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Investigating Manufacturer Selection Decisions for Built Infrastructure Assets Using a Technical Performance Metric

Sarah L. Brown

INVESTIGATING MANUFACTURER SELECTION DECISIONS FOR BUILT INFRASTRUCTURE ASSETS USING A TECHNICAL PERFORMANCE METRIC

THESIS

Sarah L. Brown, Captain, USAF
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Sarah L. Brown, BS

Captain, USAF

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Sarah L. Brown, BS

Captain, USAF

Committee Membership:

Maj Justin D. Delorit, PhD, P.E.
Chair

Lt Col Steven J. Schuldt, PhD, P.E.
Member

Dr. Louis B. Bartels, PhD, P.E.
Member

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Abstract

Facility management and built infrastructure asset management are necessary functions of any organization that utilizes buildings to operate and run their businesses. However, most organizations require facility managers to do more with less and ensure the successful operation of their assets without providing sufficient resources to accomplish this task. Therefore, in resource-scarce environments, facility managers require thoughtful and data-driven solutions to manage their assets and make the best decisions for their assets throughout their life cycle. Facility managers need novel solutions to help make these life-cycle decisions. This research provides such a solution. Capitalizing on available data, a technical performance metric is created, allowing facility managers to calculate their assets' operational performance. This performance metric provides a criterion for facility managers to make manufacturer selection decisions: choosing one manufacturer over another and picking the best brand for use in their facilities. The performance metric that informs manufacturer selection decisions provides a basis for making initial procurement decisions, thereby solving one of the life-cycle decisions facility managers must make. The performance metric is calculated utilizing basic attribute and condition assessment data. Leveraging real-world built infrastructure data from the United States Air Force (USAF), case studies are performed to calculate the technical performance of assets, show the utility of an organization making or validating manufacturer selection decisions, and to show the effect of local climate on technical asset performance.

Acknowledgments

I would first like to sincerely thank and express my appreciation for my faculty advisor, Maj Justin Delorit, for all his support throughout this process. I very much appreciate you taking me on as a student and providing mentorship all along the way. My efforts and successes are a direct result of all your guidance and knowledge, and I truly thank you for everything. I want to thank my committee members, Lt Col Steven Schuldt and Dr. Louis Bartels for their time and effort devoted to this process. Next, I would like to thank the team of researchers at the Construction Engineering Research Laboratory of the US Army Corps of Engineers for supporting my research. A big thank you to my classmates who have made this academic journey such an enjoyable one. And finally, I want to thank the village of people who have supported me throughout my life: my friends and family. Most importantly, thank you to my Sisters and Parents; without you, none of this would be possible.

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INVESTIGATING MANUFACTURER SELECTION DECISIONS FOR BUILT INFRASTRUCTURE ASSETS USING A TECHNICAL PERFORMANCE METRIC

I. Introduction

Background

Organizations in all sectors of industry require facilities to house their operations and offer their services. These facilities require built infrastructure assets to ensure their doors can remain open and provide for continued operations. Facility managers who are assigned to maintain and manage built infrastructure assets often operate with scarce budgets and manning, but they must still guarantee the successful operation of these assets. Therefore, facility management is critical to all organizations, and providing innovative solutions to current obstacles in facility management can benefit facility managers and the companies they serve.

The United States Air Force (USAF) is no different from any other organization; it relies on facilities and infrastructure to operate efficiently, successfully, and uninterrupted to provide a power-projection platform to achieve its mission. Air Force Civil Engineers are tasked to manage and maintain that infrastructure. Currently, the USAF has over 128,000 buildings, structures, and horizontal structures in its real property inventory totaling $351 billion in physical assets ("Base Structure Report" 2017). These assets all require careful management and oversight to ensure mission success and continued support of Air Force personnel.

Critical decisions need to be made during the facility management process to manage this large asset inventory successfully. Life cycle decisions like which asset to procure for use in facilities, the frequency and level of rigor at which to maintain assets, and when to make end-of-life-cycle decisions for assets must be made by facility managers. All decisions made throughout the facility management process are paramount for mission success, but the initial procurement decision sets the trajectory and may influence the successful operation of the asset throughout the rest of its lifespan. Civil Engineers should appropriately consider all options when choosing the asset to employ in facilities and consider which asset will provide the best return on investment while ensuring mission success.

Manufacturer selection is the concept of using a selection criterion to choose the manufacturer brand that provides the best operational capabilities when compared to competing manufacturers. Manufacturer selection can provide a means to determine which asset to choose when making initial procurement decisions. Investigation is required to understand how manufacturer selection decisions can be implemented into practice for assets and the practicality of making these decisions across the USAF enterprise. This thesis presents the results of the preliminary analysis into the viability of using Air Force data to make manufacturer selection decisions and what role exogenous factors like the climate may have when making manufacturer selection decisions.

Problem Statement

The Air Force Civil Engineer career field relies on utilizing data to make informed decisions for successfully managing infrastructure and building system assets. Manufacturer selection offers the ability to choose the best product for use in facilities;

however, investigation needs to occur to understand the viability of making manufacturer selection decisions.

Research Objectives

The research objectives for this thesis are:

1. Investigating whether the Air Force Enterprise has sufficient data available to make and validate manufacturer selection decisions.
2. Developing a technical performance metric to quantify the operational performance of built infrastructure assets.
3. Exploring potential climatic influences on the technical performance of built infrastructure assets.

Thesis Organization

This thesis follows a scholarly article format to address the thesis problem statement and achieve the previously mentioned research objectives. Chapters 3 and 4 have been developed as independent academic journal articles. Chapter 2 provides an extensive background into BUILDER™, an Enterprise Asset Management (EAM) system, which provides the case study data for this thesis. In Chapter 3, "Performance-based building system manufacturer selection decision framework for integration into Total Cost of Ownership evaluations," research objectives #1 and #2 will be addressed. This article builds the foundation to investigate the viability of making manufacturer selection decisions in the Air Force. A technical performance metric is developed that uses actual Air Force infrastructure data from BUILDER to illustrate the utility of a technical performance metric to quantify asset performance. This work provides the capability for technical asset performance to be implemented into Total Cost of Ownership (TCO) models to more accurately characterize all costs an asset owner incurs throughout the lifespan of owning assets and provide a criterion to make manufacturer selection decisions. This article is targeted for publication in the *Journal of Performance of Constructed Facilities*, a peer-reviewed American Society of Civil Engineers journal.

Chapter 4, "Evaluating climatic influences on technical performance of built infrastructure assets," addresses research objective #3. This work expands on the development of a technical performance metric to investigate any potential climatic influences on asset performance. Testing four climatic variables, potential correlations will be analyzed to understand any environmental links that might exist between weather variables and asset performance. This article is targeted for publication in the *Journal of Building Engineering*, a peer-reviewed Elsevier journal.

Finally, Chapter 5 provides research conclusions, highlights the significance and contributions of this research, and provides future research recommendations.

II. BUILDER Background

Overview

BUILDER™ Sustainment Management System (SMS) is a type of Enterprise Asset Management (EAM) system that provides a repository for infrastructure and asset data that asset managers rely on to help make data-driven decisions regarding facility management. BUILDER is a web-based program that was developed by the Engineer Research and Development Center (ERDC), which is an engineering and scientific research organization of the U.S. Army Corps of Engineers ("U.S. Army Engineer Research and Development Center, ERDC Overview" 2021). BUILDER provides a solution to track and manage facilities and infrastructure assets and supports facility management decisions related to when, where, and how to best sustain built infrastructure assets to make the best investment decisions ("BUILDER™ SMS" 2012).

History

In response to U.S. Government Accountability Office (GAO) critiques on how the Department of Defense (DoD) was managing their facilities and infrastructure, BUILDER was developed and eventually implemented DoD-wide ("BUILDER™ SMS" 2012). Currently, the DoD has over 270,000 facilities in its real property portfolio valued at $749 billion ("Base Structure Report" 2017). BUILDER provides a solution to manage this vast facility portfolio and provide a level of accountability regarding the condition of facilities and building infrastructure investment that had previously been unavailable. BUILDER is now in use by all branches of the military and other federal, state, local, and private organizations, enabling the ability to track and manage infrastructure assets.

Capabilities & Functionality

Since BUILDER's creation, it has quickly become the industry-leading EAM because of the vast facility management capabilities it offers that allow facility managers to track and manage their assets and provide a predictive capability to plan future investment decisions for assets. BUILDER is structured around the UNIFORMAT II building classification system, which classifies building elements into different categories to group similar structures together (Charette and Marshall 1999). UNIFORMAT II is organized into system, component, and section levels in a hierarchical fashion to group similar elements. Because BUILDER uses UNIFORMAT II, information regarding major systems (like an HVAC system or Plumbing system) within a facility can be tracked, or a facility manager can track individual components (air handlers, boilers, electrical transformers, or chillers). The hierarchical structure of UNIFORMAT II is shown below in (Fig. 1).

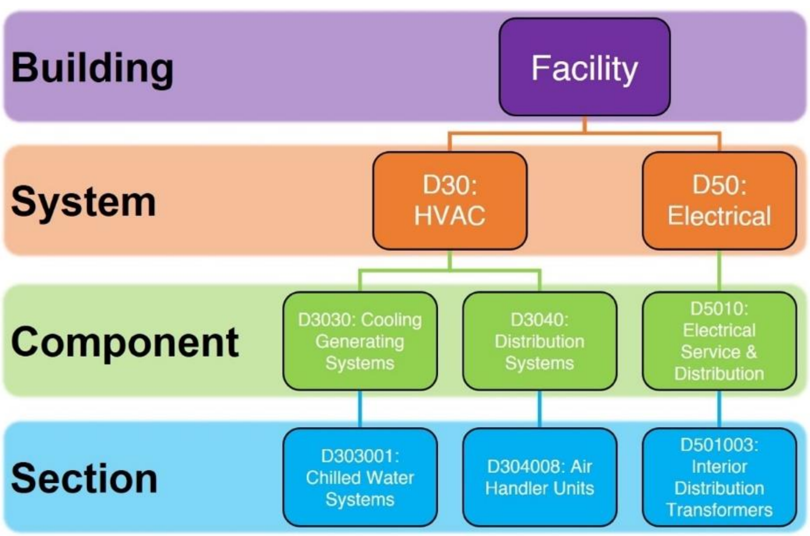

Figure 1. UNIFORMAT II Elemental Structure

BUILDER offers data management services that allow facility managers to store basic attribute data regarding facility assets and condition assessment data garnered from visual inspections. This repository of data enables BUILDER to utilize its built-in algorithms to predict many metrics that are of interest to facility managers. The remaining service life of assets, the predicted condition of assets, and short- and long-term work plans can be suggested to align with facility management decisions that need to be made throughout an asset's life cycle ("BUILDER™ SMS" 2012).

Implementation of BUILDER Data

This research utilizes available BUILDER data from the USAF to build a technical performance metric that allows several hypotheses to be tested. The technical performance metric developed in this research relies on several data fields from BUILDER like the observed condition index, installation date of the asset, manufacturer of the asset, location of the asset, and Remaining Service Life (RSL) of the asset. Observed condition index is the condition index entered from visual inspections by trained assessors, which relays an asset's health. The observed condition index is measured on a 0-100 point scale where a 100 is defined as perfect condition, fully operational, and free from any defects. A rating between 86-100 is considered a good condition in fully operational status. A rating between 71-85 indicates an asset in reduced operational status, and a rating of 70 and below indicates a loss of operational capability for an asset. Installation date indicates the date in which the asset or system was installed and put into operational status. Manufacturer is the company that manufactures the asset that is in use in the facility. The asset's location describes the location relative to the facility the asset serves, either an indoor or an outdoor unit. RSL is an estimate of the useful years of service left for an asset. RSL is measured from the present time until the asset fails and is a dynamic value that is updated upon every assessment of an asset. This research relied on these five data fields; however, BUILDER is a robust program with many different data points available and a plethora of capabilities that help facility managers successfully manage their infrastructure assets.

These BUILDER data fields should all be widely available if careful asset management procedures are implemented for an organization. This research leverages these data parameters to achieve the research objectives laid out in Chapter 1.

III. Performance-Based Building System Manufacturer Selection Decision Framework for Integration into Total Cost of Ownership Evaluations

Abstract

Facility managers are often faced with building system procurement or replacement decisions, which require that they select a system from among competitive manufacturers. Total Cost of Ownership (TCO) criteria, informed by built assets in operation in the manager's portfolio, provides some of the necessary information to select the right asset manufacturer. However, managers must also consider technical performance to complete a more robust and comprehensive analysis. Technical performance can be calculated using asset parameters such as condition, age, and variation in condition to aid in comprehensive TCO assessments. Leveraging past research and approaches, technical asset performance is calculated using an additive model that scales each parameter using a minimum-maximum normalization technique and employs weighting factors to account for decision-maker input. This equation rewards assets that are expected to have longer service lives and provides decision-makers an indication for their portfolio's performance compared against others through the inclusion of variance. Data from 20 Air Force installations across the United States and two asset types are used to show the utility of a performance metric. Overall, this analysis shows that as manufacturer diversity in portfolios decreases, performance increases for most of the asset types modeled. This paper presents new performance metrics that can be used as an additional criterion in TCO models to build a more robust decision framework for a facility management organization of any size.

Introduction

Decision-makers have traditionally faced budgetary and manpower constraints that make it challenging to effectively maintain and repair buildings and infrastructure assets to ensure adequate performance. Yet, data-driven approaches have the potential to improve many facets of the facility management process, including procurement decisions for building-installed equipment and components. For component-level units (e.g. chillers, air handlers, boilers, electrical transformers, etc.) hereafter referred to as assets, investment decisions occur across the asset life cycle, at points of initial procurement, repair and maintenance, and disposal. However, initial procurement decisions may have long-term effects and can set the course of future maintenance and repair frequency and cost. As such, emphasis must be given to asset manufacturer selection, which is defined as the choosing of one asset manufacturer over another, based on some number of selection criteria, e.g., Total Cost of Ownership (TCO) criteria.

TCO is a method to evaluate all costs over an asset's life cycle (Roda and Garetti 2014), including initial procurement, regular operating costs, spare part costs, and corrective maintenance costs. TCO provides a strategy for decision-makers to evaluate their assets (Kappner et al. 2019). Infrastructure system life-cycle costs have been estimated using TCO frameworks for facilities (Grussing 2014), roofing systems (Coffelt and Hendrickson 2010), stormwater systems (Forasté et al. 2015), and pavements (Rehan et al. 2018). These analyses provide an overview of the current body of knowledge regarding the use of life-cycle cost evaluations for infrastructure systems and provide an excellent starting point to detail the costs associated with purchasing and operating infrastructure. However, there is a lack of consideration regarding the performance of assets in the TCO framework (Roda and Garetti 2014; Xu et al. 2012). Roda et al. (2014) aimed to fill this gap through the creation of a performance-driven TCO model for assets in the manufacturing industry (Roda et al. 2020). However, this same methodology has not been applied to building systems or built infrastructure.

This gap in research provides motivation to evaluate building system performance statistics and propose a metric that represents asset performance in competitive markets. Ultimately, a performance-based metric could be a component of the TCO framework that enables the selection of manufacturers that produce the highest performing asset for use in their facilities and not simply those that have the lowest initial cost.

