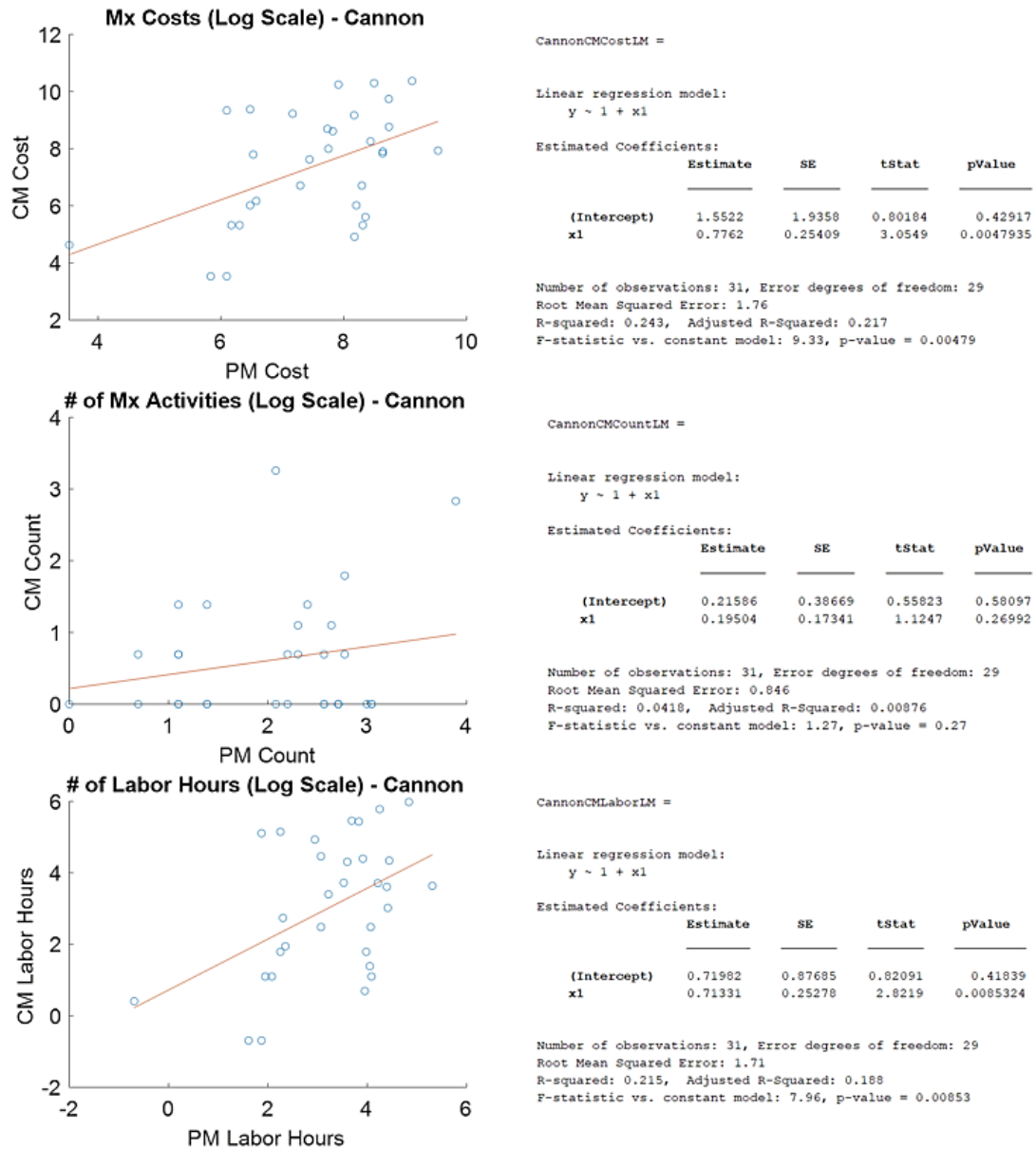


Figure B2.1: Cannon AFB Single Linear Regressions

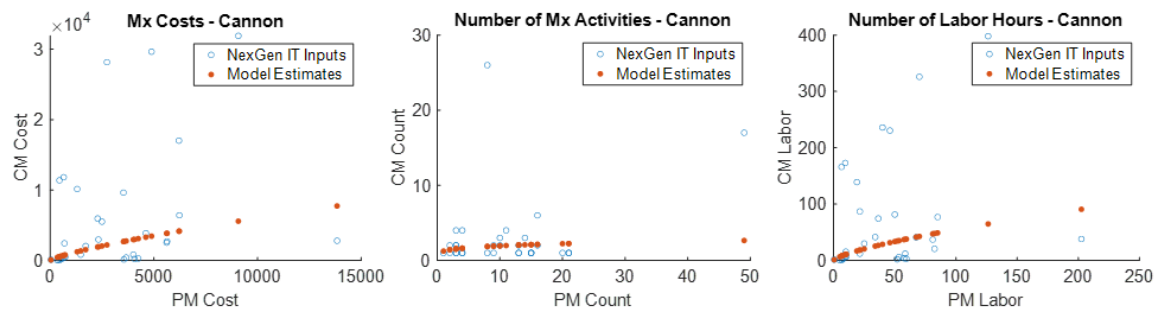


Figure B2.2: Cannon AFB Model Framework

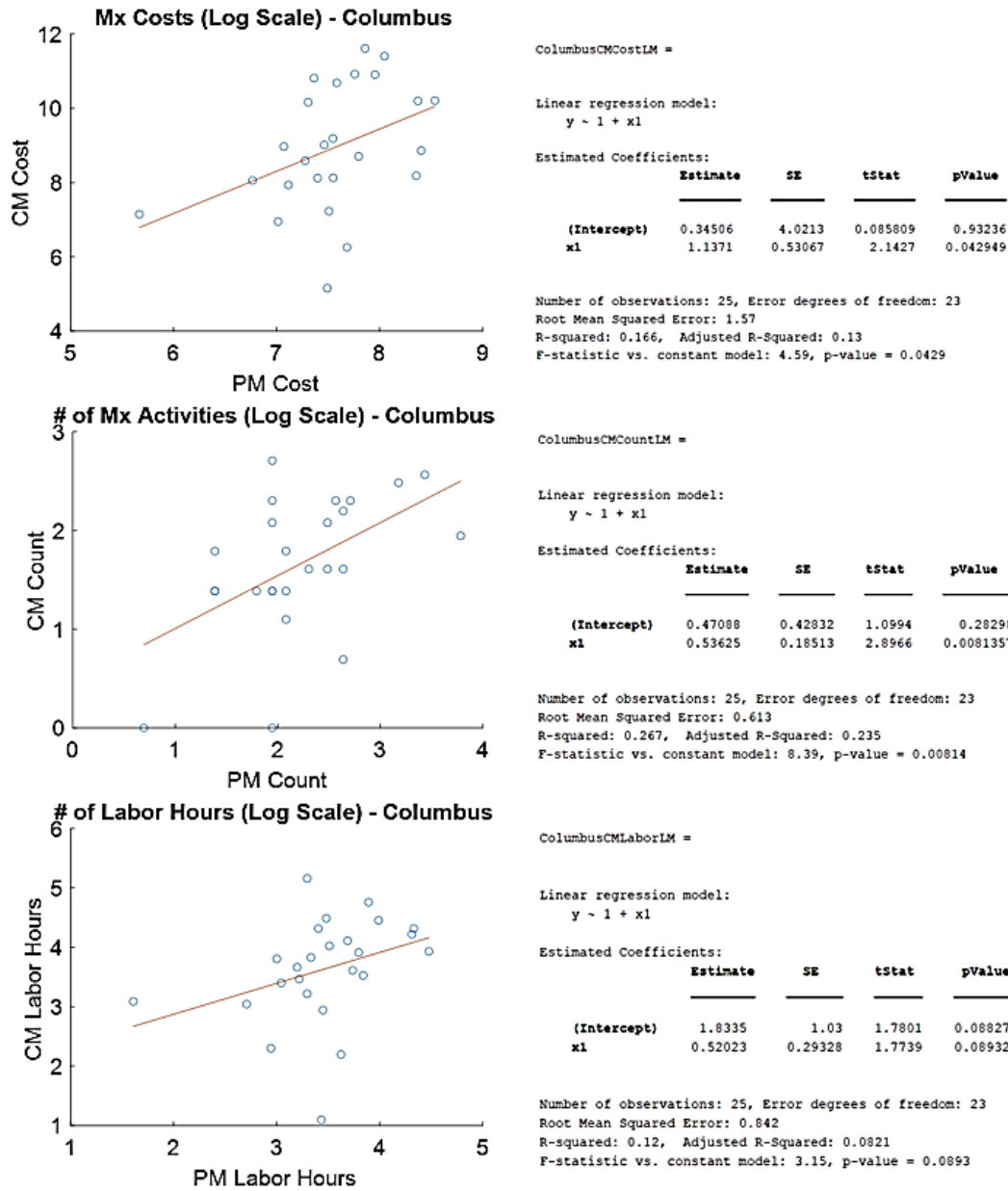


Figure B3.1: Columbus AFB Single Linear Regressions

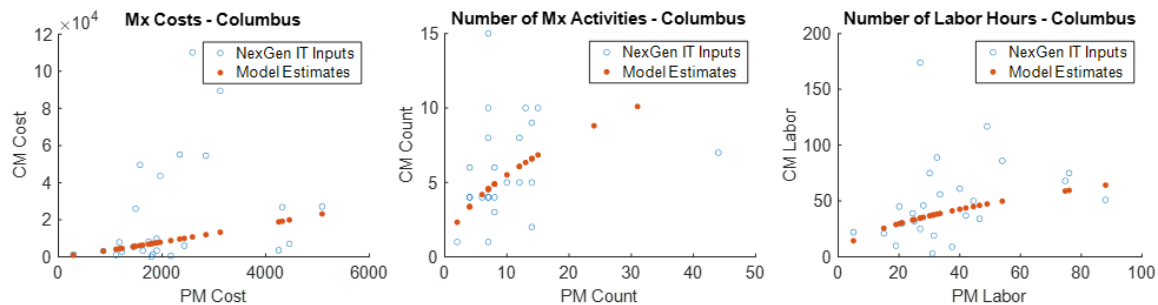


