



**NOT ALL TONS ARE CREATED EQUAL: ANALYZING AERIAL PORT  
CAPABILITY TO DEFINE THE *WORKING TON***

THESIS

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THESIS

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Degree of Master of Science in Logistics & Supply Chain Management

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Captain, USAF

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### **Abstract**

United States Transportation Command (TRANSCOM) along with Air Mobility Command (AMC) provides airlift assets that accomplish thousands of missions around the world every week for cargo distribution. The current unit of measure is a short ton, which is the primary metric used in decision making. However, the short ton measurement does not adequately predict the amount of work necessary to properly prepare different cargo types for airlift. Utilizing the short ton metric leads to inadequate forecasting times for cargo preparation and aircraft loading, which leads to delayed missions. The root of the problem is that the metric used does not provide enough fidelity for accurate forecasts, and in essence, all tons of cargo moved are not created equal concerning preparation and loading. For example, a ton of hazardous material takes more preparation than a ton of standard cargo.

This research utilizes a stepwise regression model that accounts for the different cargo types, such as loose stock, palletized cargo, rolling stock, standard cargo, pallet trains of size 2, 3, 4, 5, and 6, hazardous cargo classifications, and special handling codes (classified). This model can be used by AMC to increase the efficiency of planning for cargo preparation and cargo load times by providing greater fidelity on different load-types than just their weight. Seven of the cargo characteristics are found to be statistically significant and are validated with split data and implementation at Travis, AFB. This analysis has led to a new metric called the *working ton*. The *working ton* metric is created utilizing the stepwise regression model's standardized betas. The values of these coefficients indicate the relative effect of each variable. Hazard category one

and the standard pallet are shown to be the most significant variables, having the greatest effect on the amount of time it takes to load an aircraft. This research proposes a new metric for AMC and TRANSCOM to use that will significantly aid in their ability to predict work-levels and improve future mission timelines.

*To my amazingly supportive and loving husband, my parents, and finally my close friends  
whom supported me through this journey.*

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Casey L. Owens

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# NOT ALL TONS ARE CREATED EQUAL: ANALYZING AERIAL PORT CAPABILITY TO DEFINE THE *WORKING TON*