Performance-based manufacturer selection can provide many benefits and efficiencies to facility managers, including the creation of a streamlined and repeatable procurement process, simplification of maintenance through asset standardization, and reduction of the number and diversity of spare parts required to perform preventative and corrective maintenance. Initial procurement decisions can be simplified by directing facility managers to source assets that are required in many facilities, e.g., chillers and air handlers, from a single manufacturer. Procuring assets from a single manufacturer makes the ordering process repeatable, which promotes efficiency and leads to lower initial costs (Lee and Drake 2010). As technicians learn the specifications of one asset manufacturer, they leverage knowledge gained through repetition to reduce time spent on preventative and corrective maintenance activities. Standardizing assets has the advantage of decreasing time and money spent on maintenance (Tavakoli et al. 1989). Spare part management can be simplified through the reduction of the quantity and costs associated with the number of part types stored (McGean 2001; Neelamkavil 2011). In total, manufacturer selection enables facility managers to lower costs and reduce complexity within their asset portfolio.

The concept of performance-based manufacturer selection can apply to many organizational levels and infrastructure portfolio sizes, including academia, medical, government, or large businesses. Though, independent of organizational or portfolio complexity, each facility manager faces the same challenge: to make or recommend decisions that efficiently manage assets. Facility managers in all industry tiers can leverage the benefits of performance-based manufacturer selection to build an inventory of assets that provide the greatest return on investment considering both performance and total life-cycle costs. As outlined above, the efficiencies of a performance-based manufacturer selection approach affect various aspects of the asset life cycle, but they have not been well-described in literature for built infrastructure portfolios. This research expands on the current body of knowledge to consider a performance-based metric to support manufacturer selection decisions and supplement traditional TCO evaluations to increase robustness. In addition, this research develops a novel framework, enabling data-driven manufacturer selection that makes use of actual observed performance data associated with component condition. To develop the data-driven methodology, data were gathered for United States Air Force (USAF) building component assets across 20 separate geographic installations. To demonstrate and validate the approach, this research focused on two types of building components, chillers and air handlers, chosen because they are routinely found in facilities and there are several major manufacturers. Using observed condition, remaining service life, and a location-specific condition variance, a performance metric is developed that provides facility managers a measure of asset performance for use in the manufacturer selection process.

Data & Case Study

Manufacturer selection requires sufficient and appropriate data be collected and available to make thoughtful and accurate performance-based decisions. One critical source of data comes from periodic condition assessments of the asset throughout its life cycle. This condition data must be collected in a standardized and repeatable way, and with some regularity, e.g., during scheduled preventative maintenance, to ensure all condition information is on the same scale and comparable. Other specific asset information must be available, including the installation date, inspection dates, and manufacturer name. Combining this basic attribute data with the observed condition data enables the creation of the performance-based metric to make manufacturer selection decisions. This requires a database or management program to track this asset information. An Enterprise Asset Management (EAM) system provides a repository for this information. BUILDER™ Sustainment Management System (SMS) is the asset management system used for condition assessment and facility management within the Department of Defense (DoD), and it offers the necessary tracking and management features to make manufacturer selection decisions. Additional information on the organization and features of BUILDER has been reviewed in the literature (Bartels et al. 2020; Grussing et al. 2016).

The BUILDER SMS is a DoD-developed facility life-cycle management program used by the entire DoD and other federal, state, local, and private organizations to track and manage infrastructure assets ("BUILDER™ SMS" 2012). BUILDER's purpose is the support of facility management decisions related to when, where, and how to best sustain built infrastructure assets in order to make better investment decisions ("Sustainment Management System" 2020). The SMS program provides a large database of historic asset condition information that can be used to create, validate, and test an asset performance metric. It spans the diverse variety of building system and components, and stores related information including asset installation year, manufacturer, and observed condition state. Asset installation year is the date on which the asset was installed into the facility and first put into operational status. Manufacturer information lists the company that built the asset. Asset condition is measured on a 100-point index scale, which represents the health of an asset. A condition of 100 is considered as-new, free from any defects, distresses, or signs of deterioration, while 0 is complete failure. Condition data is derived from visual inspections performed by trained assessors and condition data is entered into BUILDER either by the assessor or data-entry specialists. Per USAF business rules, all assets must be assessed no less than once every five years, but may be more frequent if completed during recurring preventative maintenance activities.

Data from the USAF and its infrastructure assets are used to build, validate, and verify the use of a performance-based manufacturer selection metric. The data show a variety of manufacturers across USAF buildings for a given asset type. This enables the USAF enterprise to compare the performance of building component assets by manufacturer across all of its operating locations. The performance metric framework presented here is designed to be simple and flexible such that any organization that tracks performance and manufacturer data can reproduce this analysis or include additional decision criteria valued by the organization, such as up-time, service call frequency, etc.

Data Filtering

In line with BUILDER's goals, the data is used to supply information to the performance metric, which may ultimately be used as a component of a TCO manufacturer selection decision model. Before proceeding, SMS data requires initial filtering. While BUILDER provides a wealth of data that can be used to construct a performance-based metric; the raw data requires pre-processing to align the data with the objectives of the metric. The performance metric, described in following Methodology section, is an age-based index that captures asset performance as it degrades between assessments. Because installation and assessment dates vary across assets, the raw data in BUILDER needs to be modified to transform the temporal basis from an absolute date to a relative asset age. All dates are anchored by the asset's installation date, which is a value stored in BUILDER. For example, an asset that was installed on January 1, 2000, and first inspected on January 1, 2005, is 5 years old at the time of inspection. This transformation in temporal scale ensures that assets are being compared against assets of similar ages, and not installation date.

Next, assets were removed from the analysis if the observed condition saw an increase between subsequent inspections. Typically, an increase in condition indicates a repair or overhaul was performed between inspections, and these situations can have an effect on the resulting life-cycle analysis. These assets were removed in order to retain only those assets that were unlikely to have had a repair or overhaul completed between inspections. Retaining assets with a positive change in condition between inspections would be confounding to the calculation of performance metric.

Finally, any assets with an observed condition less than 100 at installation (age equal to zero) were removed. Logically, assets should be brand new, and in perfect condition at the time of installation, so this exclusion criterion is meant to filter out assets that may have been erroneously entered into the database, or assets with initial defects (either due to manufacturing or installation) that would typically be covered during the warranty period. The Air Force does not purchase reconditioned or used assets. The starting data population was 8,579 data points representing all the unique chiller and air handler assets at the selected installations. Initial filtering criteria resulted in reducing the overall data population by 18% (1,582 assets were removed). Once initial data filtering is performed, condition as a function of age can be observed, though it does not provide a complete picture of asset performance (Fig. 2).

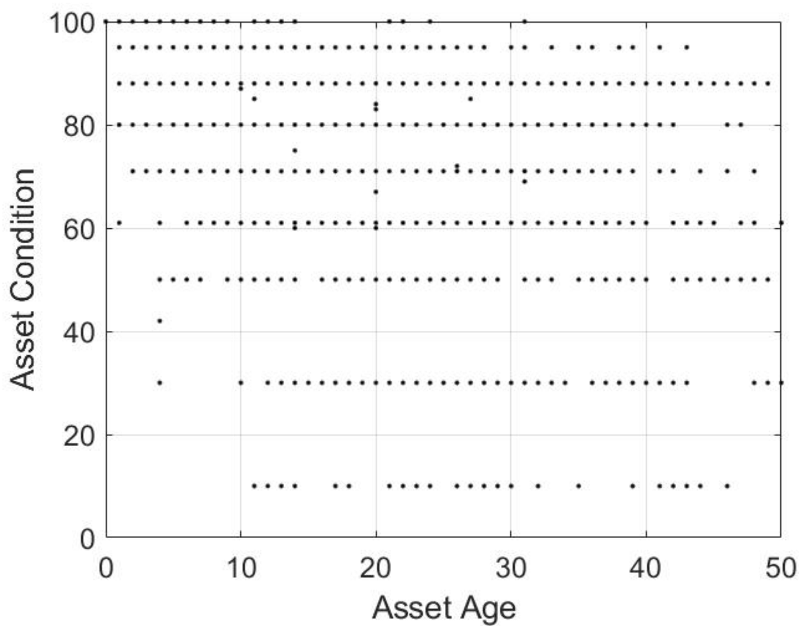

Figure 2. Example of Asset Age versus Condition

Asset and Location Selection

The United States Air Force has a long history of recording and tracking its asset condition data in BUILDER (11 years of condition assessment data). Data from 20 Air Force installations were included in this analysis, with installations drawn from across the contiguous United States (Fig. 3). These installations are all spatially dispersed within the U.S., to provide a representative sample from the approximately 60 active-duty Air Force installations. These installations were selected to represent various mission sets within the Air Force, as to not bias the analysis toward one particular function, e.g., mobility versus fighter aircraft missions. The 20 installations represent a sampling of 1,631 individual facilities and include 35% of the total chillers in the Air Force and 33% of all air handlers in Air Force inventory within the contiguous U.S.

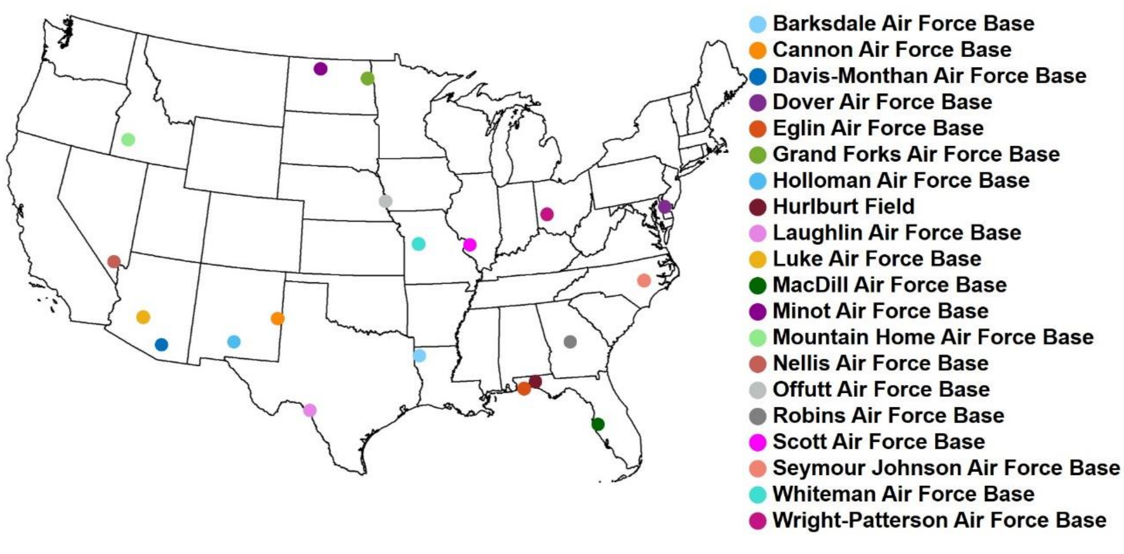

Figure 3. Location of USAF Installations

For this research, air handler and chiller asset types were chosen because they represent assets that require a large initial investment, have several major competitive manufacturers, have moderate service lives (about 20 years for chillers, and 24 years for air handlers), and are complex enough to have multiple parts that combine to generate condition changes over their lifespan. For chillers, two manufacturers are compared, which include a total of 991 units across the 20 Air Force installations considered in this work. While there are many major manufacturers for chiller units, the two most common across the 20 installations were chosen that represent 46% of all chillers at these installations. There is a large diversity in chillers, both in terms of location (indoor and outdoor) and size (20 ton - 1,500 ton). For air handlers, three manufacturers are included in the analysis, which produces 2,763 individual units. These three manufacturers represent 43% of the total air handlers at the selected installations. Again, both indoor and outdoor air handlers are included, and units ranging from 2,000 Cubic Feet per Minute (CFM) to 75,000 CFM are included. The goal of this study is to show the use of a performance-based metric to make manufacturer selection decisions. As such, manufacturer names are unimportant and are removed from the presentation of the results to avoid any endorsement of one manufacturer over another. However, each manufacturer is prevalent in the United States and the international market. The chosen manufacturers of this analysis represent roughly half of all assets at each installation, but the distributions do equal 100% of units within that installation's portfolio. There were some manufacturers that represent only a small percentage of assets at an installation, as well as manufacturers that are only regionally available which would not be suitable for manufacturer selection decisions at a national level for an organization like the USAF. Despite distributions not including all assets at an installation, this selection of manufacturers captures the dominant manufacturers at each location.

Sufficient data must be available for an organization's assets to reproduce the performance metric as laid out in this paper. As such, asset owners should ensure that manufacturer data and asset condition data are properly tracked and maintained. For this study, assets with incomplete or obviously erroneous manufacturer or inspection data were excluded from this analysis. The exclusion of assets without manufacturer information resulted in reducing available data points by 38% (3,243 assets are removed) producing the final data count of 3,754 assets for analysis. If organizations take care to record all metadata for their built infrastructure assets, they will increase the pool of available data to use in an analysis such as this.

Methodology

This study produces a metric that measures the technical performance of an asset, which can be used to guide manufacturer selection decisions. The performance metric developed in this work is based on asset condition at the time of inspection, remaining service life, and the total variation in asset condition compared to similar assets. It provides decision-makers a basis of comparison for determining which assets are performing better than another. As previously stated, this performance metric provides a quantification of the technical performance of an asset, which can be used as a criterion in a TCO evaluation (Fig. 4). The performance metric, if valued meaningfully as compared with cost of ownership criteria, could be used to strengthen or change manufacturer selection decisions.