Figure B3.2: Columbus AFB Model Framework

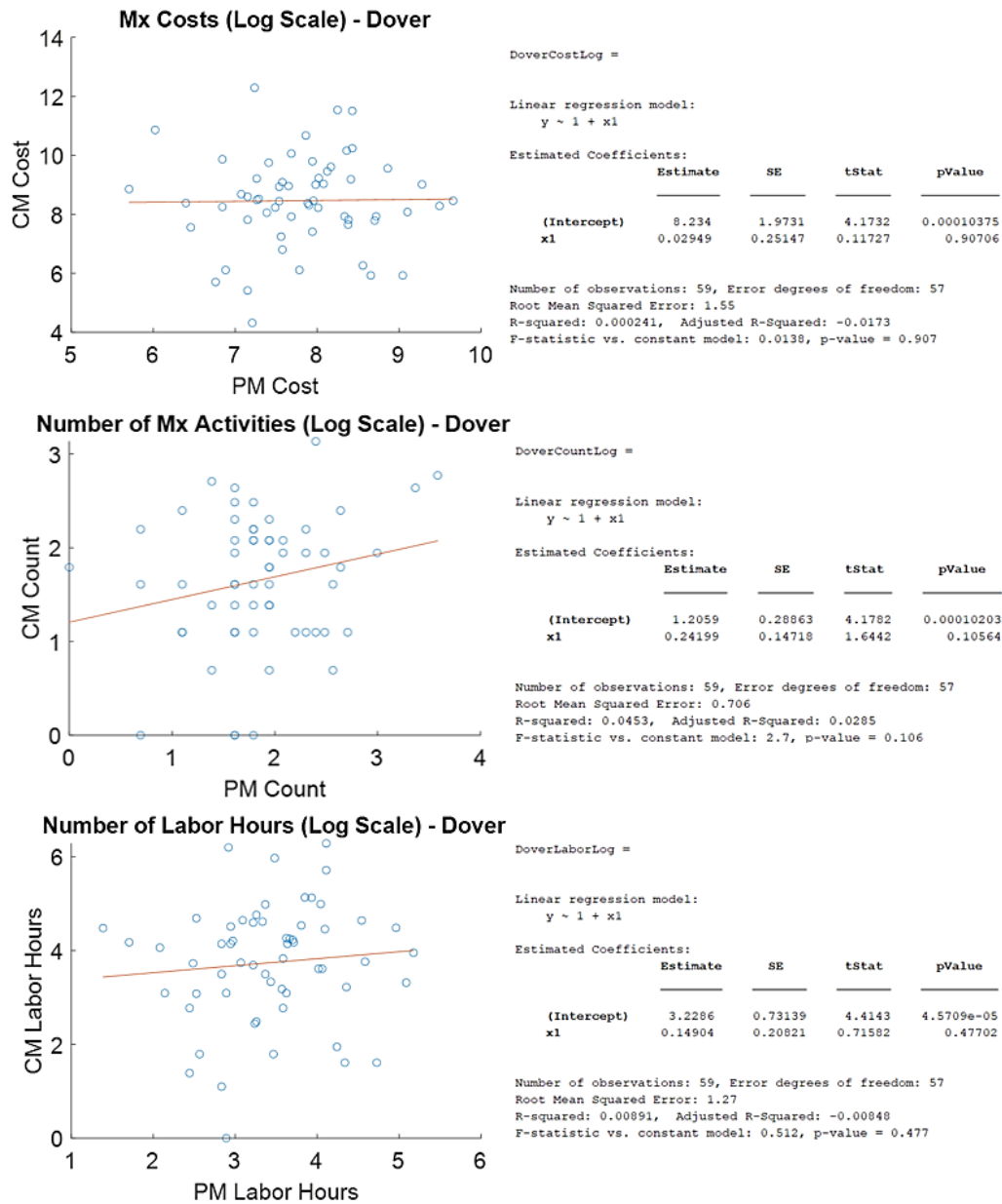


Figure B4.1: Dover AFB Single Linear Regressions

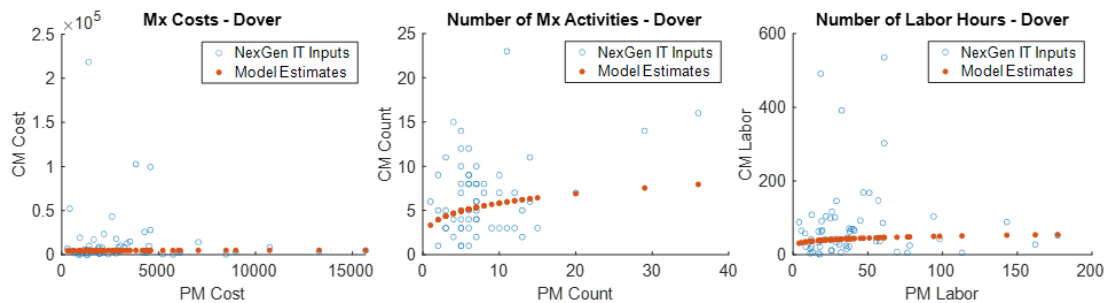


Figure B4.2: Dover AFB Model Framework

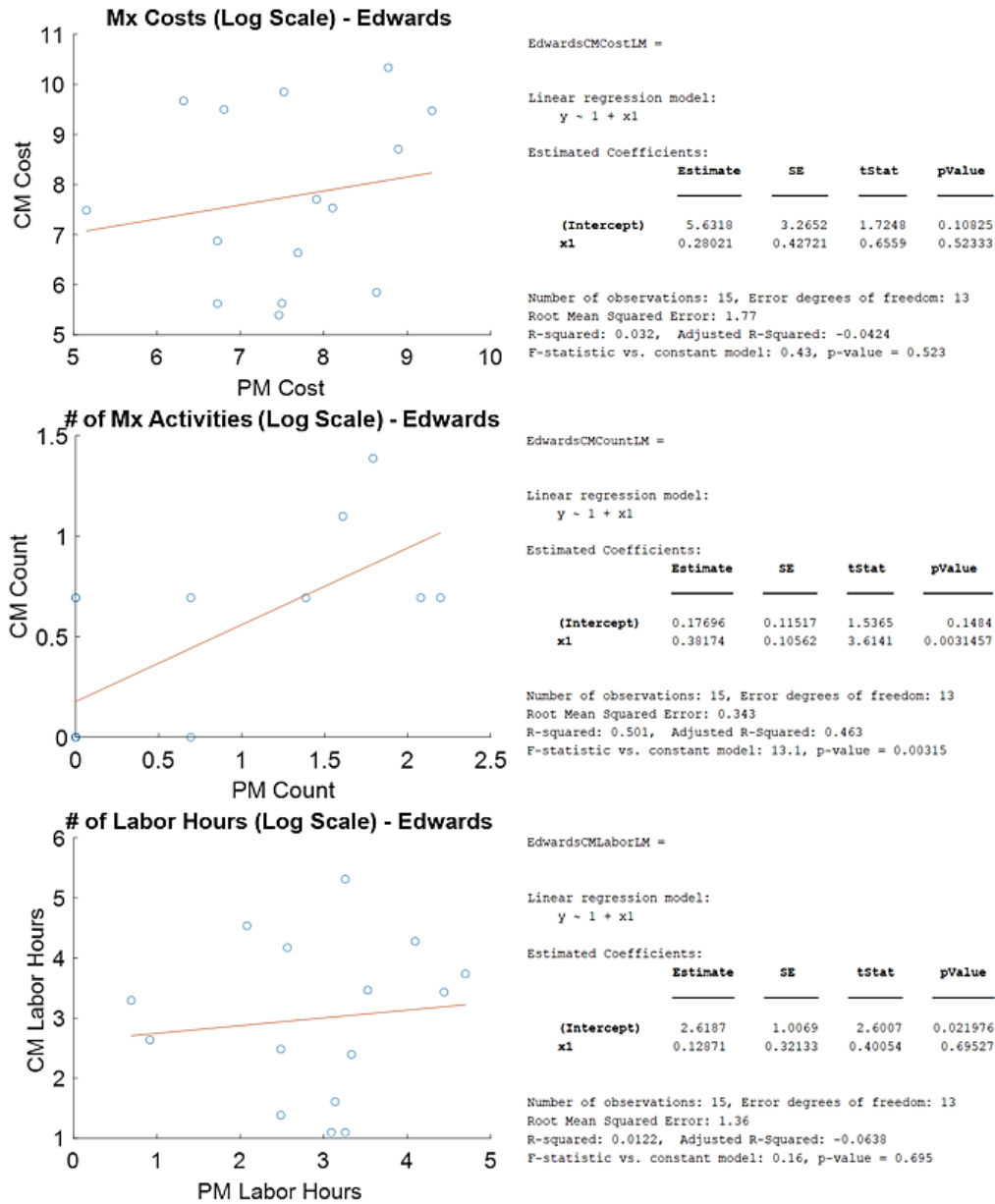