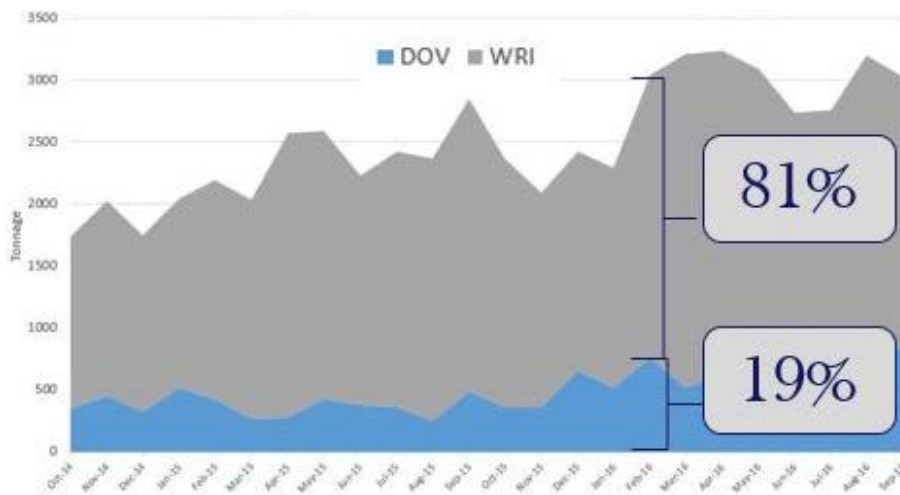
## I. Introduction

### 1.1 Background

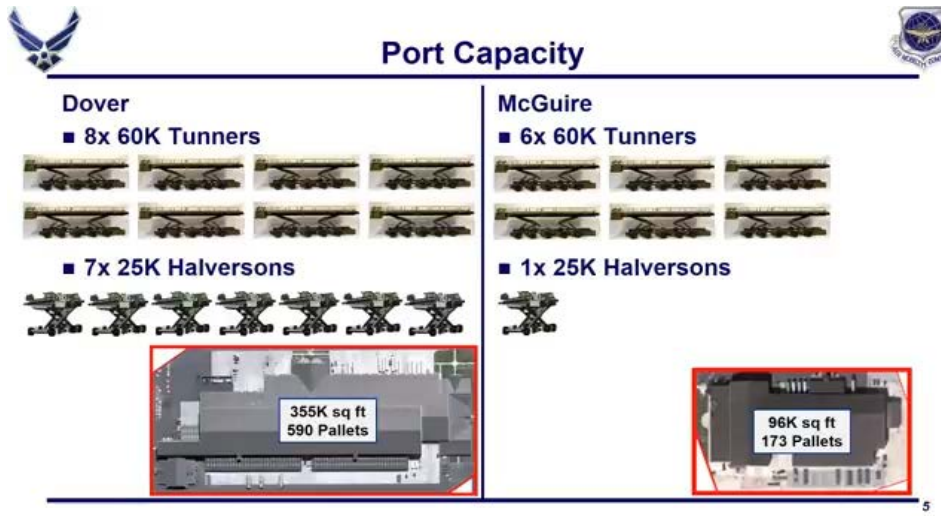
The United States Transportation Command (TRANSCOM) is responsible for regulations and guidance on all things mobility and deployment related to include cargo aircraft loading and proper packaging (United States Transportation Command, 2016). TRANSCOM accomplishes thousands of missions around the world every week with the help of Air Mobility Command (AMC). One of the major priorities of AMC is to execute and sustain Rapid Global Mobility, anywhere in the world in a matter of hours (Air Mobility Command, 2017). Rapid Global Mobility can be defined as deploying U.S. armed forces to the right place at the right time.

A study performed by AMC A4/Air Cargo Movement Policy at Dover Air Force Base and Joint Base McGuire-Dix-Lakehurst (McGuire), found that over the last ten years, average cargo workload (amount of time and effort it takes to pack and load cargo) was not proportional to the maximum port capacity (amount of space and resources available to pack and load cargo) at each location (HQ AMC Air Cargo Movement Policy, 2017b). McGuire is the busiest port on the east coast concerning short tons, but Dover has more resources and manpower because of the capability needed to support a wartime surge. The current wartime surge comes from the Afghanistan channel missions that have slowly tapered off in the last ten years. As the shift to the Pacific continues, this same wartime surge could happen on the West coast. In the study performed by AMC,

the result was to realign channel cargo to be consolidated at Dover instead of McGuire to balance the workload with maximum capability. Figure 1 shows the percentage of tonnage moved by Dover (DOV) and McGuire (WRI) along with Figure 2 showing the associated military handling equipment at each base. Figure 2 specifically outlines there is twice as much equipment and four times as much storage at Dover; whereas Figure 1 shows that McGuire moves more cargo by tonnage. Why is there a large difference in the workload currently being performed and the capacity of that base with the resources allocated? AMC wants the workload to be proportional to the capacity to maintain training and utilize resources (HQ AMC Air Cargo Movement Policy, 2017a).



**Figure 1: Channel Workload by Tonnage (HQ AMC Air Cargo Movement Policy, 2017a)**



**Figure 2: Dover & McGuire Equipment (HQ AMC Air Cargo Movement Policy, 2017a)**

AMC utilizes the short ton as a standard unit of measure, which is equal to two thousand pounds. Although this unit of measure is useful when comparing weight output, it does not measure the workload needed for various types of equipment. For example, five short tons of explosives require greater effort than five short tons of palletized equipment. The short ton was initially implemented to help determine how much weight can go onto an aircraft, not to achieve a workload output. AMC A4/Air Cargo Movement Policy has assessed aerial port workload and capacity using short tons and determined the short ton alone does not quantify the other aspects of work accomplished by the aerial port (HQ AMC Air Caro Movement Policy, 2017a, 2017b). So, what does quantify work being done at an aerial port, if it is not the number of short tons moved? One method to start quantifying work is to analyze the type of cargo after it arrives at the aerial port. This information will tell us if the load times are similar for cargo with the same characteristics. These characteristics will be used to create a new

unit of measure called the *working ton* that can then be used to measure workload of a specific type of cargo.