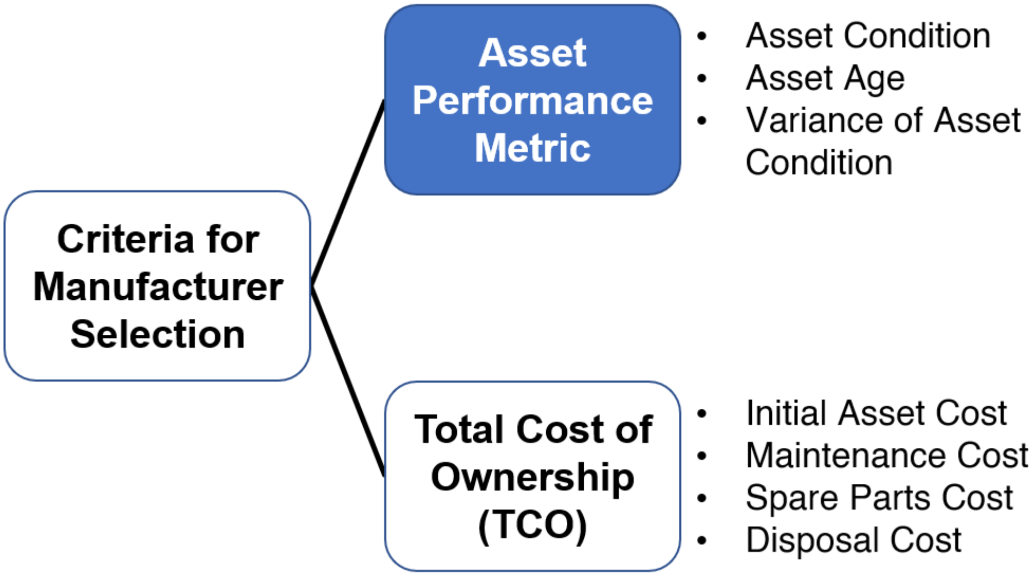

Figure 4. Framework Diagram for Manufacturer Selection

To create the performance metric, an equation following a weighted sum model approach is adopted. The weighted sum model enables decision-makers to select the equation parameters that are most important by varying the corresponding weights. Equation 1 below shows the performance metric equation that is used in this analysis.

$$\boldsymbol{Performance} = (w_i \times \boldsymbol{Condition_{scaled}}) + (w_i \times \boldsymbol{RSL_{scaled}}) + (w_i \times [\mathbf{1} - \boldsymbol{RMSE_{scaled}}]) \quad (1)$$

A performance metric value of one (1) indicates the highest performance compared to like assets, and zero (0) is the lowest performance when compared to like assets. Using a minimum-maximum normalization technique, each parameter of the performance metric is scaled. For each case, a parameter value of one (1) indicates the highest value within the dataset, and a zero (0) indicates the lowest value within that dataset for that parameter. A zero value does not indicate absolute zero, but simply represents the minimum value within that dataset. The minimum-maximum normalization is a standard method of scaling where each value is transformed to a number relative to its distance from the minimum and maximum values within the dataset. All values for each parameter are scaled prior to final calculation of the performance metric. The implementation of the weighting factors attached to each parameter in the equation results in the summative performance metric being a value between zero (0) and one (1).

This equation uses three data parameters to describe the technical performance of an asset at a point in time. $Condition_{scaled}$ is the observed condition of the asset, which is converted from the raw condition assessment (0-100), and is obtained directly from the BUILDER database.

RSL_{scaled} is a measure of the remaining service life (RSL) and is the number of years remaining until the component is expected to fail and need replacement. RSL is a value taken directly from BUILDER and it is based on the BUILDER degradation curve, adjusted for past inspection observations. This means that RSL is dynamic to adjust to how the asset is actually performing, if the asset is degrading faster than originally expected the RSL value will decrease. It is also scaled to a number between zero and one. This parameter provides for a measure of asset age that rewards assets that have more years of useful service life left rather than those that are expected to fail sooner.

$RMSE_{scaled}$ provides for a consideration of condition variance, representing the total variation in the condition of assets at one location, when compared to the average condition of all assets within the analysis. Root-Mean-Square Error (RMSE) is a measure of variability and utilized for this analysis. A higher RMSE value indicates large variation, and a smaller value indicates a lower variation. Computing software is used to calculate the RMSE of each manufacturer's assets at a location compared to the entirety of that brand of manufacturer's assets in the analysis. So, there will be one value of RMSE for each manufacturer at each location, this value is calculated based on the comparison of assets of similar ages. RMSE is also scaled to a value between zero and one. The scaled RMSE value is subtracted from one to allow for assets with conditions closer to the mean to have a greater influence than assets that have a high degree of difference from the mean condition. Ultimately, facility managers should value assets that perform consistently, as this enables more skillful forecasting of maintenance, repair, and replacement. Because condition variation is measured for a location's assets against all assets in the inventory, a manufacturer's variation parameter will be the same for all assets at one location.

As previously stated, the calculation of performance metric also includes weighting factors that allow for decision-maker input to indicate which of the three parameters is the most important for decision-making: condition, age, or variability. Each parameter has a weighting factor, which is some fraction of one, and all weighting factors must be greater than or equal to zero $(w_i \geq 0)$ and sum to one $(\sum w_i = 1)$. For example, a decision-maker may decide that condition and variability in condition are paramount and give them weighting factors of 0.4 and 0.4, respectively, which leaves age to have a weighting factor of 0.2. For the analyses in this study, all weighting factors were set to equal weights $(w_i = 0.333)$.

Table 1 shows the example calculation of performance metric for three air handler assets, of different manufacturers at one location. These three assets are example units and the result of the scaling operation to each parameter comes from a larger subset of data (within the specific manufacturer brand at the location, the result of those operations are shown here). Each parameter of the performance metric calculation is shown in a column with the actual value and in parenthesis the scaled value after the minimum-maximum normalization operation. The final column represents the calculated performance metric for the asset. This example shows that asset 2 has the highest performance metric since it is in the best condition relative to the other two assets and has the most anticipated years of service life left. Asset 2 has the best value for variability meaning its condition is most similar to the average condition for similar assets; however, a lower condition and RSL result in a lower performance metric for asset 2. Finally, asset 3 is in very poor condition, has a high variability value and only one year left of anticipated service life, therefore, asset 3 has the lowest performance metric value of the three assets.

Table 1. Example Calculation of Performance Metric

Asset	**Asset Condition** $Condition,$ $(Condition_{scaled})$	**Remaining Service Life** $RSL,\ (RSL_{scaled})$	**Variability in Asset Condition** $RMSE, (1 - RMSE_{scaled})$	**Performance Metric**
1	80 (0.4872)	4 (0.1600)	8.8357 (0.8662)	0.5045
2	88 (0.7941)	7 (0.7500)	10.9868 (0.7853)	0.7765
3	61 (0.2444)	1 (0.0769)	10.2158 (0.6940)	0.3384

Results

Boxplots illustrate the performance of assets, for each Air Force installation, between the 25th and 75th percentiles (Fig. 5). The markers represent median asset performance. The figure columns represent the two asset types, chillers (left) and air handlers (right). The plots in each column represent the manufacturers (two for chillers and three for air handlers). Each plot includes the percent distribution on the horizontal axis, which is the percentage of a particular manufacturer each installation has in its inventory. The performance metric is shown on the vertical axis. The average performance within each manufacturer category is shown by the horizontal dotted line on each plot. This value represents the average performance of a manufacturer across the selected installations. Using the average value of the performance metric at each installation, a line of best fit, which is represented by green and red dashed lines, illustrates whether there is a relationship between performance and manufacturer consistency across installations. For most assets and manufacturers presented here, there is a positive relationship (green dashed line). This suggests that organic manufacturer selection, whether purposeful or not, results in increased asset performance at that installation. For example, Manufacturer A for air handlers shows a positive trend in performance metric, increasing from 0.43 to 0.65 as percent distribution increases. This positive trend suggests that increasing the amount of one manufacturer in an installation's portfolio has a positive effect on the performance of those assets. Overall, these best fit lines have low correlation values, so they do not provide statistically significant results, but they do illustrate a general trend in the relationship between percent distribution and asset performance. This increase in performance may be due to the efficiency gained by technicians maintaining a less diverse pool of assets. The trendlines point to some of the benefits of manufacturer selection addressed in the Introduction section.

For chiller units, the boxplots show that Manufacturer A has an average performance metric of 0.61, and Manufacturer B has an average performance metric of

0.59. Chiller units have percent distribution values between 2.08% and 63.53%. For air handlers, boxplots show that Manufacturer A has an average performance metric of 0.56, Manufacturer B has an average performance metric of 0.59, and Manufacturer C has an average performance metric of 0.52. Air handler units have percent distribution values range between 0.76% and 33.74%. Boxplots provide a summary figure for facility managers to make manufacturer selection decisions at the installation-level. Installations can compute the performance metric for all their assets of varying manufacturers to identify whether there is a manufacturer that provides higher performance at their installation over another. This information can aid in manufacturer selection decisions.

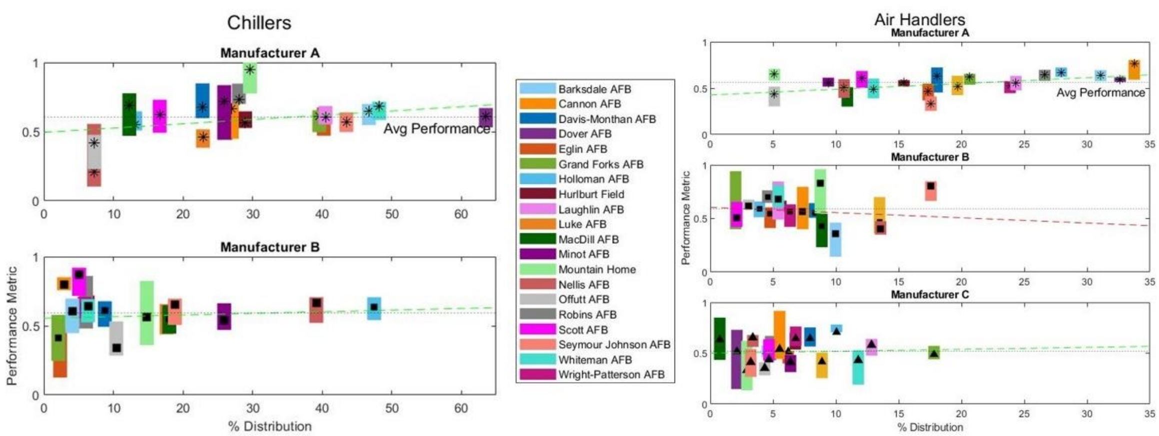

Figure 5. Location-specific Performance Metric Plots

Bi-directional boxplots, which are similar to rangefinder plots, combine the installation-level performance and percent distribution metrics to more concisely display manufacturer performance (Fig. 6). These boxplots provide an overview of how a manufacturer performs across all Air Force installations compared to another and could provide a useful framework for an organization with multiple operating locations to make enterprise-level decisions. These boxplots show that for chiller units, the performance metric of Manufacturer A ranges between 0.00 and 1.00, but 50% of the assets have performances that fall between 0.48 and 0.69. Manufacturer B has a slightly smaller range of performance (0.00 - 0.94), though its interquartile range is the same as Manufacturer A, falling between 0.48 and 0.69. For air handlers, Manufacturer A has a range of performance metric between 0.01 and 1.00, with the majority of the assets falling between 0.47 and 0.65. Manufacturer B of air handlers has a performance between 0.01 and 0.96, with 50% of the assets ranging between 0.40 and 0.68. Manufacturer C of air handlers has a range of performance metrics between 0.00 and 0.97 but the majority of the data falls between the values of 0.42 and 0.65. The air handler analysis shows that the average performance metric of Manufacturer A is very similar to Manufacturer B and Manufacturer C. Given the relative performance similarity between all manufacturers, the enterprise may allow facility managers to select whichever manufacturer provides the highest performance at their individual locations. The bi-directional boxplots provide a useful validation tool for enterprise-wide decisions that may not be as apparent on the location-specific boxplots (Fig. 5). However, the bi-directional plots do lose the visualization of any trends in the data for performance metric and percent distribution across installations. An enterprise-level facility manager could employ this tool to validate manufacturer selection decisions made by spatially distributed operating locations.

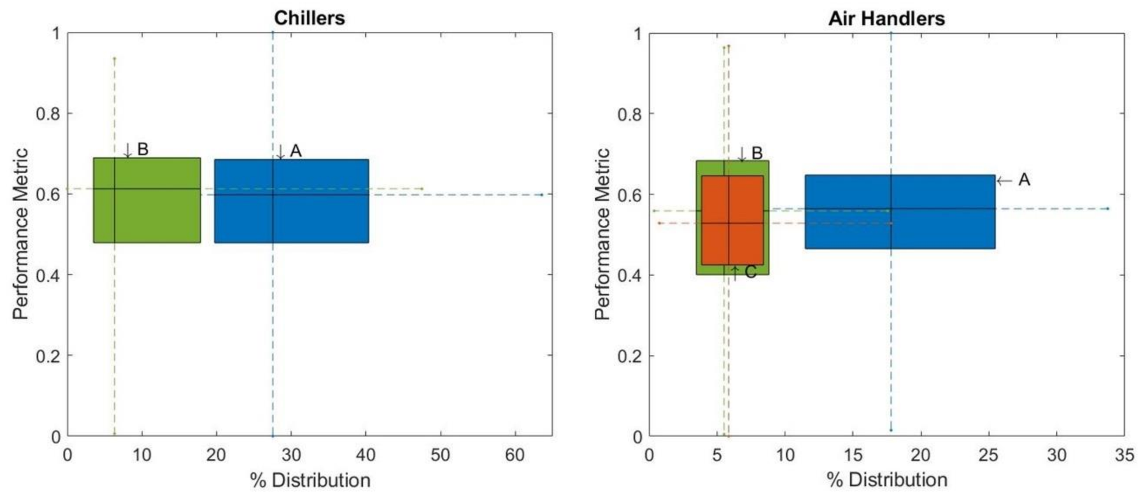

Figure 6. Bi-directional Manufacturer Plots for Performance Metric

Discussion

The results presented in the previous Results section illustrate the utility of a metric targeted to evaluate the technical performance of assets, in order to augment, make, and validate manufacturer selection decisions. Facility managers at individual locations can use the results of the location-specific performance metric analysis (Fig. 5) to compare which manufacturer provides the best technical performance at their location and make procurement decisions accordingly. If the analysis shows that the manufacturer they are most heavily invested in provides the best performance, then they can continue to invest in that manufacturer brand. If the location-specific boxplots show that better performance is achieved by a manufacturer that they currently are not heavily invested in, then the facility managers can use that analysis as rationale to switch manufacturers when procuring new assets.

The bi-directional boxplots provide oversight for enterprise-level facility managers and show the overall manufacturer portfolio at all operating locations. This tool allows them to validate manufacturer selection decisions that are made at lower tiers of their organization. It provides them a tool to see which manufacturer brands their locations are most heavily invested in and whether those are good investment choices based on the performance metric. In the case of the 20 Air Force installations analyzed in this study, the bi-directional boxplots show that overall, enterprise-level decisions should not be made to only choose one manufacturer. For this case, the average performance metrics of all manufacturers are similar enough that directing installations to choose one manufacturer over another does not make sense. Enterprise-level facility mangers could use the location-specific performance metric analysis to help bases validate their choice for manufacturers. For example, if a location chooses to proceed with the procurement of a particular asset manufacturer, but the data shows that manufacturer does not provide a higher performance than another, an enterprise-wide facility manager could choose to redirect the location to choose a manufacturer that does provide higher performance. An example of this redirection is when comparing the performance of air handlers at two Air Force installations (Fig. 7a). This plot shows that at each installation there is a manufacturer that provides higher performance when compared to other manufacturers. For Barksdale Air Force Base, LA, Manufacturer A provides higher performance than Manufacturer B & C. For Seymour Johnson Air Force Base, NC, Manufacturer B provides higher performance than that of Manufacturer A & C. Even though Manufacturer A & B have the same investment rate in terms of the percent distribution, Manufacturer B provides greater performance than that of Manufacturer A and shows a clear choice in which manufacturer to select. These distinctions between which manufacturer is superior makes selection clear at the installation-level. However, if Barksdale Air Force Base were to choose Manufacturer B for future manufacturer selection decisions, an enterprise-wide facility manager could use this tool to show the installation the data that proves that their assets that are Manufacturer B do not perform as well as Manufacturer A, and therefore they should continue to invest in Manufacturer A. At Seymour Johnson, the installation can use the data to see that while Manufacturer B provides a higher performance, their portfolio is split between Manufacturer B and Manufacturer A. Decision makers could use the data to decide that as their assets that are of Manufacturer A reach the end of their service life, they be replaced with those of Manufacturer B.