Figure B5.1: Edwards AFB Single Linear Regressions

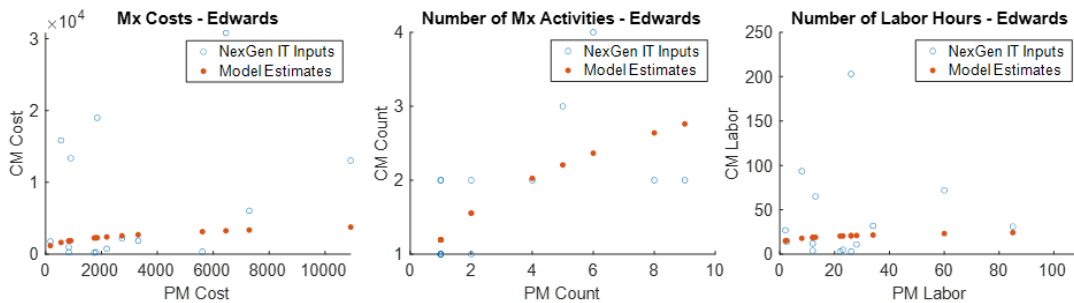


Figure B5.2: Edwards AFB Model Framework

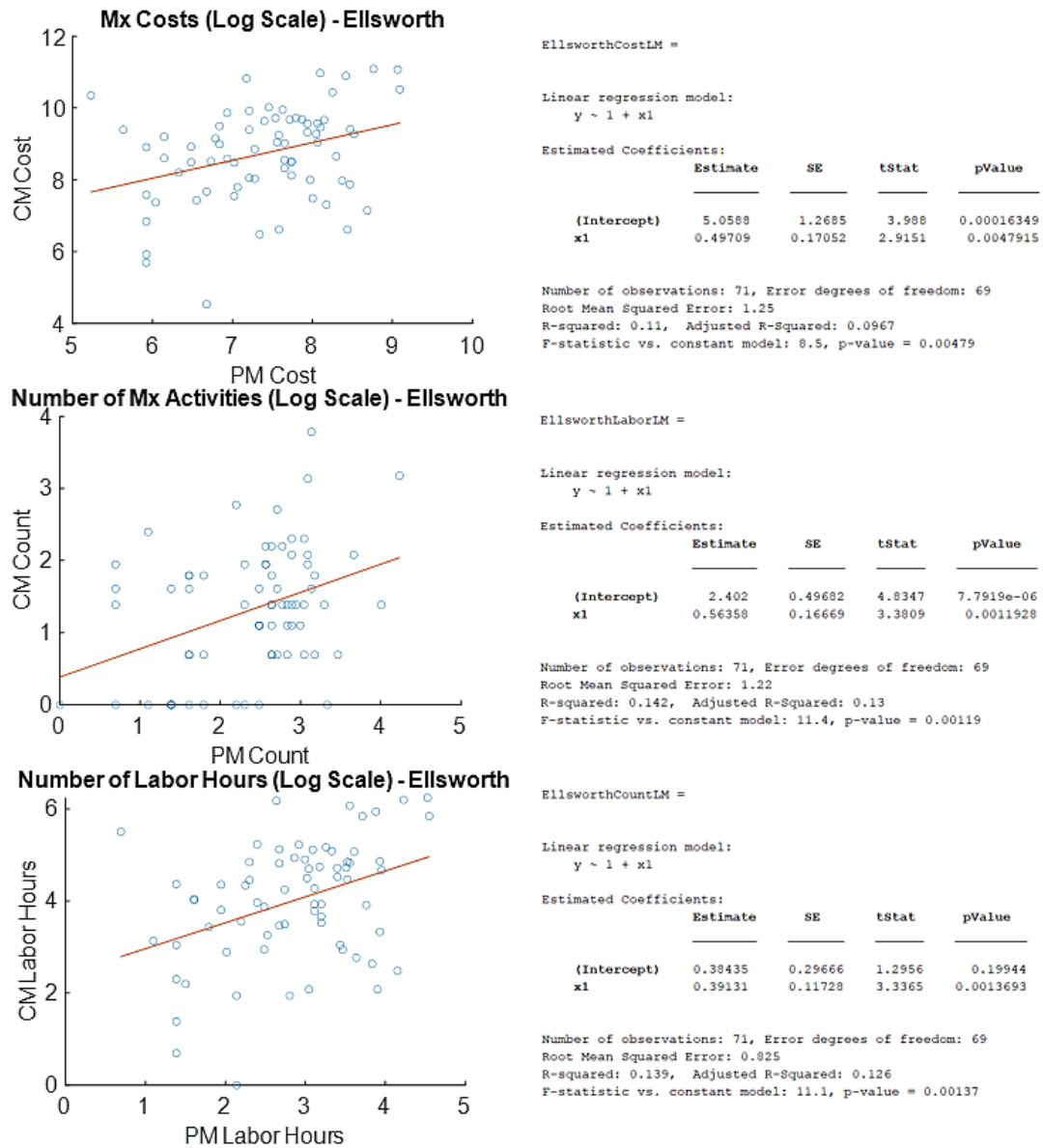


Figure B6.1: Ellsworth AFB Single Linear Regressions

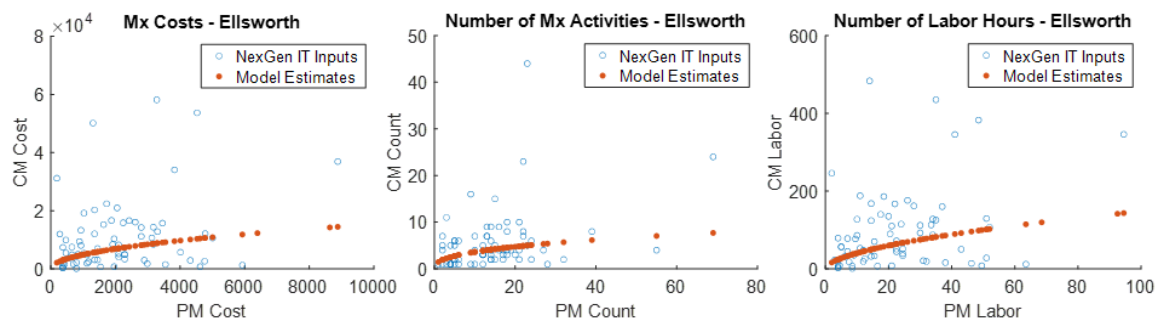


Figure B6.2: Ellsworth AFB Model Framework