Most studies on cargo are typically focused on optimizing space and minimizing shipping costs (Baker, Morton, Rosenthal, & Williams, 2002; Fok, Ka, & Chun, 2004; Yan, Lo, & Shih, 2006). Also, most research focusing on aircraft typically addresses the problem of how to load the maximum number of containers while balancing and minimizing the fuel consumption (Fok et al., 2004; Mongeau & Bes, 2003; Yan et al., 2006). However, it is critical that future work measures the correct performance indicators that signal to leadership the effectiveness of capability vs. capacity. This leaves open an avenue of research regarding the man-hours and work necessary to load the aircraft. The current study fills this research gap specific to Air Force cargo. In particular, it focuses on creating a new unit of measure that will equate to the amount of work necessary to properly load cargo for airlift. In this study, we define the *working ton* by identifying whether or not, and by how much, different inputs affect the amount of time it takes to load an aircraft. This research proposes a new metric for AMC and TRANSCOM to use that will significantly aid in their ability to predict work-levels and improve future mission timelines.

## **1.2 Research Question and Investigative Questions**

The objective of this research is to build a tool that accounts for the amount of time it takes for cargo loading to develop a *working ton* as shown in Figure 3. The research questions for analysis identify each independent variable and look at how they are affecting the overall load time. The overarching research question is what cargo

characteristics are statistically most influential to AMC when loading cargo for airlift?

To answer the research question, the following investigative questions (IQ) will be addressed:

IQ1: How does cargo load type (i.e., pallet, rolling stock, or loose stock) affect overall cargo load time?

IQ2: How does the number of pallet positions taken up by a single piece of cargo affect the overall cargo load time?

IQ3: Are there specific hazardous categories that affect overall load time more than others?

IQ4: Does classified cargo affect overall load time more than general cargo?



**Figure 3: Working Ton**

### 1.3 Research Focus

This research focuses on cargo leaving four different AMC bases. Two bases were chosen on the East coast and two on the West coast to help prevent any bias from entering the study. This study will analyze and compare the following bases; 436<sup>th</sup> Airlift Wing at Dover AFB, Delaware, 87<sup>th</sup> Air Base Wing at Joint Base McGuire-Dix-Lakehurst, New Jersey, 60<sup>th</sup> Air Mobility Wing at Travis AFB, California, and the 62<sup>nd</sup> Airlift Wing at Joint Base Lewis-McChord, Washington. This research will focus on C-17's due to the bulk of cargo moving on that particular type of aircraft. It creates

simplicity for this study, and all cargo is prepared for airlift, in the same way, no matter the type of aircraft.

#### **1.4 Methodology**

A retrospective study is accomplished to address the research question. This includes historical data synchronization and stepwise regression methods. These are used to build a model that will determine load times for aircraft based on cargo type. This model will then be used to create an excel tool for AMC bases to define a *working ton*. Data synchronization is used to merge database information from multiple sources into a usable excel format. This format is then imported into a statistical software called JMP® for model development.

The stepwise regression analysis was validated by checking for normality, constant variance, independence, and outliers. These specific statistical analysis functions will be discussed further in Chapter IV. Following these tests, and based on the regression coefficients; a regression equation is computed and used to determine how long specific cargo should take to be loaded with certain characteristics. The tool for AMC will be developed with excel to create a *working ton* output that will equal load time.

#### **1.5 Assumptions and Limitations**

There are many assumptions and limitations that could impact this analysis and model success. These lie within the aircraft, the aircrew operating the aircraft, and the port capacity by the amount of material handling equipment located at each base. These

are standard assumptions that are sometimes not identified when analyzing aerial port capability. This research will examine missions originating at the location due to the nature that many channel missions have several final destinations where cargo is on-loaded and off-loaded a number of different times.