This analysis provides the tools to help decision makers at both a local-installation level as well as an enterprise-wide level to aid in decision-making. Additionally, the previous example also points out that each of these two installations reaches separate conclusions as to which air handler brand to select, either Manufacturer A or Manufacturer B. The bi-directional boxplot for air handlers (Fig. 6b), show relatively equal performance from each of these manufacturers, so this shows more evidence that for the Air Force, there should not be an enterprise-wide decision for manufacturer selection of air handlers.

Additionally, this tool aids in decision-making that is helpful to make and validate manufacturer selection decisions. This analysis provides a measure of technical performance not previously described in the literature for building systems and built infrastructure that can be included in TCO calculations. And while this novel approach solves a problem for facility managers, technical performance alone does not provide the only means of comparison when selecting an asset. The technical performance analysis allows facility managers to see which manufacturer brand provides the highest performance for their assets, but it does not speak to the costs related to purchasing and maintaining an asset. Technical performance needs to be factored into a TCO assessment so total costs, as well as technical performance, can be considered when facility managers make initial procurement decisions.

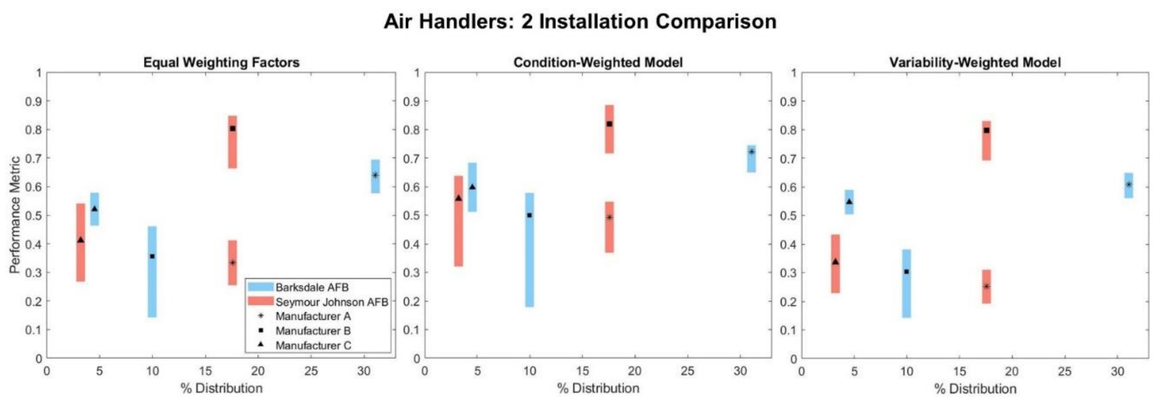

Figure 7. Boxplots of 2 Base Analysis for Performance Metric

As previously stated, the weighting factors that are included in the performance metric calculation provide the opportunity for decision-makers to decide which of the three parameters are the most important when calculating the technical performance of assets. These weighting factors can be varied to provide a customized formula for performance metric, that is tailored to the preferences of the decision-maker. Varying the weighting factors to create a condition-weighted model (Fig. 7b) or a variability-weighted model (Fig. 7c) show the effects each parameter has on the performance metric. These two examples display the same data as the equal weighting factors model (Fig. 7a) with the only change being the weights used for calculation in the performance metric equation. The condition-weighted model more heavily weights the condition of the asset ($w_i = 0.50$), and the age and variability parameters are equally weighted ($w_i = 0.25$). In the variability-weighted model, the variation in condition is more heavily weighted ($w_i = 0.50$) and the condition and age parameters are equally weighted ($w_i = 0.25$). These shifts in the weighting of parameters show the effect that decision-maker preference may have on the outcome of a manufacturer selection decision. Overall, the decision as to which manufacturer to select does not change, but the variability-weighted model has tighter spreads of performance metric which may help make the best manufacturer become more evident. Additional parameters could also be added into this performance metric calculation, such as the frequency of preventative maintenance required, which would capture how often technicians need to attend to the asset to keep it in good working condition. The likelihood of corrective maintenance could also be factored into the calculation of performance metric to describe what the probability is of an asset needing a major repair to keep it in good condition. To qualify if an asset is over- or under-performing relative to its expectation, a ratio of the RSL to the remaining years left based on original design life could be added as an additional parameter. Because RSL changes depending on the condition of the asset at each assessment, if the assessment shows the asset is degrading quicker than expectation the RSL will shorten to a value smaller than the years left based on original design life. This ratio would provide an indication if the asset is doing better or worse than expected relative to its age. These additional parameters would also include weighting factors to allow the decision-maker influence over the fraction of performance metric that is attributed to each parameter. The equation developed here to calculate the performance of assets shows it can be used to make and validate manufacturer selection decisions, though the performance metric framework is flexible and customizable to allow for additional parameters to be added and weighting factors to be optimized to the decision-maker's preference.

While the framework has been developed so that it is flexible such that facility managers and decision makers can tailor it to meet their needs, the parameterization presented here does provide value in its current form. The inclusion of asset condition, remaining service life, and variability in asset condition describe major considerations for facility managers to consider. Asset condition depicts current operating efficiencies (or lack thereof) of assets, remaining service life quantifies how far into an asset's useful service life it currently is, and variability in asset condition provides a measure of consistency for facility managers to understand if this asset will perform similarly to other assets. These parameters capture what are likely the most important data points for decision makers to consider when making initial procurement decisions. So, while the framework itself is flexible, this analysis has dialed into useful parameters that provide facility managers a way to make manufacturer selection decisions based on asset condition that is service life and variance-informed.

In addition to the utility of developing a technical performance metric, this analysis also underscores the general benefits of collecting and maintaining built infrastructure data. Collecting data enables facility managers to leverage data to make sound decisions that benefit their organizations. Whether facility managers need to decide which maintenance regiment to implement for their asset portfolios, or which asset to select when building their portfolios, data provides a tool to enable sound decision making. This study focuses on Air Force data that highlights, with just 11 years of condition assessment data, how a performance metric can be calculated enabling a determination, at multiple levels, of the technical performance of assets in order to make manufacturer selection decisions.

One potential obstacle of using this technical performance metric to make and validate manufacturer selection decisions is overcoming the lack of data for new technologies and new manufacturers that become available in the future. This methodology is predicated on using historical data from manufacturers to quantify the performance of their assets, and without data facility managers are unable to calculate the performance of newer manufacturers that they have not invested in. Additionally, this proposed implementation of making performance-based manufacturer selection decisions does not safeguard against one manufacturer having a monopoly over all assets in a portfolio and subsequently reducing their effort to deliver high performing assets. If a location solely invests in one manufacturer after completing this analysis they have no point of comparison for those assets against any other manufacturer, nor does that manufacturer have incentive to provide for sustained performance of those assets. Overall, both of these points are legitimate concerns for facility managers, but the authors believe the benefits of a performance-based manufacturer selection outweigh no selection criteria as the alternative.

This analysis includes asset data from 20 Air Force installations that were spatially distributed across the contiguous United States. These installations are located in different climate zones that are subjected to varying amounts and extremes of climate variables like temperature, rainfall, humidity, and solar irradiance. Also, indoor and outdoor chillers and air handlers were included, which have different levels of climatic exposure depending on their location. Climate variables may play a role in asset condition and ultimately affect asset performance, which could be investigated by analyzing any trends in performance across climate zones. Further research could be carried out to analyze any possible influences of climatic conditions on asset performance. This level of analysis may lead to conclusions on manufacturer performance in a particular climate zone.

Conclusion

Analyzing the technical performance of assets offers a data-driven solution to provide facility managers at all levels of infrastructure management the analytical tools to make and validate performance-based manufacturer selection decisions. The measurement of the technical performance of assets shows the utility of a metric to assess the technical aspects of an asset. As research points out, this technical performance has not widely been included in TCO evaluations, which is a limiting factor of TCO models. Without any consideration for technical performance of assets, TCO evaluations miss the opportunity to capture the operational capabilities of assets. Ultimately, a performance-based metric should be incorporated as a criterion in Total Cost of Ownership assessments (Fig. 4).

Using asset condition, a measure of remaining asset service life, and variation in asset condition, a performance metric is created to assess the technical performance of an asset. Using condition data collected on thousands of Air Force buildings, performance metrics are calculated for each asset type and bi-directional boxplots are used to visualize the results. The performance metric of chillers and air handlers at 20 different Air Force installations show how different levels of asset management can utilize this analysis to make manufacturer selection decisions. The multi-level analysis shows the utility for different levels of organizations, local installation-levels that are managing assets day-to-day, as well as enterprise-level management that oversees the operation of several locations. The location-specific boxplots as well as bi-directional boxplots highlight the benefit of performance metric calculation to make manufacturer selection decisions at many tiers of an organization. The equation for performance metric is customizable with the use of weighting factors that allow for decision-maker preference in which asset parameter should carry the most weight for technical performance. Additional parameters can also be included in the calculation to account for other asset-related variables depending on the goal of decision-makers.

Future research should implement the technical performance of assets into a Total Cost of Ownership model to capture all asset costs over their life cycle. With the addition of initial procurement, maintenance, and repair costs, the performance can be added to aid decision-makers in choosing the right asset for their inventory. Performance is one aspect of the Total Cost of Ownership, but combining it with other costs provides a holistic assessment of all costs incurred over the lifespan of an asset.

Technical Performance analysis provides a starting point for manufacturer selection decisions and enables facility managers to choose the brand of manufacturer that offers the highest technical performance. This methodology can empower facility managers in all industries and at all echelons of built asset management the solution to choose the right manufacturer for their portfolio.

IV. Evaluating Climatic Influences on Technical Performance of Built Infrastructure Assets

Abstract

Facility managers are tasked with making efficient and cost-effective investment decisions to maximize asset life-cycle performance. Evaluating technical asset performance provides a benchmark for facility managers to understand their assets' operational capabilities and current performance. Integrating a technical performance metric into Total Cost of Ownership (TCO) models provides a holistic picture of the operational efficiencies of assets in addition to the economic burden of owning these assets. This criterion can be used to make asset manufacturer selection decisions, i.e., choosing the brand of manufacturer that provides the highest performance amongst all brand competitors. Understanding the environmental conditions to which assets are subjected provides facility managers another data point to understand asset performance. This research builds upon previous work that established a performance-based manufacturer selection metric by investigating the linkages between asset performance and exposure to local climate. Built infrastructure data from 20 Air Force installations from across the United States is used to calculate chillers and air handlers' technical performance. The link between observations of Heating Degree Days (HDD), Cooling Degree Days (CDD), Solar Irradiance, and the number of Humidity days above 55% relative humidity from weather stations nearest installations and asset performance is investigated using Analysis of Variance (ANOVA) testing, and correlation coefficients. The analysis shows a link between asset performance and exposure to climate; most assets in each climate zone had

a moderate to strong relationship between their performance and cumulative climate exposure. The ANOVA testing showed that climate zone and asset manufacturer do influence the performance of assets. Ultimately, facility managers should implement technical performance metrics as a consideration for TCO models, and understanding the influence of climate on technical performance is an important step.

Introduction

Facility managers overseeing the operation and sustainment of built infrastructure assets are tasked to make data-driven decisions throughout the life cycle of assets, often in resource-scarce environments. These decisions begin with selecting an asset to purchase from a manufacturer for use in their facility. This decision is made with expectations about the asset's performance and longevity. Additional consideration must be given as to the frequency and robustness of a preventative and corrective maintenance program. Throughout the asset's life cycle, facility managers continue to make decisions up until disposal, at which time they need to replace the asset entirely. All of these decisions and associated costs can be evaluated using Total Cost of Ownership (TCO) models, which calculate all costs incurred by owners of any physical assets over the asset's lifespan (Durán et al. 2016).

TCO models have been reviewed widely in literature, and they are used extensively by facility managers to understand all costs related to owning assets. Various infrastructure system costs have been evaluated through a TCO framework, including facilities, roofing systems, stormwater systems, and pavements (Coffelt and Hendrickson 2010; Forasté et al. 2015; Grussing 2014; Rehan et al. 2018). Performing a TCO evaluation enables facility managers to understand the true cost of owning and operating an asset and provide a point of comparison if facility managers employ different asset manufacturers for use in their portfolios. Comparing different asset manufacturers allows facility managers to employ the best performing asset in their inventory that provides the best return on investment when considering all costs. However, most TCO models do not consider asset performance in the cost analysis (Roda and Garetti 2014). Failing to consider asset performance leaves facility managers with an incomplete understanding of total costs for assets, e.g., the least expensive asset may not provide the highest performance.

Efforts in the manufacturing industry have been made to include asset performance as a TCO model factor (Roda et al. 2020). Using this research as a guide, modeling of technical performance of built infrastructure assets to aid in manufacturer selection decisions has been completed (Brown et al. 2021). Manufacturer selection is the idea of choosing one manufacturer over another based on some number of selection criteria, which can be factored into TCO models. To calculate asset performance, a technical performance metric has been created that utilizes built infrastructure data such as asset condition, remaining asset service life, and variation in asset condition from similar assets to quantify the performance of assets.

These recent contributions to the body of knowledge help develop more holistic TCO models that consider all financial aspects, from direct costs like initial procurement costs to indirect costs that may stem from performance-related criteria. Ultimately, viewing asset life-cycle decisions through a technical performance lens helps facility managers understand how their assets are performing and what benefit or lack-there-of they are receiving in terms of the successful operation of those assets. Calculation of asset performance also enables facility managers to investigate exogenous factors impacting asset performance. One of these factors might be the climate in which that asset is operated. It is well cited in literature that climate, and especially extreme climate events, impact infrastructure systems. Civil engineering infrastructure has been studied to understand the effects of climate on assets (Dowds and Aultman-Hall 2015; Liao et al. 2018; Shi et al. 2020). Climate may affect the frequency and rigor of asset maintenance; winter weather conditions may increase maintenance operations for pavements (Chinowsky et al. 2013; Dao et al. 2019). Climate conditions may also affect the expected life cycle of assets by increasing deterioration rates for those assets (Tari et al. 2015). As a product of climate change, changing weather conditions may also affect infrastructure systems that are vulnerable to the effects of extreme weather events (Douglas et al. 2017; Guest et al. 2020; Pregnolato et al. 2017). Literature has provided a link to the effect of climate on assets at a macro-level, but investigating specific climate zones can help answer the question: what if any role does climate play in the technical performance of built infrastructure assets?

While previous research has investigated the role of climate on assets, this study is the first to evaluate the effects of climate on the performance of assets, completed at the manufacturer-level, and the first to propose that climate should be included as a component of a performance-based manufacturer selection process. Trends in climate variables are investigated to determine if climate affects asset performance and how different asset manufacturers respond to climate influences. Leveraging the authors' previous work, United States Air Force (USAF) assets from 20 separate geographic installations, spanning three different climate zones according to the Köppen-Geiger classification, are used. Two asset types, chillers and air handlers, are investigated to detail the relationship of climate with technical asset performance. This research aims to evaluate the link between asset performance and climate to help facilities managers make manufacturer selection decisions to employ the asset manufacturer that provides the highest performance in their facilities, tailored to their climate zone.