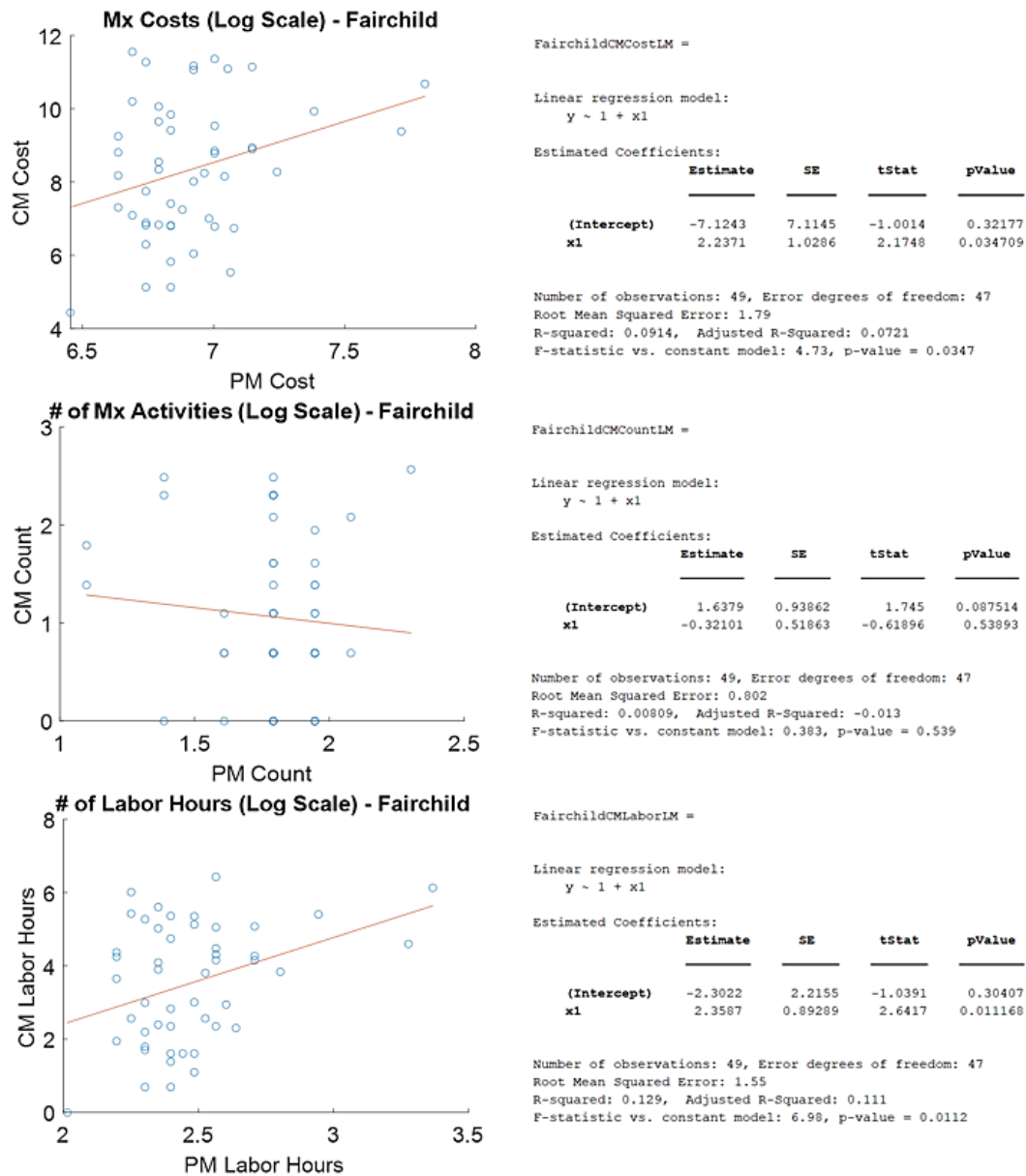


Figure B7.1: Fairchild AFB Single Linear Regressions

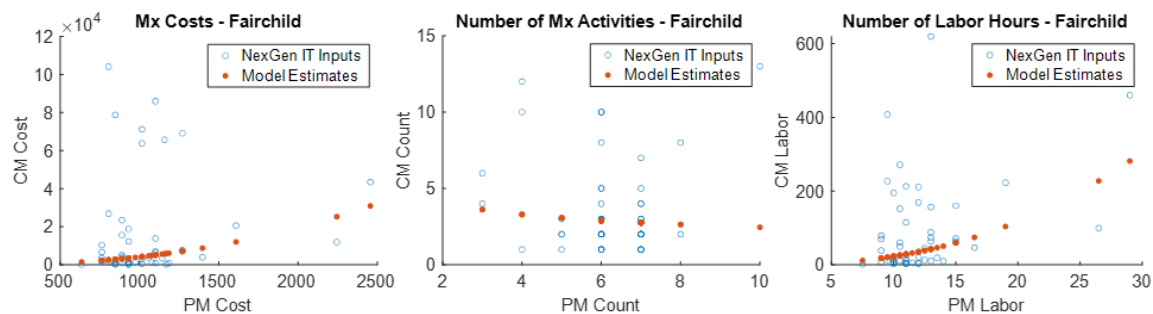


Figure B7.2: Fairchild AFB Model Framework

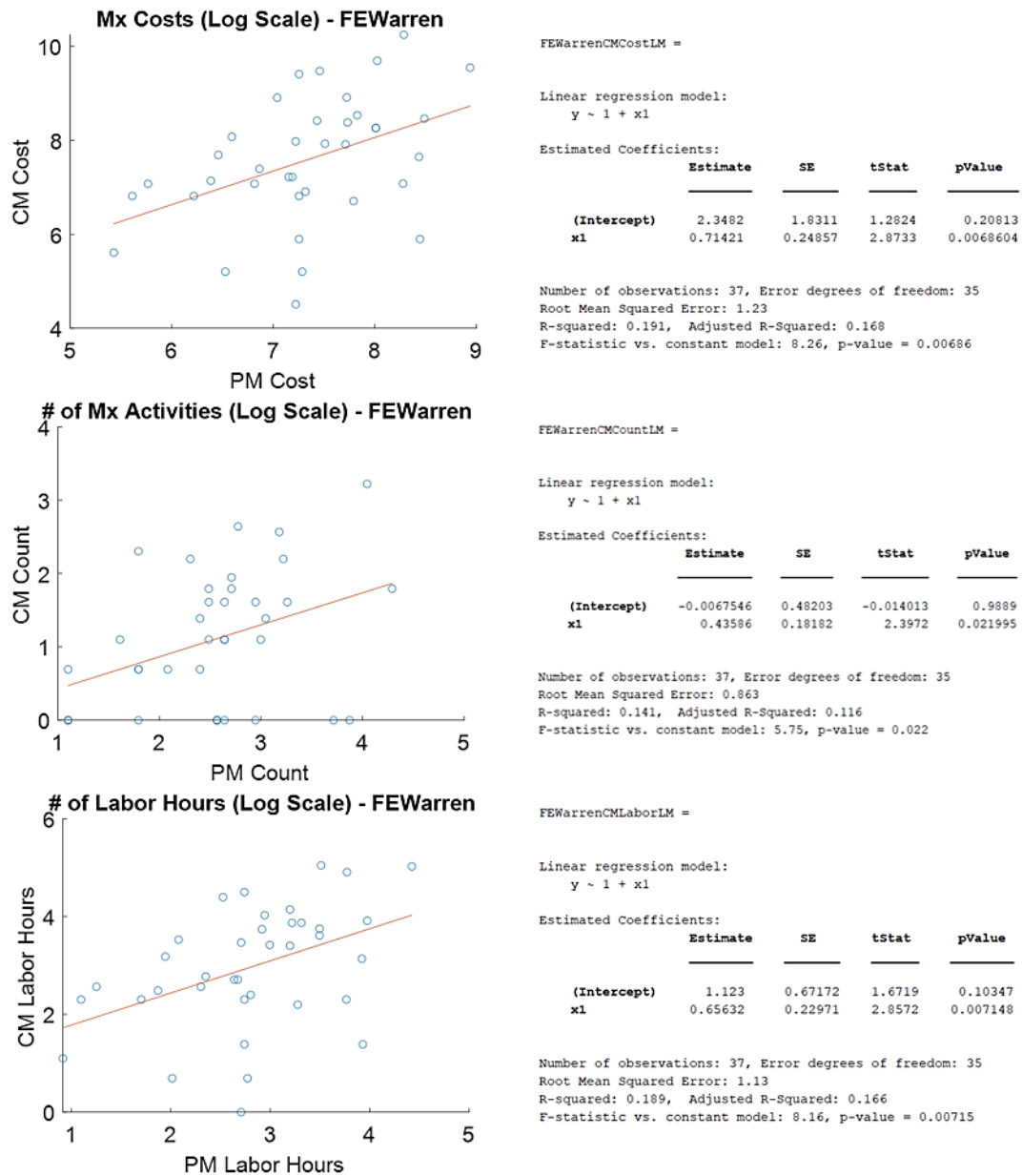


Figure B8.1: F.E. Warren AFB Single Linear Regressions

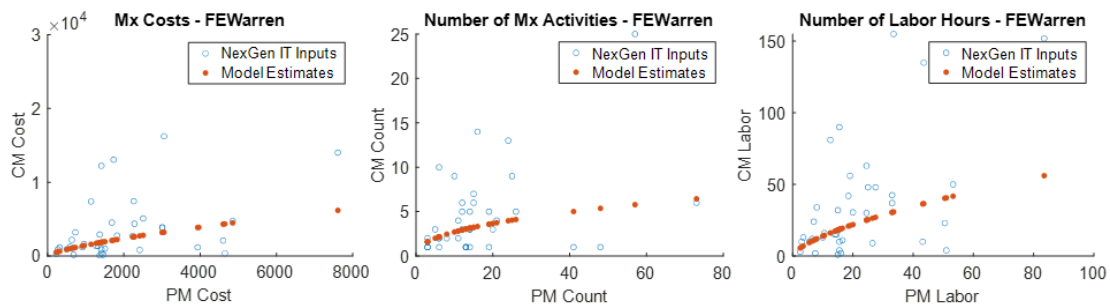


Figure B8.2: F.E. Warren AFB Model Framework

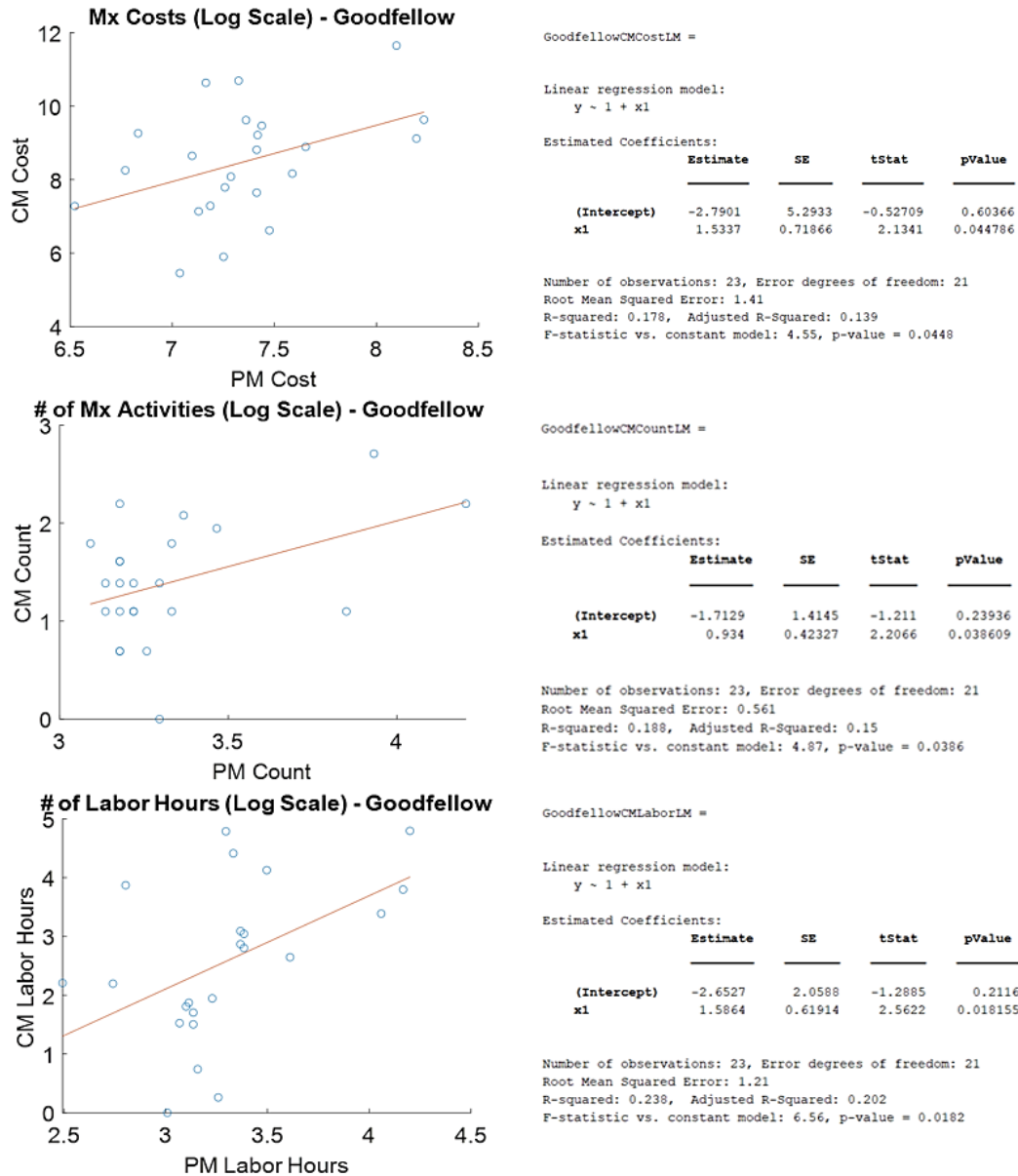


Figure B9.1: Goodfellow AFB Single Linear Regressions

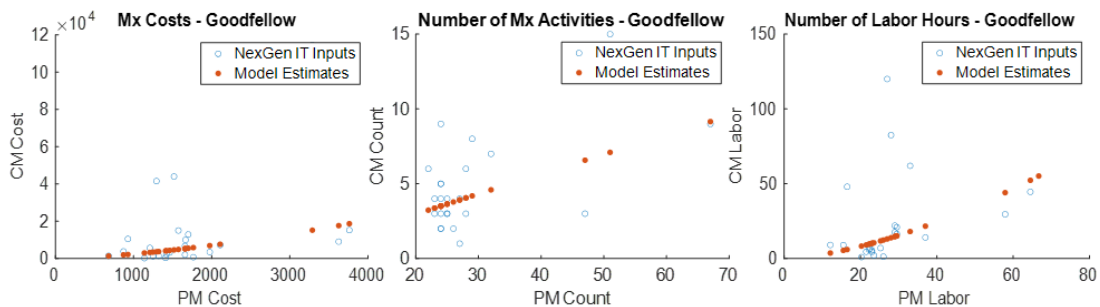


Figure B9.2: Goodfellow AFB Model Framework

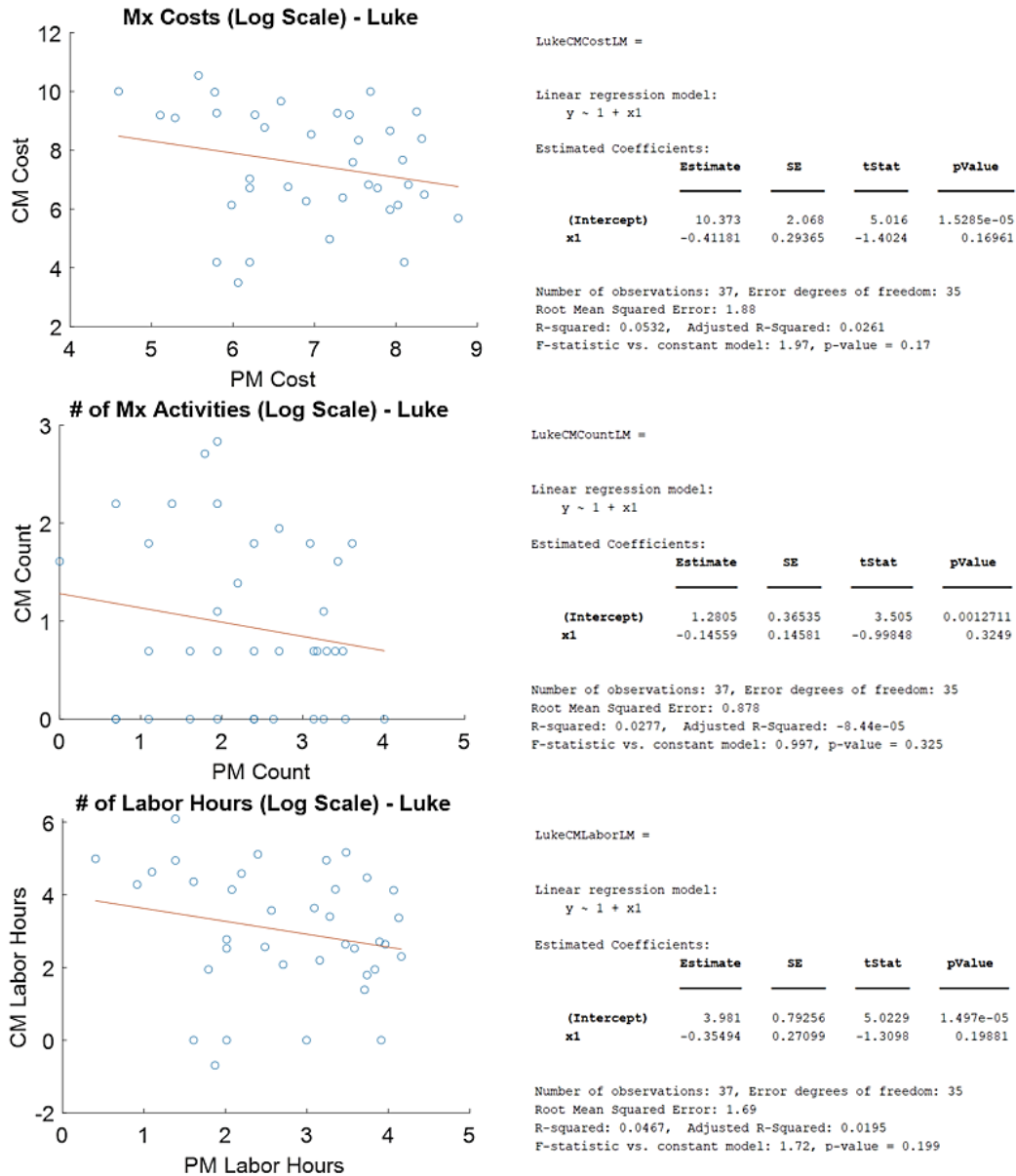