Data & Case Study

A case study using observed, manufacturer-level observed infrastructure data is conducted to investigate the link between built infrastructure asset performance and climate. This case study builds upon the work of Brown et al. (2021) in the development of a performance-based metric to quantify the performance of assets and link relevant climate data to investigate any trends that may exist.

Selection of Assets and Locations

This analysis used built infrastructure asset data from BUILDER™ Sustainment Management System, an industry-leading program used to track and manage infrastructure assets ("BUILDER™ SMS" 2012). BUILDER has been adopted across the Department of Defense (DoD) and it is used in the private sector by many educational and municipal organizations ("Sustainment Management System" 2020). Additional information regarding the features, capabilities, and organization of BUILDER has been discussed and can be found in Bartels et al. (2020) and Grussing et al. (2016). BUILDER supplied the following data points for this analysis:

1) asset condition, which is a 0 to 100-point value that represents the health of an asset as observed by a trained inspector, and the assessment's corresponding inspection date;

2) the installation date of the asset, or when it was first put into service;

3) the asset's remaining service life (RSL, years) is the number of useful years left an asset has in service adjusted to account for the current degradation rate of the asset;

4) the manufacturer of the asset; and

5) the location of the asset (indoor versus outdoor unit).

The USAF utilizes BUILDER to manage its infrastructure assets, and its data was utilized for this case study. A total of 20 Air Force installations from across the Contiguous United States are studied (Fig. 8). These locations were chosen to provide a sample of installations from each Köppen-Geiger climate zone to portray locations subjected to different climates. These locations represent one-third of all Air Force installations within the Contiguous U.S., providing a good representation of the USAF's data.

Two asset types were included in this analysis, chillers and air handlers. These assets have relatively long expected service lives: 20 years for chillers and 24 years for air handlers, exhibit condition degradation throughout their lifespans, and have several major manufacturers. Additionally, both of these asset types are subjected to environmental impacts throughout their operation. The study includes package units from 20 tons to 1,500 tons for chillers and 2,000 cubic feet per minute (CFM) to 75,000 CFM for air handlers. In order to relating asset performance to climate variables, each asset is grouped by its manufacturer. Two chiller manufacturers are studied and hereafter labeled Manufacturer A and Manufacturer B. Three air handler manufacturers are studied, Manufacturer A, Manufacturer B, and Manufacturer C. This analysis aims not to provide definitive conclusions about which manufacturer, by name, an organization should procure. Instead, it aims to show the utility of investigating the link between manufacturer performance and climate variables. Manufacturer names have been omitted to avoid any endorsement of one brand over another.

Climate Classifications & Climate Variables

The Köppen-Geiger climate classification categorizes each part of the globe into climate zones based on precipitation and temperature data for the region (Peel et al. 2007). The Köppen-Geiger classification further divides each climate zone into sub-regions for more accurate grouping by like climate areas; however, the five main climate zones are utilized for this analysis. A map of the Köppen-Geiger climate zones pertinent to this study has been created (Fig. 8) utilizing open-access data of Köppen-Geiger climate zones (Beck et al. 2018). The 20 Air Force installations included in this analysis are marked on the map. Based on Köppen-Geiger classification, seven installations fall within the Arid zone, seven in the Temperate zone, and six in the Cold region.

The climatic variables chosen for analysis are Heating Degree Days (HDD), Cooling Degree Days (CDD), Total Solar Irradiance, and Total number of Humidity Days above 55% relative humidity. These variables were selected because numerous citations in the literature point to their effect on the operation of assets (Crawley 1998; Jazaeri et al. 2019; de Rubeis et al. 2020) as well as the current climatic design standards used for Heating, Ventilation, and Air Conditioning (HVAC) units ("ASHRAE Handbook - Fundamentals" 2009; Roth 2017). Based on this information, it is hypothesized that they may influence the technical performance of assets. HDDs are an environmental measure of how cold the climate is for a given day below a specific threshold value; CDD is a measure of how warm the climate is for a given day above a threshold value ("Degree-days

- U.S. Energy Information Administration (EIA)" 2020). A standard value of 65°F is used for the threshold value for both HDD and CDD. Total Solar Irradiance is the total light intensity observed in watts per square meter between sunrise and sunset for a day. This value provides a measure of the amount of exposure assets have to the sun. Total number of Humidity Days above 55% relative humidity is the count of days where the average relative humidity was above 55%, which provides a metric for how humid the environment is that the asset is operating in. All weather data was sourced from AccuWeather's propriety database. The chosen climate variables do not provide an exhaustive look at all climatic variables which may affect an asset's performance but provide a starting point for analysis. These chosen variables target the climatic variables that influence chillers and air handlers based on how they operate and are backed up by research.

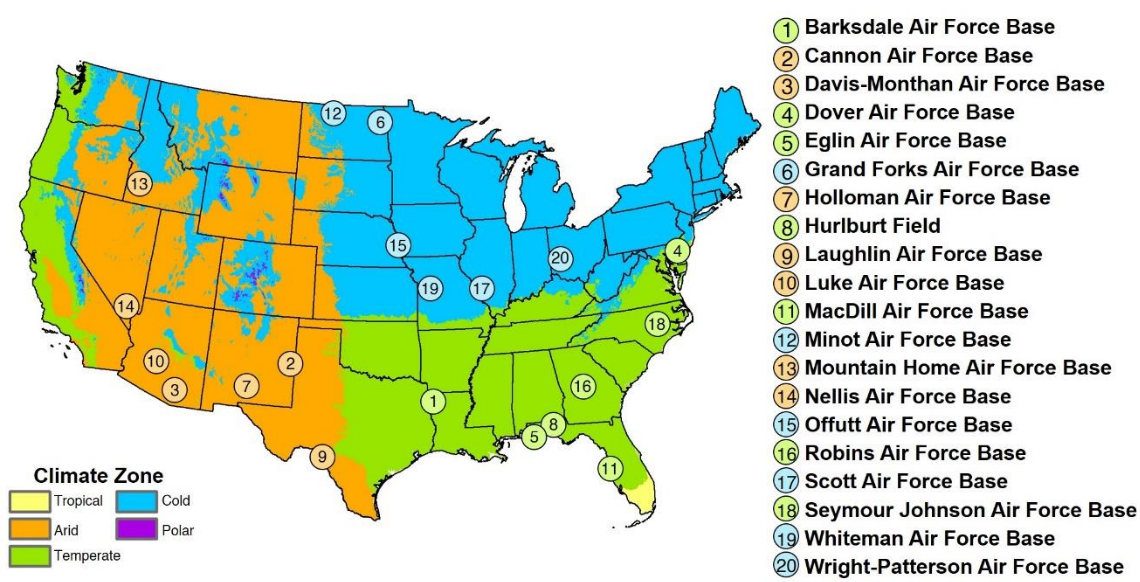

Figure 8. Köppen-Geiger Climate Zone Classifications

Initial Data Filtering & Statistics

The built infrastructure data stored in BUILDER provides a wealth of information for the case study and investigating the link between asset performance and climate. However, initial pre-processing was required to organize the data in a ready-state for analysis. Initial data filtering and processing actions included rebaselining the temporal scale of stored data from an absolute date to a relative asset age to compare all assets on a similar basis. Any assets with a change in condition greater than or equal to zero between inspections were removed to only consider assets that have not had a major repair or improvement. Any assets that had a condition less than 100 at the installation time were removed because assets should be in perfect condition at the installation date. This pre-processing step was meant to exclude assets that may have been incorrectly entered into the BUILDER database. Lastly, any assets with missing or incomplete data fields were removed. A complete record of an asset's manufacturer, condition, and RSL must be available to calculate asset performance. An extensive explanation of this filtering and exclusion process has been covered in Brown et al. (2021). For this climatic influence analysis, an additional filtering criterion was applied to remove assets that had an installation year before 1985 or an installation year after 2018. This step was done to align the asset data with the temporal range of available climate data. The data sourced from AccuWeather was daily climatic data from 1985-2018.

The initial population of asset data available from BUILDER included 8,579 unique chiller and air handler units from the 20 Air Force installations. Data filtering and exclusion criteria reduced the data population by 66% (5,705 assets were removed). This large percentage highlights the need for rigorous asset management programs that track and manage data for their built infrastructure assets. Despite the percentage of removed assets, the analysis still contains 2,874 unique assets from 1,341 facilities at the 20 Air Force installations. This filtered population of assets contains 765 chiller units and 2,109 air handlers. Of the chiller units, 33% of units are located in the Arid climate zone, 42% are located in the Temperate climate zone, and 25% are in the Cold climate zone. For the air handlers, 23% are located in the Arid climate zone, 48% are located in the Temperate climate zone, and 29% are located in the Cold climate zone.

Further breakdown of the number of units of each manufacturer brand within each climate zone is detailed in Table 2. This table shows the prevalence of each manufacturer within the climate zone. Overall, there are a majority of manufacturer A branded chillers across the three climate zones. Manufacture A is also the most prevalent brand in operation for air handlers for these Air Force installations.

Table 2. Manufacturer Prevalence within Each Climate Zone

Asset Type	Climate Zone	Manufacturer	Prevalence of Manufacturer in Climate Zone
Chillers	Arid	Manufacturer A	49%
		Manufacturer B	51%
	Temperate	Manufacturer A	82%
		Manufacturer B	18%
	Cold	Manufacturer A	84%
		Manufacturer B	16%
Air Handlers	Arid	Manufacturer A	50%
		Manufacturer B	29%
		Manufacturer C	21%
	Temperate	Manufacturer A	63%
		Manufacturer B	20%
		Manufacturer C	16%
	Cold	Manufacturer A	59%
		Manufacturer B	14%
		Manufacturer C	27%

Methodology

Asset Performance Metric

Investigating the link between asset performance and climate requires a metric to quantify asset performance, the authors have formulated a way to do this using available built infrastructure data. This methodology creates an age-based metric that uses asset condition and includes a measure of condition variation to compute each asset's performance value. Equation 1 below is the equation used to calculate asset performance.

$$\boldsymbol{Performance} = (w_i \times \boldsymbol{Condition_{scaled}}) + (w_i \times \boldsymbol{RSL_{scaled}}) + (w_i \times [\mathbf{1} - \boldsymbol{RMSE_{scaled}}]) \qquad (1)$$

This equation follows a weighted sum model approach to utilize three parameters to calculate asset performance. The first parameter is $Condition_{scaled}$, which is the observed condition of the asset directly taken from the BUILDER database. The 0-100 point value for condition is scaled to a number between zero (0) and one (1) using a minimum-maximum normalization technique. The next parameter is RSL_{scaled}, which is a measure of the remaining service life (RSL) of the asset and represents the number of years between the current age and the asset’s expected service life. RSL is updated after each asset assessment to either decrease or stay the same depending on the asset's current deterioration rate. For example, if the asset is degrading quicker than expected, the RSL is decreased. This number is also scaled to a value between zero (0) and one (1). The final parameter of the equation is $RMSE_{scaled}$, which provides a consideration for condition variation. The inclusion of this parameter compares the condition of assets at one location to the mean condition for all similar assets in the organization’s inventory. The variation is computed using root-mean-square error (RMSE), which is a formulation of distance of individual means to an overall population mean. Facility managers should value assets that behave similarly to the majority of their assets because this allows for more predictable operation and easier time planning maintenance activities. This parameter is also scaled to a number between zero (0) and one (1) and then subtracted from one. This final subtraction operation allows assets that exhibit conditions closer to the mean to have greater influence in the performance equation.

Each parameter in the performance metric equation has a weighting factor attached, allowing decision-makers to choose which parameter is most important and should carry the highest weight. Each weighting factor must be greater than or equal to zero $(w_i \geq 0)$ and all factors must sum to one ($\sum w_i = 1$). This analysis has equally weighted each parameter ($w_i = 0.333$). The final performance metric is a value between zero (0) and one (1), where one (1) indicates the highest performance when compared to like assets and zero (0) indicates the lowest performance compared to like assets. This equation provides a way to quantify asset performance based on asset condition and informed by service life and variance. A detailed description of this equation and example calculations can be found in the authors' previous work (Brown et al. 2021).

Query Weather Database & Calculating Cumulative Totals

The AccuWeather database was first queried to match a local weather station with the latitude and longitude coordinates of the Air Force installation to calculate the cumulative climate exposure of each asset at each installation. The proprietary AccuWeather database contained weather data for 1,938 weather stations across the U.S. Each weather station had the coordinates, and these could be matched with the coordinates for the 20 locations of interest. The average distance between the weather station and its corresponding Air Force installation was only 0.85 miles, so the climate data selected is indicative of the conditions experienced at the Air Force installation. Once the weather stations were linked with the Air Force installations, each location's data could be mined for the climate variables of interest: HDD, CDD, Solar Irradiance, and Humidity Days.

This analysis matches each chiller and air handler unit with cumulative climate exposure between assessment dates. This methodology allows for a link to be made between each climate variable and the asset's performance. First, each asset’s installation date is marked as the first day of interest, and a counter begins that sums the number of days between the installation date and the asset's assessment date at which condition data was recorded. This exact timeframe (number of days) is found in the climate database, and the cumulative amount of climate exposure for each variable described above is totaled for that same period. For example, if a chiller was installed on January 10, 2005 and was first assessed on January 10, 2010, the counter would return 1,826 days. The weather variable database is then queried to find January 10, 2005 and records the variable of interest for that day. The program then sums the number of accumulated climate units, e.g., HDDs, until the assessment date on January 10, 2010 (1,826 total days). This cumulative approach is meant to account for asset exposure between condition assessments. This cumulative value is paired with the performance of the asset calculated at that point in time. This methodology is followed for each asset's assessment date at each installation for each climate variable of interest.

Visualizations & Statistical Analysis

After calculating the cumulative climate exposure for each asset, scatterplots can be generated to inspect the relationship between asset performance and climate variables, as they enable easy visualization of trends. Scatterplots are generated for each asset (chillers and air handlers), each climate region (Arid, Temperate, and Cold), and each climate variable (HDD, CDD, Solar Irradiance, and Humidity Days). The cumulative climate exposure is shown on each scatterplot on the horizontal axis, and asset performance is shown on the vertical axis. Each point on the scatterplot represents an individual asset. Select scatterplots are shown in the following Results section, and all scatterplots are shown in the Appendix. In addition to scatterplots, a Pearson correlation coefficient (r) is calculated to measure the linear correlation between cumulative climate exposure and asset performance. For this analysis, an absolute correlation value less than 0.1 indicates no relationship $(0.1 > |r|)$, an absolute correlation value between 0.1 and 0.3 is considered a weak correlation $(0.1 \leq |r| < 0.3)$. A correlation coefficient between 0.3 and 0.5 is considered a moderate correlation $(0.3 \leq |r| < 0.5)$, and a value greater than or equal to 0.5 indicates a strong relationship $(0.5 \leq |r|)$. These threshold values are general guidelines often cited in literature (Cohen 2013). Correlation coefficients are shown for each scatterplot as well as in Tables 3 and 4 of the following Results section.