Figure B10.1: Luke AFB Single Linear Regressions

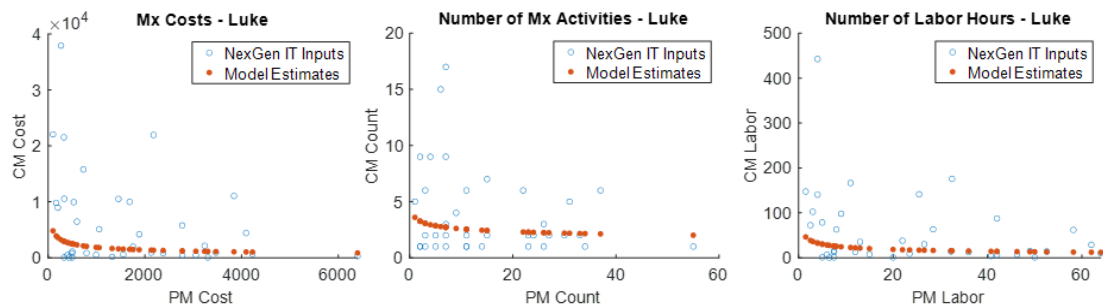


Figure B10.2: Luke AFB Model Framework

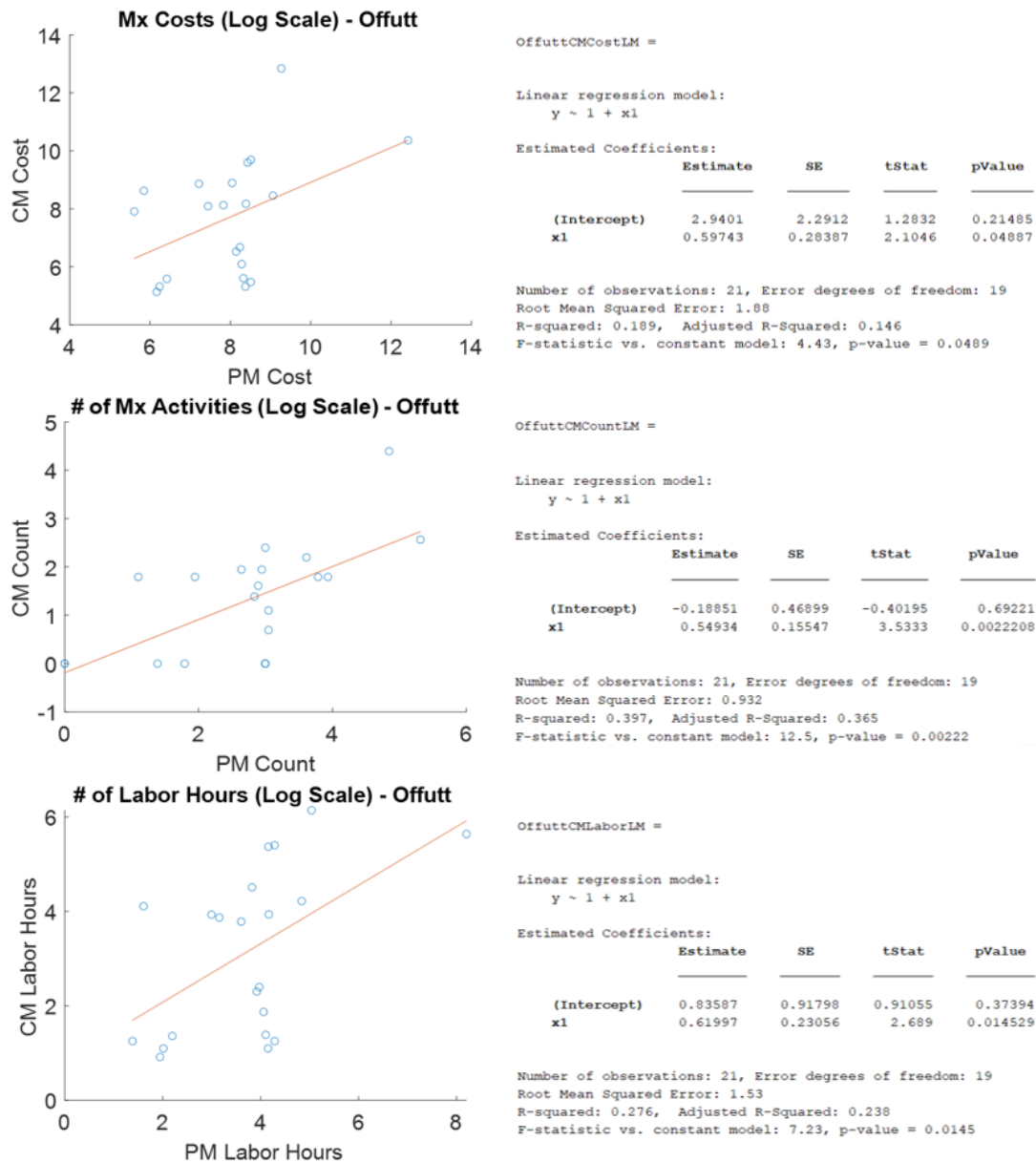


Figure B11.1: Offutt AFB Single Linear Regressions

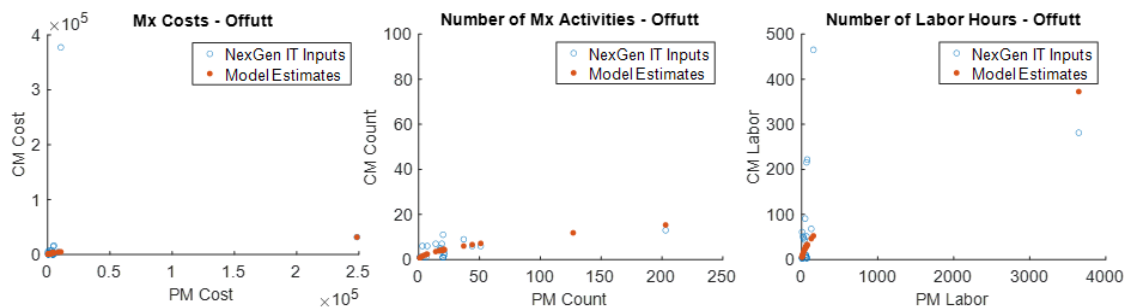
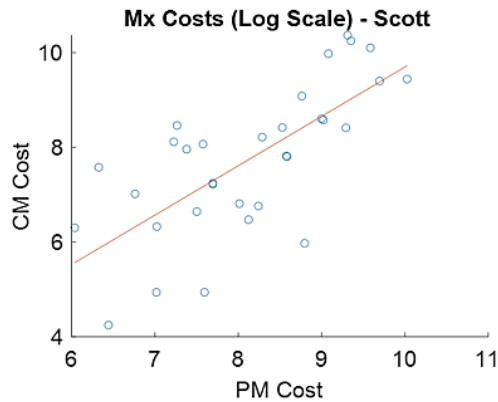