In addition to correlation analysis, an analysis of variance (ANOVA) was performed to determine if a statistically significant difference in the mean performance metric of assets between the different factor levels is present. This test is performed for chillers and air handlers, and different factor levels, i.e., climate zone, asset manufacturer, and asset location (indoor versus outdoor unit), are tested within each asset group. The ANOVA testing provides context to whether the different factor levels contribute to a difference in the average performance metric. The ANOVA results are explored in-depth in the next section.

Results

After calculating the cumulative climate exposure for the time period between assessments for assets, the data could be visualized in scatter plots. These scatterplots show the cumulative climate exposure on the horizontal axis and the zero (0) to one (1) performance metric values on the vertical axis. These figures provide a visual of any relationships that exist between the variables. On each scatter plot, each point represents a unique asset. Plots are color-coded by the manufacturer of the asset. Alongside each scatter plot, the correlation coefficient is shown for each manufacturer. As expected, most correlation values are negative, likely due to the climate variable's inherent time component. As time passes, the total for each climate variable increases, and it is implied that more time is passing is connected to assets aging. However, variation in the correlation value between manufacturers suggests that each climate variable and performance combination is different. Most relationships are weak to moderate, though some climate variables have a strong correlation to asset performance. All scatterplots are shown in the Appendix. Chiller units in the Cold climate zone (Fig. 9) are shown here to highlight strong correlations and assets with minimal dispersion between asset performance and cumulative climate exposure. These scatterplots show a negative linear trend in the data. Manufacturer A shows a strong correlation between all climate variables and asset performance. Manufacturer B has a moderate correlation between CDD and asset performance and a strong relationship between HDD, Solar Irradiance, and Humidity Days. The tight dispersion shows the low variability that exists between cumulative climate exposure and asset performance for this climate zone.

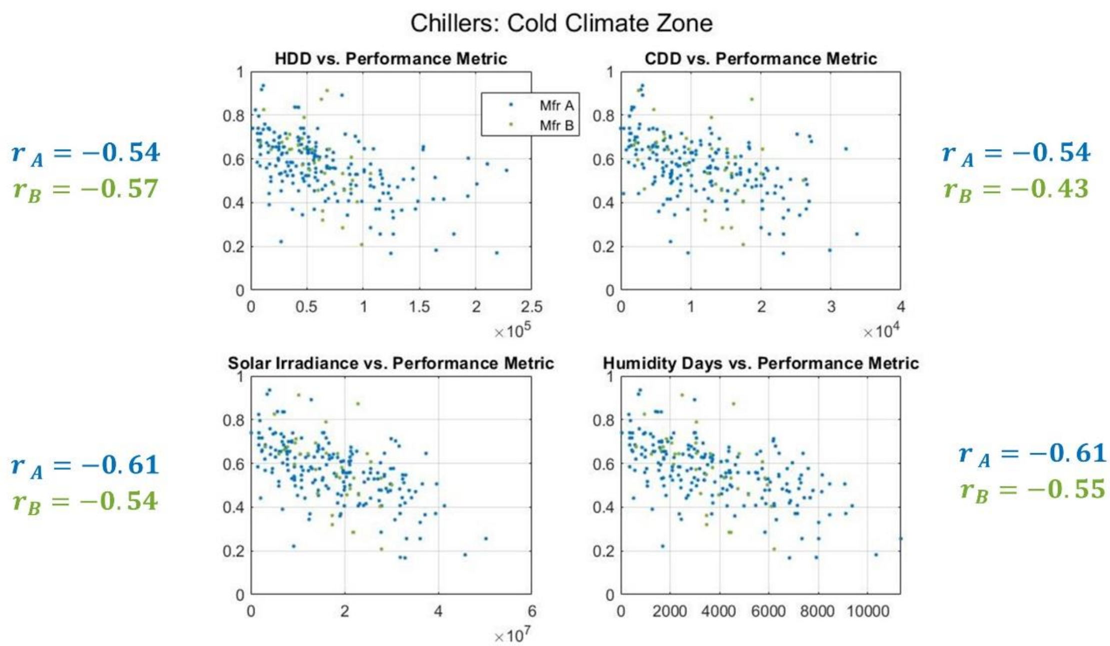

Figure 9. Correlation Analysis for Chillers in Cold Zone

Air Handlers in the Temperate climate zone (Fig. 10) are shown to highlight results with more dispersion. The greater dispersion for these plots indicates that there is a high degree of variability within the data. These results show negative linear trends for the manufacturers across all the climate variables. Manufacturer A shows a weak correlation for HDD and moderate correlation for CDD, Solar Irradiance, and Humidity Days. Manufacturer B shows a weak correlation for HDD and a strong correlation for CDD, Solar Irradiance, and Humidity Days. Manufacturer C shows a moderate relationship for HDD and shows weak relationships for CDD, Solar Irradiance, and Humidity Days.

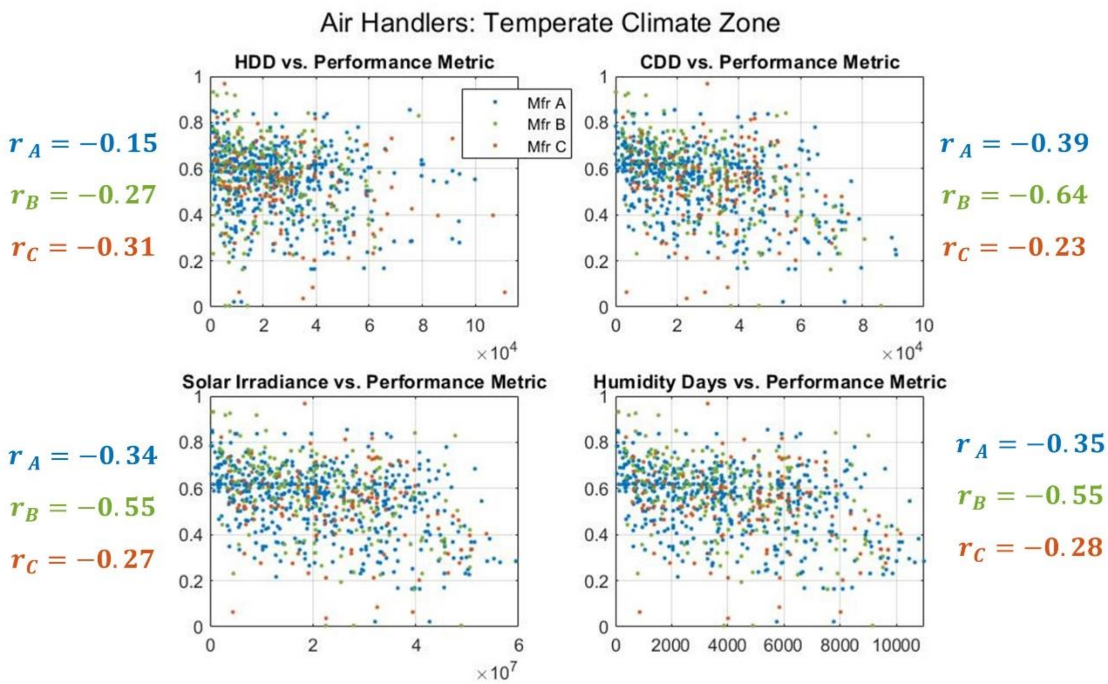

Figure 10. Correlation Analysis for Air Handlers in Temperate Zone

The selected scatterplots and correlation coefficients generalize the statistical relationships between cumulative climate exposure and asset performance for the three climate zones of study for chillers and air handlers. By further grouping assets by their location in relation to the facility they service–either indoor or outdoor units–further investigation can be performed to see if the asset's location plays a role in linking asset performance and cumulative climate exposure. Tables 3 and 4 below provide an overview of this level of analysis. These tables show each asset's correlation coefficient, in each climate zone, for each manufacturer, by location. These tables also contain the correlation coefficients shown previously in Figure 9 and 10. The correlation coefficients in the tables are color-coded to correspond to correlation strength. A gray color indicates no relationship

$(0.1 > |r|)$, a light orange indicates a week correlation $(0.1 \leq |r| < 0.3)$. A light green color indicates a moderate correlation $(0.3 \leq |r| < 0.5)$, and a dark green color indicates a strong correlation coefficient $(0.5 \leq |r|)$. The bold type shows the major grouping of the assets by manufacturer before grouping by indoor or outdoor units. Additionally, calculating the p-value for each correlation provides context to whether the correlation coefficient is statistically significant. Asterisks denote the statistical significance following each correlation value.

Table 3. Correlation Coefficient Table for Chillers

Climate Zone	Manufacturer	Indoor / Outdoor Unit	Sample Size	HDD	CDD	Solar Irradiance	Humidity
All Climate Zones	Manufacturer A	Both	721	-0.30**	-0.34**	-0.42**	-0.24**
		Indoor	243	-0.32**	-0.28**	-0.36**	-0.27**
		Outdoor	478	-0.29**	-0.38**	-0.46**	-0.23**
	Manufacturer B	Both	287	-0.25**	-0.35**	-0.40**	-0.30**
		Indoor	200	-0.17	-0.37**	-0.41**	-0.27**
		Outdoor	87	-0.28**	-0.33**	-0.39**	-0.32**
Arid	Manufacturer A	Both	162	-0.25**	-0.43**	-0.45**	-0.11
		Indoor	40	-0.46**	-0.34**	-0.37**	-0.14
		Outdoor	122	-0.23**	-0.47**	-0.49**	-0.10
	Manufacturer B	Both	170	-0.35**	-0.44**	-0.46**	-0.36**
		Indoor	58	-0.31**	-0.50**	-0.53**	-0.48**
		Outdoor	112	-0.36**	-0.39**	-0.42**	-0.30**
Cold	Manufacturer A	Both	211	-0.54**	-0.54**	-0.61**	-0.61**
		Indoor	66	-0.60**	-0.58**	-0.68**	-0.67**
		Outdoor	145	-0.51**	-0.52**	-0.58**	-0.58**
	Manufacturer B	Both	40	-0.57**	-0.43**	-0.54**	-0.55**
		Indoor	11	-0.55*	-0.49	-0.59*	-0.62**
		Outdoor	29	-0.65**	-0.41**	-0.55**	-0.57**
Temperate	Manufacturer A	Both	348	-0.24**	-0.30**	-0.28**	-0.30**
		Indoor	137	-0.20**	-0.31**	-0.24**	-0.28**
		Outdoor	211	-0.29**	-0.30**	-0.34**	-0.34**
		Both	77	-0.10	-0.37**	-0.32**	-0.31**

	Manufacturer B	Indoor	18	-0.20	-0.29	-0.29	-0.31
		Outdoor	59	-0.06	-0.42**	-0.35**	-0.33**

*Correlation is significant at the 0.10 level
**Correlation is significant at the 0.05 level

Table 3 shows all the correlation coefficient values for chiller units and the statistical significance of each value. Overall, there are many moderate and strong correlation values between asset performance metric and cumulative climate exposure within the different climate regions. This table also highlights that in some cases, grouping assets by their location in relation to the facility they serve (indoor or outdoor unit) strengthens the relationship. For example, the statistical significance of humidity and asset performance of Manufacturer B assets increase when comparing indoor and outdoor units, as opposed to all units combined for Cold climate zone. Across all climate variables and for both manufacturers, the Cold climate zone shows moderate to strong relationships between the climate variables and asset performance. This result shows that asset performance is highly influenced by cumulative climate exposure within the Cold climate zone. In the Arid climate zone, both manufacturers show a moderate correlation between CDD and Solar Irradiance, showing that hot temperatures and sun exposure influence asset performance. For the Temperate climate zone, CDD and Humidity show moderate correlation levels to asset performance, indicating that hot temperatures and humid environments influence assets in the Temperate region.

Table 4. Correlation Coefficient Table for Air Handlers

Climate Zone	Manufacturer	Indoor / Outdoor Unit	Sample Size	HDD	CDD	Solar Irradiance	Humidity
All Climate Zones	Manufacturer A	**Both**	**1517**	**-0.19****	**-0.35****	**-0.40****	**-0.34****
		Indoor	1449	-0.18**	-0.34**	-0.38**	-0.33**
		Outdoor	68	-0.39**	-0.64**	-0.63**	-0.50**
	Manufacturer B	**Both**	**527**	**-0.14****	**-0.55****	**-0.52****	**-0.19****
		Indoor	498	-0.14**	-0.53**	-0.50**	-0.22**
		Outdoor	29	-0.18	-0.84**	-0.78**	0.32*
	Manufacturer C	**Both**	**530**	**-0.21****	**-0.24****	**-0.29****	**-0.28****
		Indoor	494	-0.22**	-0.22**	-0.28**	-0.30**
		Outdoor	36	-0.03	-0.61**	-0.51**	0.23
Arid	Manufacturer A	**Both**	**293**	**-0.25****	**-0.63****	**-0.60****	**-0.24****
		Indoor	266	-0.23**	-0.60**	-0.59**	-0.25**
		Outdoor	27	-0.39**	-0.94**	-0.76**	-0.28
	Manufacturer B	**Both**	**168**	**-0.19****	**-0.48****	**-0.46****	**0.08**
		Indoor	146	-0.19**	-0.45**	-0.43**	0.07
		Outdoor	22	0.13	-0.90**	-0.82**	0.37*
	Manufacturer C	**Both**	**122**	**0.07**	**-0.51****	**-0.34****	**-0.21****
		Indoor	115	0.06	-0.47**	-0.31**	-0.24**
		Outdoor	7	0.03	-0.97**	-0.96**	-0.78**
Cold	Manufacturer A	**Both**	**437**	**-0.18****	**-0.37****	**-0.34****	**-0.30****
		Indoor	426	-0.18**	-0.37**	-0.34**	-0.30**
		Outdoor	11	-0.38	-0.35	-0.43	-0.43
	Manufacturer B	**Both**	**104**	**-0.40****	**-0.49****	**-0.48****	**-0.47****
		Indoor	100	-0.41**	-0.50**	-0.49**	-0.47**
		Outdoor	4	-0.71	-0.59	-0.65	-0.69
	Manufacturer C	**Both**	**205**	**-0.40****	**-0.27****	**-0.38****	**-0.36****
		Indoor	179	-0.40**	-0.28**	-0.38**	-0.37**
		Outdoor	26	-0.38*	0.03	-0.13	-0.14
Temperate	Manufacturer A	**Both**	**787**	**-0.15****	**-0.39****	**-0.34****	**-0.35****
		Indoor	757	-0.13**	-0.38**	-0.33**	-0.34**
		Outdoor	30	-0.41**	-0.56**	-0.56**	-0.56**
	Manufacturer B	**Both**	**255**	**-0.27****	**-0.64****	**-0.55****	**-0.55****
		Indoor	252	-0.27**	-0.64**	-0.55**	-0.55**
		Outdoor	3	-0.74	-0.97	-0.89	-0.91
	Manufacturer C	**Both**	**203**	**-0.31****	**-0.23****	**-0.27****	**-0.28****
		Indoor	200	-0.31**	-0.24**	-0.28**	-0.29**

		Outdoor	3	0.67	0.76	0.75	0.79

*Correlation is significant at the 0.10 level
**Correlation is significant at the 0.05 level

Table 4 shows the correlation coefficient values and statistical significance for the air handlers in the analysis. There are many moderate and many strong correlation values across all the climate zones, indicating that cumulative climate exposure influences asset performance. The Temperate region shows the most strong correlation values that might indicate that the Temperate region's asset performance is highly influenced by cumulative climate exposure. Within the Temperate climate zone, CDD, Solar Irradiance, and Humidity appear to have the strongest correlation values across the three manufacturers meaning that asset performance in the Temperate zone is most affected by the cooling demand, exposure to the sun, and humidity. In the Arid climate zone, asset performance is most affected by CDD and Solar Irradiance, showing the highest correlation values, meaning that hot temperatures and exposure to the sun influence asset performance. Most correlation values are weak and moderate for the Cold climate zone, except for Manufacturer B, which shows strong correlation values for some outdoor units. These results show that, on average, the Cold climate zone's asset performance is not highly affected by cumulative climate exposure, except for Manufacturer B.