Figure B11.2: Offutt AFB Model Framework



ScottCMCostLM =

Linear regression model:
 $y \sim 1 + x1$

Estimated Coefficients:

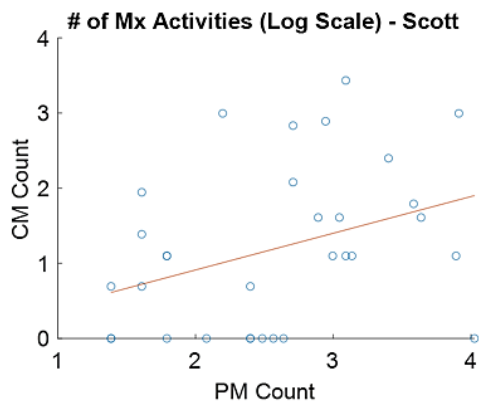
	Estimate	SE	tStat	pValue
(Intercept)	-0.73095	1.5609	-0.46829	0.64296
x1	1.0427	0.19067	5.4685	6.2056e-06

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:
 $y \sim 1 + x1$

Estimated Coefficients:

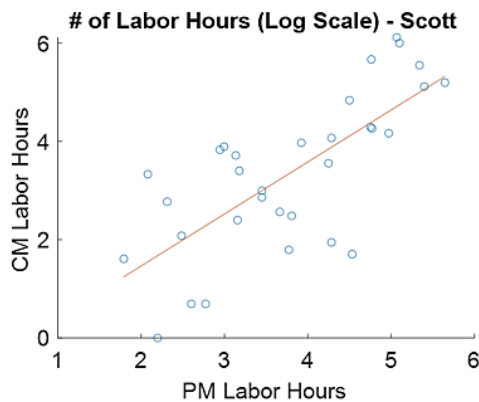
	Estimate	SE	tStat	pValue
(Intercept)	-0.065497	0.62534	-0.10474	0.91728
x1	0.48855	0.23202	2.1057	0.04371