Across the analyses for both chillers and air handlers, some sample sizes are small when assets are grouped by location. Sourcing additional data could provide more strength to the correlation coefficients and make some relationships stronger and more statistically significant.

The chiller ANOVA test results (Table 5) show that only the interaction element between climate zone and manufacturer produces different average performance metrics. This factor level where the p-value is lower than the critical p-value, 0.05 for this analysis, provides statistical evidence of a difference in means. This result suggests that Manufacturer A assets perform differently in the Arid climate zone from those in the Temperate climate zone and those in the Cold climate zone. The same is true of Manufacturer B; assets perform differently in each climate zone. Overall, these results show that there are differences in asset performance across the different climate zones and between the two manufacturers.

Table 5. ANOVA Test Results for Chillers

Factor Source	Sum of Squares	Degrees of Freedom	Mean Squares	F-Statistic	p-value
Climate Zone	0.0109	2	0.00546	0.21	0.8076
Location of Asset (Indoor/Outdoor)	0.0118	1	0.01175	0.46	0.4979
Manufacturer	0.0007	1	0.00070	0.03	0.8681
Interaction between Climate Zone & Location of Asset (Indoor/Outdoor)	0.0181	2	0.00907	0.35	0.7014
Interaction between Climate Zone & Manufacturer	0.4705	2	0.23527	9.21	0.0001
Interaction between Location of Asset (Indoor/Outdoor) & Manufacturer	0.0397	1	0.03973	1.55	0.2127
Error	25.5048	998	0.02556		
Total	26.2396	1007			

The same result is shown for air handlers (Table 6). This ANOVA test shows that the interaction element between climate zone and manufacturer impacts the asset performance metrics. The p-value for this factor is lower than the critical p-value of 0.05, which provides the statistical evidence. These air handler results show that each manufacturer performs differently in each climate zone, e.g., Manufacturer A assets perform differently in the Arid climate zone than those in the Temperate climate zone and differently from those in the Cold climate zone.

Table 6. ANOVA Test Results for Air Handlers

Factor Source	Sum of Squares	Degrees of Freedom	Mean Squares	F-Statistic	p-value
Climate Zone	0.0415	2	0.02073	0.88	0.4149
Location of Asset (Indoor/Outdoor)	0.0516	1	0.05161	2.19	0.1390
Manufacturer	0.0333	2	0.01666	0.71	0.4931
Interaction between Climate Zone & Location of Asset (Indoor/Outdoor)	0.0401	2	0.02004	0.85	0.4270
Interaction between Climate Zone & Manufacturer	1.3181	4	0.32952	13.99	0.0000
Interaction between Location of Asset (Indoor/Outdoor) & Manufacturer	0.0054	2	0.00268	0.11	0.8924
Error	60.2655	2558	0.02356		
Total	62.0485	2571			

The ANOVA testing (Table 5 and 6) highlights that the interaction element between climate zone and asset manufacturer are influential on asset performance, but that other variables are not influential. Alone, climate zone does not create performance differences amongst assets. Location of assets (indoor or outdoor units) does not create performance differences, and by itself, asset manufacturer does not create performance differences. Nevertheless, when investigating different manufacturers in different climate zones, performance differences are apparent. These results suggest which factor levels are influential in creating asset performance differences and which are not.

Discussion

The statistical analysis performed and detailed in the previous Results section indicates that there is a moderate level of influence that environmental factors play in asset performance across both space and time. Many of the different groupings of assets showed moderate and strong correlation values. The ANOVA results show that climate zone and manufacturer of assets affect asset performance such that each manufacturer performs differently in each climate zone. These results are illustrated when cumulative climate exposure is plotted against asset performance, and correlation coefficient values show moderate associations between the variables. The results can help facility managers see which asset manufacturer provides the best performance for the climate zones in which their assets operate. By choosing the manufacturer that exhibits the best performance when faced with the most influential climate variables for their region, they can ensure they employ high performing assets that may ultimately lead to a lower total cost when factored into TCO models.

Previous work concluded that there was not sufficient evidence to support manufacturer selection decisions at an enterprise level for the Air Force. Using the technical performance metric for assets enabled installations to make the manufacturer selection best for their specific location, but there was no clear decision at the enterprise level. Grouping Air Force installations by climate region shows that assets within the same climate zone react to climatic variables similarly. This climatic analysis provides further support that making manufacturer selection decisions at local installation-levels may make the most sense instead of enterprise-wide solutions.

These investigatory results show that asset performance is not the same across all manufacturers of assets. Making manufacturer selection decisions based on a technical performance metric can be useful to a facility manager. The results may help guide operational decisions a facility manager needs to make throughout an asset's life cycle. The influence of climate variables may impact these decisions, like what is the effect on asset degradation. If a facility manager in a particular climate zone anticipates a specific degradation profile for their assets, based on the long-term averages of weather variables, and then the climate zone experiences extremes for these averages, a facility manager may be able to predict potential changes to their asset's degradation profiles.

Additionally, the climate zones and climate variables drive asset performance, and as such degradation predictions could be partially informed with a climate-based assessment model. As the average climate changes for some areas around the United States, and more extreme weather events occur more often and with greater intensity, the effect on asset performance could be predicted by relying on the relationships calculated here. Moreover, as climate change effects become more prevalent in some areas, understanding the link between climate and asset performance may strengthen.

One limitation of this study is the limited scope of climate variables investigated. The decision to include HDD, CDD, Solar Irradiance, and Humidity Days as the variables of interest was based on the operational effects these variables have on chillers and air handlers; however, these four variables are not the only climatic factors that may affect chillers and air handlers. Future research could be focused on expanding the scope of variables included to fully understand all climatic factors that may affect assets' technical performance.

This research also highlights the analysis capabilities that are available when organizations track and manage built infrastructure data. The USAF has more than ten years of condition assessment data available. Statistical analyses can be performed to show the relationship that exists between asset performance and climatic variables. Organizations that manage facilities and the accompanying assets on any level, whether it is a small organization that owns a few facilities or a large organization similar to the USAF that has a multitude of facilities geographically spread out, built infrastructure data can be leveraged to perform statistical analysis to help make data-driven decisions for their organization. Accurate data management policies can help organizations know and understand their assets to make the best decisions for their asset portfolios. This research also exposes the potential limitations that exist from incomplete data records. A large portion of the original data points had to be excluded from the analysis because there was missing data regarding the manufacturer of the asset. By implementing robust data management procedures, organizations can increase the amount of data available to them for analysis.

Conclusion

This research set out to examine the role that four climate variables, HDD, CDD, Solar Irradiance, and Humidity Days, might play in asset performance when assessed via a technical performance metric. This analysis showed that all of these climate variables impacted chillers and air handler units in some way through the many different combinations of analyses that were targeted. In most cases, asset performance was negatively linked to the climate variables studies, which implies that climate variables influence asset performance such that it decreases the performance of assets. By comparing results by one of the three Köppen-Geiger climate zones (Arid, Temperate, Cold) that exist for the 20 Air Force installations of interest, the climate variables' role on asset performance could be observed. Additionally, by looking at the asset's location in relation to the facility it serves (indoor versus outdoor unit), an understanding could be made to see if asset placement plays a role in asset performance, which it does.

Ultimately, this research builds on extensive research that already exists in the field for using TCO models to describe all costs of ownership for built infrastructure assets. By employing a technical performance metric that describes an asset's performance based on condition, age, and variation in condition, an economic consideration can be factored into TCO models to account for this technical performance. A climatic analysis helps facility managers further understand their assets' technical performance, specific to their climate zone. This analysis further links the impact of climate on built infrastructure assets and can provide another criterion for facility managers to use when making manufacturer selection decisions. This analysis also highlights the evaluation capabilities that are available when organizations employ rigorous data management programs to track and manage their infrastructure assets.

V. Conclusions and Recommendations

Research Conclusions

This thesis focused on the research to investigate the viability of manufacturer selection for organizations, specifically the USAF. In alignment with this focus, three research objectives were defined:

1. Investigating whether the Air Force Enterprise has sufficient data available to make and validate manufacturer selection decisions.
2. Develop a technical performance metric to quantify the operational performance of built infrastructure assets.
3. Explore potential climatic influences on the technical performance of built infrastructure assets.

First, a background of BUILDER SMS was presented that provided context to the data and case study utilized in this research. BUILDER is the EAM used by the entirety of the DoD, and its numerous functions and capabilities offered the perfect solution to address the research objectives. In Chapter 3, a technical performance metric was created to quantify the operating performance of built infrastructure assets and achieve the second research objective. Capitalizing on BUILDER's USAF data, a case study was created to evaluate the feasibility of making and validating manufacturer selection decisions. Overall, the case study showed that the USAF does have sufficient data available and can make manufacturer selection decisions at local installations. However, based on the analysis data, manufacturer selection decisions should not be mandated at the enterprise level. However, tools were developed to help manufacturer decisions be validated at an enterprise level; these results achieved research objective one.

Through the investigating of climate data in Chapter 4, research objective three was realized. An analysis of the relationship between four climate variables and asset performance was examined across three climate zones. Overall, there was sufficient evidence that there is a link between climatic variables and asset performance. These results can help inform decision-makers about how their assets may perform in each environment depending on the presence of different climate variables. In total, this thesis accomplished all stated research objectives and provided novel research to contribute to the body of knowledge.

Research Significance

For organizations operating in resource-scarce environments, facility managers are often tasked to decide when and how to replace assets or procure new assets to meet their mission needs. Relying on data provides evidence as to what is the best asset to provide the best performance. This research provided the method to utilize data in order to make these decisions. A novel approach was used to fill a gap in the current body of knowledge and provide a data-driven solution to one aspect of facility management.

Research Contributions

This research demonstrated the applicability of using BUILDER data to make data-driven decisions, which is often the goal of any facility management program. The importance of collecting quality data was shown and what can be done if quality data is collected. This research provided a novel approach to quantifying the technical performance of built infrastructure assets, which has previously been identified as a literature gap. This research also investigated the exogenous factors that may affect asset performance and provided facility managers with an understanding of the effects of climatic variables on asset performance. Finally, this research provided a flexible framework to calculate technical asset performance, which can seamlessly be implemented into Total Cost of Ownership models.

Recommendations for Future Research

This research highlighted the ability to utilize available built infrastructure data to create a quantified technical performance metric for built infrastructure assets. With only five different data fields, asset performance was calculated, which provides facility managers a metric to use when making decisions throughout an asset's life cycle. In this case, during initial procurement decisions, asset performance could inform manufacturer selection decisions. This framework highlights the power of data and the potential it holds for facility managers. Additionally, data quality and availability are also important; organizations should employ robust data management practices to capture and record all valuable data during the facility management process. It is recommended that organizations who manage asset portfolios, regardless of size, invest in data management practices that enable them to capitalize on data to calculate the technical performance of assets and any other metrics that are of importance for their organizations.

In coordination with organizations collecting more data, this facility management data can be combined with workplace management data like NexGen IT data that captures additional data parameters. These parameters may include preventative maintenance requirements and schedules, service calls related to specific asset failures, or funding information related to asset operation activities. Combining condition-based facility management data with workplace management data could provide insights to the interaction between the different data parameters.

In order to expand on the climate analysis performed in this research, additional climate variables could be analyzed to investigate their influence on asset performance. In addition to the four variables included in this analysis, parameters to consider precipitation amount and type (rainfall, snowfall, hail, etc.) could be included. A wind velocity parameter could be added which may account for high wind velocity effect on some outdoor units. Lastly, a composite corrosion parameter could be included to quantify the corrosive effects of an environment on an asset, like excessive salinity in the air. In addition to increasing the number of climate variables included in the analysis, the model created to link environmental climates and asset performance could be used in a forecast mode. Utilizing the model in a forecast mode could highlight the effects of future climate predictions on asset performance. Representative Concentration Pathways (RCP) could be used to show the effect on asset performance as climate changes in accordance with greenhouse gas concentration trajectories.

The technical performance of assets was investigated in this research to quantify how assets in operation are performing compared to similar assets. This research provides one aspect that can be used to evaluate the Total Cost of Ownership (TCO) of assets, but the technical performance of assets is not the only factor. Integrating assets' technical performance into a TCO framework can provide facility managers and decision-makers a holistic picture of all costs incurred over an asset’s life cycle. In addition to technical performance, costs related to purchasing, maintaining, servicing, outfitting with spare parts, and disposing of assets should be evaluated to offer a robust analysis of total costs. This research should be expanded to calculate all costs related to owning and operating assets. In addition to investigating additional costs, research should be conducted to understand the influence of some aspects of owning an asset on their performance. These additional considerations could be the availability of spare parts or bench stock as they may influence worker productivity. If the number and diversity of spare parts kept on hand are reduced, what effects may this have on worker productivity that in turn may influence asset performance?

Finally, the concept of manufacturer selection was investigated in this research, and a solution to quantify asset performance was calculated to help facility managers choose the right brand to employ in their asset portfolios. Manufacturer selection uses a criterion to select an asset during the initial procurement process instead of the current status quo of having no criteria to help make procurement decisions. Manufacturer selection should continue to be investigated and researched to arm facility managers with the right tools to help them build the best asset portfolio to help them achieve their missions. These tools must include indicators to help facility managers not only decide what is the right decision, but when to make that decision. The trigger point to indicate when a change to an asset inventory must be made is as important as what asset to use. Whether facility managers replace assets with the right manufacturer through attrition, or if the replacement is condition- or age-based, the decision point as to when is the optimal time to replace assets according to these manufacturer selection decisions should be researched.

Appendix: Climate Scatterplots

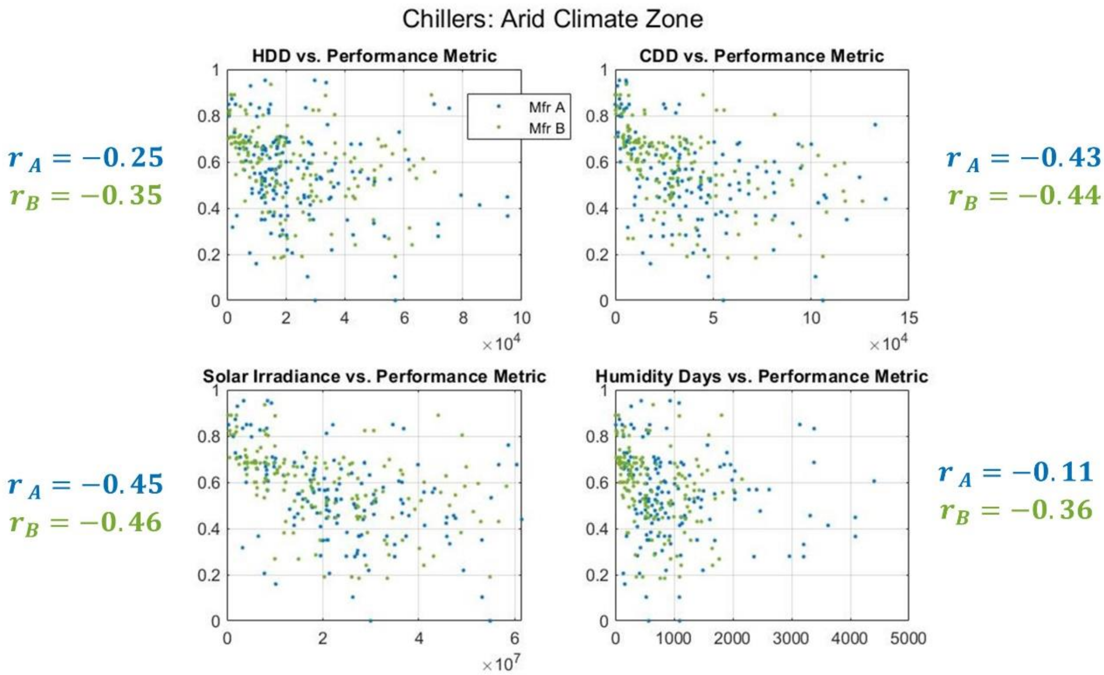

Figure A. Correlation Analysis for Chillers in Arid Zone

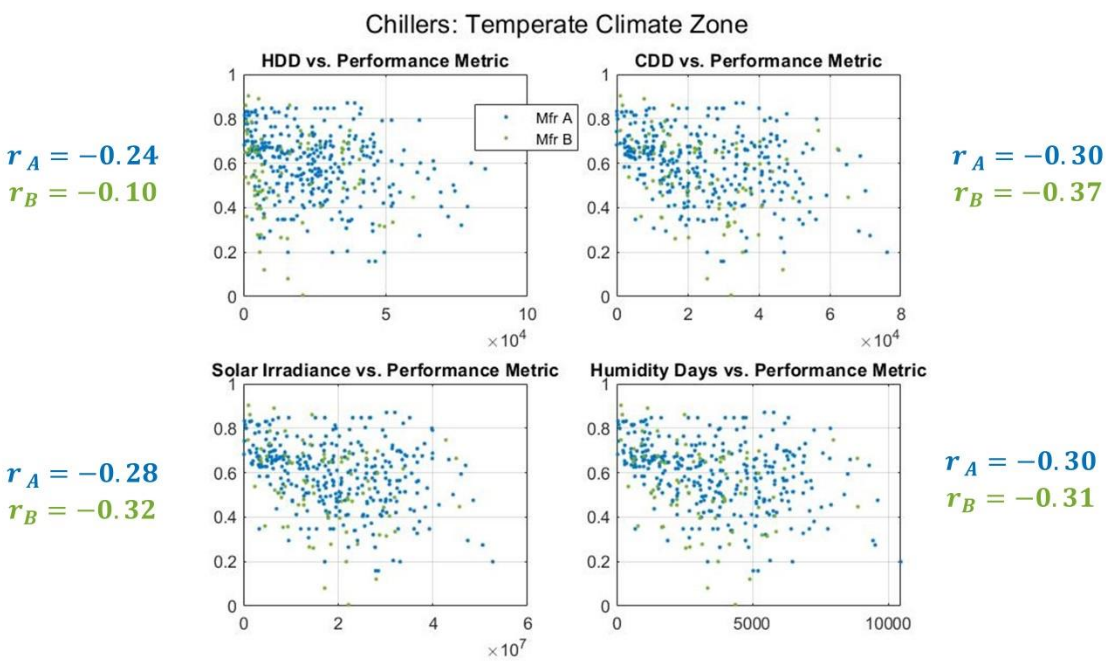

Figure B. Correlation Analysis for Chillers in Temperate Zone

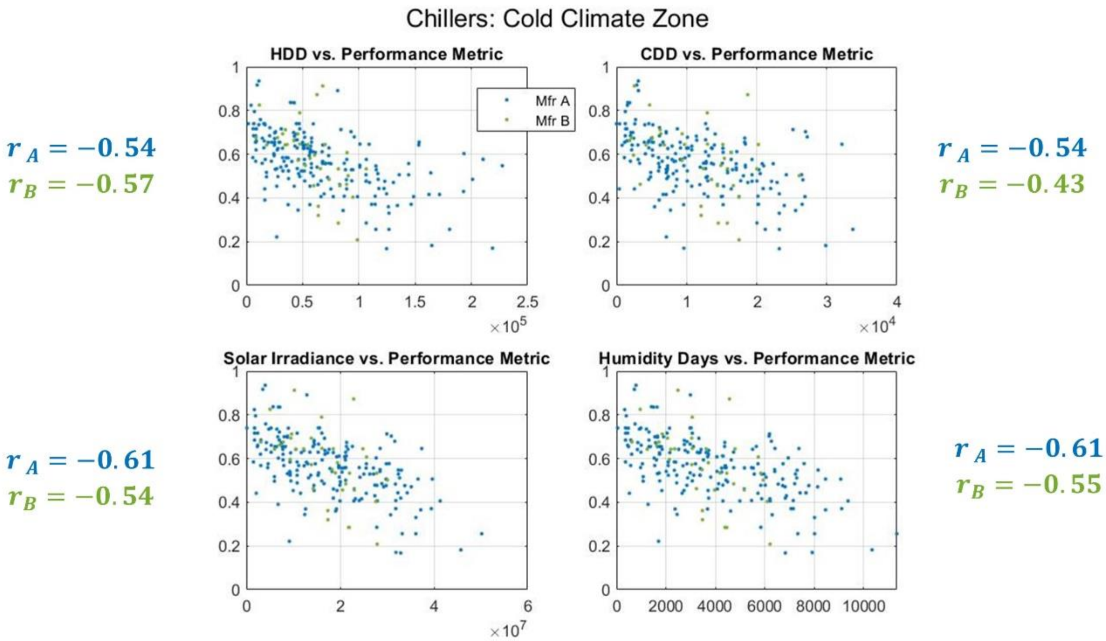

Figure C. Correlation Analysis for Chillers in Cold Zone

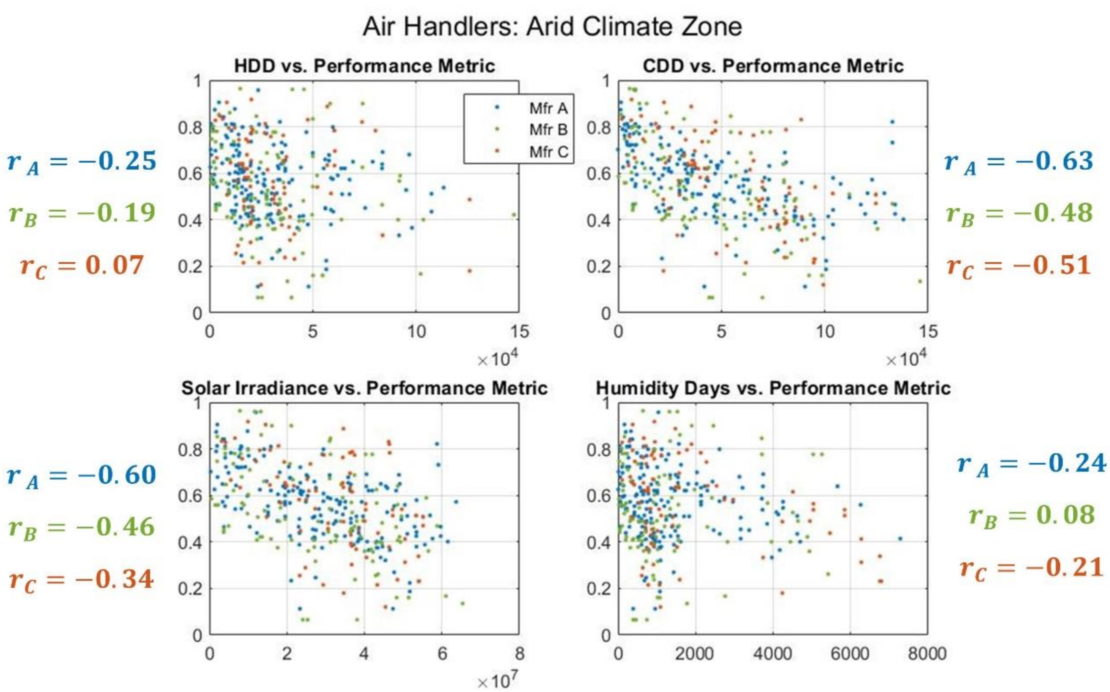

Figure D. Correlation Analysis for Air Handlers in Arid Zone

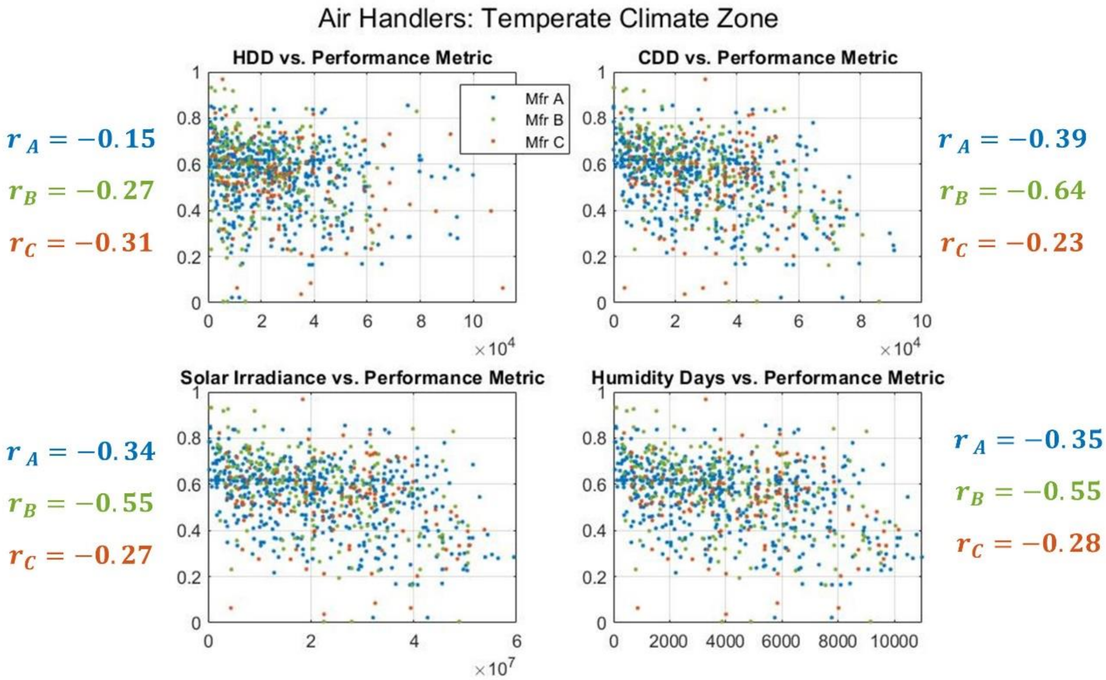

Figure E. Correlation Analysis for Air Handlers in Temperate Zone

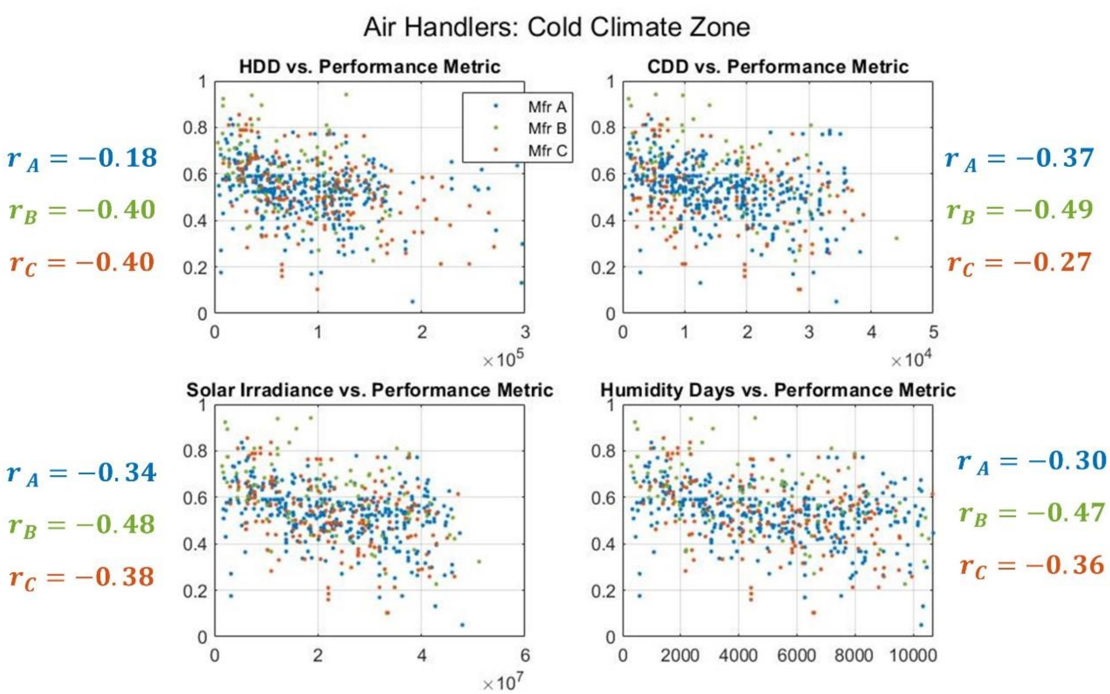

Figure F. Correlation Analysis for Air Handlers in Cold Zone

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14. ABSTRACT

Facility and built infrastructure asset management are necessary functions of any organization that utilizes buildings to operate their businesses. However, most organizations require facility managers to ensure the successful operation of their assets without providing sufficient resources to accomplish this task. Therefore, in resource-scarce environments, facility managers require data-driven solutions to manage their assets and make the best decisions. Facility managers need novel solutions to help make asset life-cycle decisions. This research provides such a solution. Capitalizing on available data, a technical performance metric is created, allowing facility managers to calculate their assets' operational performance. This performance metric provides a criterion to make manufacturer selection decisions: choosing one manufacturer over another and picking the best brand for use in their facilities. The performance metric that informs manufacturer selection decisions provides a basis for making initial procurement decisions, thereby solving one of the life-cycle decisions facility managers must make. Performance is calculated utilizing basic attribute and condition assessment data. Leveraging real-world data from the United States Air Force, case studies are performed to calculate the performance of assets, show the utility of an organization making or validating manufacturer selection decisions, and to show the effect of local climate on asset performance.

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