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:
 $y \sim 1 + x1$

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

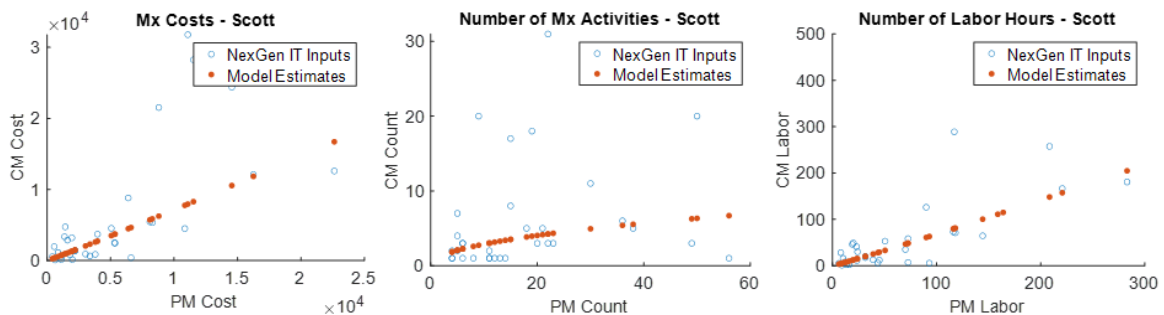


Figure B12.2: Scott AFB Model Framework

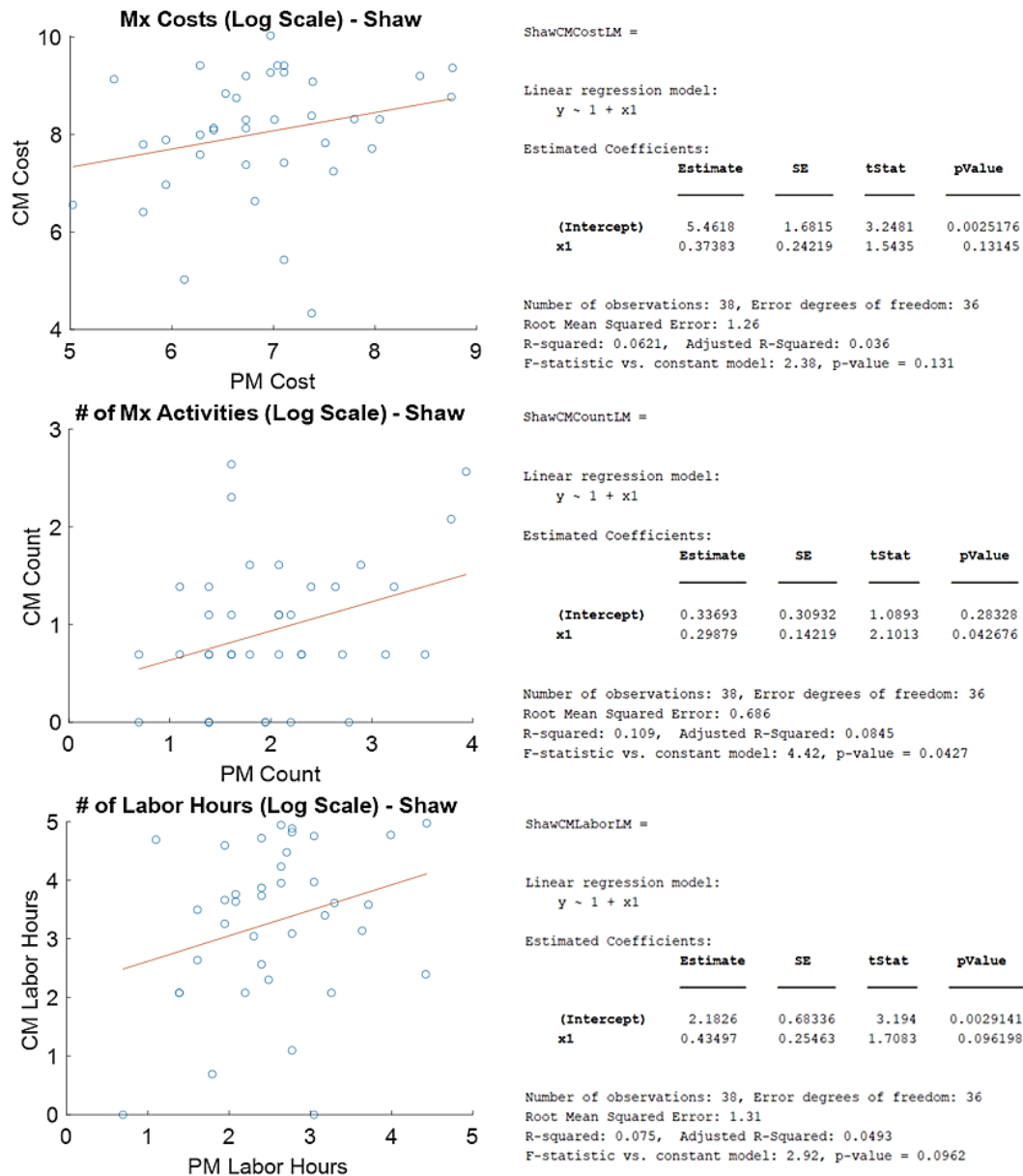


Figure B13.1: Shaw AFB Single Linear Regressions

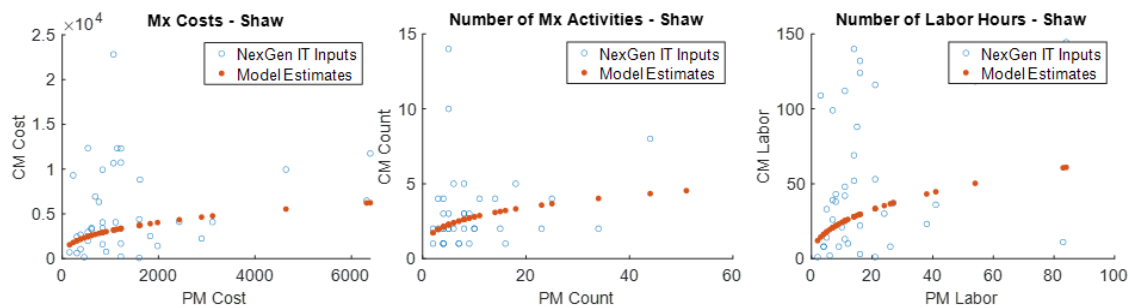


Figure B13.2: Shaw AFB Model Framework

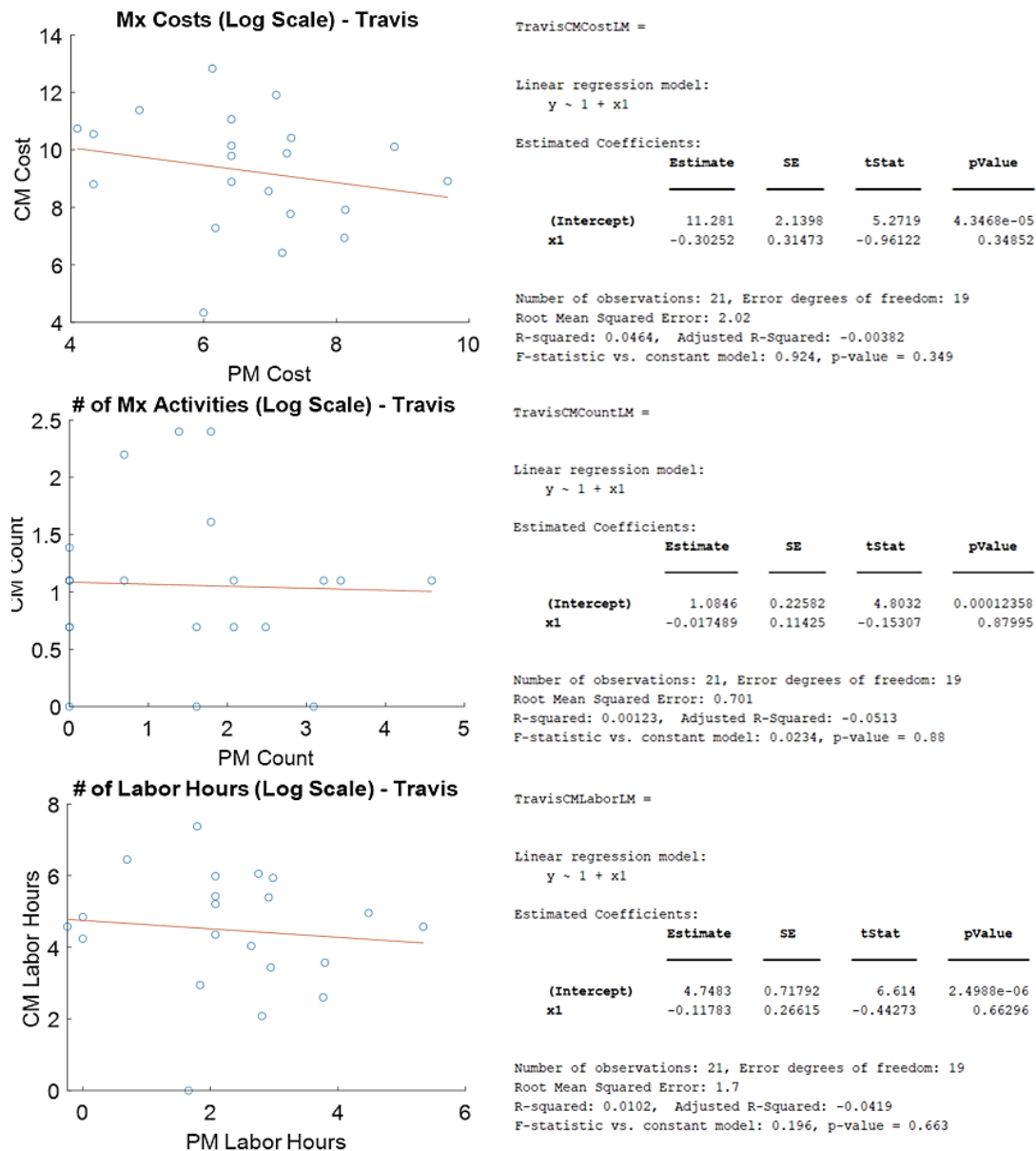


Figure B14.1: Travis AFB Single Linear Regressions

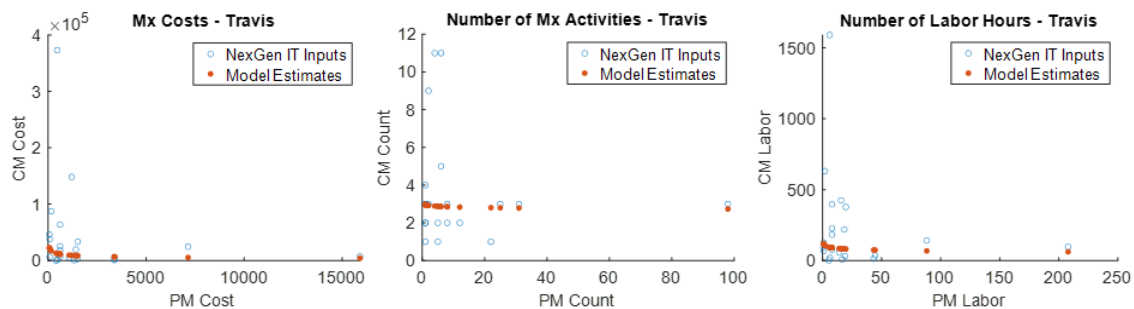


Figure B14.2: Travis AFB Model Framework

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
$p\text{-value} \leq 0.05$	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
$0.05 < p\text{-value} \leq 0.15$	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
$p\text{-value} > 0.15$	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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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:
 $y \sim 1 + x1 + x2 + x3$

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

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

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
		<i>p</i> -value	0.7310	0.2160	0.7680
Cannon	31	Adj. R ²	0.1080	-0.0578	0.1100
		<i>p</i> -value	0.1880	0.6320	0.1850
Columbus	25	Adj. R ²	0.0935	0.1670	-0.1270
		<i>p</i> -value	0.2640	0.1550	0.7650
Dover	59	Adj. R ²	-0.4680	0.0269	-0.0201
		<i>p</i> -value	0.9390	0.2160	0.6050
Edwards	15	Adj. R ²	0.0413	0.5710	-0.4670
		<i>p</i> -value	0.4370	0.0351	0.9420
Ellsworth	71	Adj. R ²	0.0810	0.2700	0.1040
		<i>p</i> -value	0.0747	0.0002	0.0409
Fairchild	49	Adj. R ²	0.0945	0.0474	0.1350
		<i>p</i> -value	0.1150	0.2380	0.0565
FE Warren	37	Adj. R ²	0.1330	0.2010	0.1220
		<i>p</i> -value	0.0908	0.0333	0.1070
Goodfellow	23	Adj. R ²	0.3270	0.0655	0.1740
		<i>p</i> -value	0.0478	0.3300	0.1690
Luke	37	Adj. R ²	0.0668	-0.1220	-0.0034
		<i>p</i> -value	0.2360	0.9060	0.4560
Offutt	21	Adj. R ²	0.6220	0.5140	0.5290
		<i>p</i> -value	0.0019	0.0094	0.0077
Scott	32	Adj. R ²	0.5440	0.4990	0.5250
		<i>p</i> -value	0.0002	0.0005	0.0003
Shaw	38	Adj. R ²	-0.0747	0.1790	-0.0151
		<i>p</i> -value	0.7500	0.0558	0.5020
Travis	21	Adj. R ²	-0.0909	-0.2070	-0.1110
		<i>p</i> -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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:
 $y \sim 1 + x1*x2 + x1*x3 + x2*x3$

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:

$$y \sim 1 + x1*x2 + x1*x3 + x2*x3$$

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:

$$y \sim 1 + x1*x2 + x1*x3 + x2*x3$$

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:

$$y \sim 1 + x1*x2 + x1*x3 + x2*x3$$

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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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.												
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