The assumptions are:

- Aircrew operating the same type of aircraft have the same abilities
- Aerial ports have the needed equipment to download and upload all types of cargo
- Aerial port members have the same ability to download and upload cargo
- AMC utilizes a four-person load team
- Schedule of Events was given from HQ AMC to determine load times, and they are constant and true

Limitations impacting this study mainly come from acquiring the data to analyze the load times of different bases. The major limitations are listed below:

- Not all aircrew and aerial port members have the same ability to download and upload cargo
- The data system Global Air Transportation and Execution System (GATES) from which information was pulled is not perfect and relies on Airmen to input data correctly
  - Data is not kept if a reoccurring mission number is used
  - Delay codes are recycled and not specific to the instance
  - Numerous data points had no cargo load start or cargo load complete time and were omitted for this study

## 1.6 Summary

The motivation for this thesis came from the idea that AMC is basing manpower and resources off of a unit of measure that does not give a workload equivalent. Currently, the load teams for AMC show up at an aircraft four hours before aircraft departure, no matter what was included in the load. The Air Force has a current manpower shortage and should be doing everything it can to utilize resources and Airmen efficiently. However, the Air Force currently has Airmen hurry up and load the aircraft, only to wait for its departure. If AMC had a better unit of measure to definitively identify how long it would take to load an aircraft, Airmen would be better utilized. The *working ton* has the potential to improve scheduling of manpower and allocation of resources.

Chapter I presented background information for the research and a way ahead for this study. This topic is important to the future of AMC, as planning and developing a metric to measure cargo capability that does not rely on the short ton will contribute to analyzing aerial port capability. This is the first step toward AMC's goal. The remainder of this paper is organized as follows. The next section summarizes the relevant literature from logistic operations, regulations, aerial port documentation, and subsequently presents the research hypotheses. The research method is then presented, followed by the data analysis and a detailed discussion of the findings. The concluding chapter discusses the implications and potential usage of the results from this research and new avenues of future research before concluding.

## **II. Literature Review**

### **2.1 Introduction**

This chapter presents an overview of current research in aircraft loading and cargo characteristics. Chapter II explains how Resource Orchestration Theory helps tie together the variables and creates an overarching explanation of why resources are utilized in particular ways. This section identifies the many techniques and areas of focus to analyze cargo load planning methods and cargo load execution. This literature review discusses the independent and dependent variables then identifies the hypothesis associated with this study for each one.

### **2.2 Research Orchestration Theory**

AMC has a firm grip on the distribution network in the military, and the network is a vital resource by which all of the Department of Defense moves around assets. This study seeks to improve the distribution network by giving leadership a better metric to make decisions on the number of resources necessary to load aircraft. This metric is further highlighted by resource orchestration theory which seeks to explain how organizations can use their assets, or resources, more effectively (Sirmon, Hitt, Ireland, & Gilbert, 2011). The important part of the theory, in relation to this study, is how well the resources are managed (Ketchen, Wowak, & Craighead, 2014). The first part of managing resources appropriately is tracking them correctly and articulating it to leadership. Part of tracking correctly is based on the metrics that leaders use and hold their people accountable. This theory was used in a hub and spoke study to identify how distribution can be a key resource (Skipper, Cunningham, Boone, & Hill, 2016). The

article articulates that increasing efficiency and effectiveness of the distribution network is a key objective of the military. This theory is a combination of resource management theory and asset orchestration with an emphasis on management and how leaders control the resources in their organization (Ketchen et al., 2014). A large part of research orchestration theory, where it explains the efficiency of utilizing resources, is due to tracking and working with the right metrics. Organizations that manage and utilize the distribution network more effectively should develop a competitive advantage. The way managers are tracking and utilizing resources will play a vital role in how the mobility community operates and how the correct metrics are used within the organization.

### **2.3 Aircraft Cargo Loading**

Cargo loading is not unique to air operations, and it is discussed in the literature with general vehicles and vessels. Recently, the literature has switched from more of a focus on the operational process and industry development to the quantitative decision methods needed to help support the growing freight industry. The literature indicates that airlines are clearly the dominant players in the cargo industry (Rong & Grunow, 2009; Yan, Chen, & Chen, 2008).

As a modeling problem, aircraft loading is defined as a 3D bin packing problem (BPP), which is one of the basic problems in combinatorial optimization. Mongeau and Bes (2003), addressed the problem of how to load the maximum number of containers into an aircraft, with a tradeoff between minimizing fuel consumption and satisfying safety requirements. Yan et al. (2006), built a cargo container load planning model and examined this model with the operations of FedEx. Yan et al. (2008) extended the

aircraft loading problem to a stochastic environment and built a mixed integer non-linear model for cargo container loading by considering a number of controllable and uncontrollable disturbances. This is useful because daily operations of cargo transportation have a number of disturbances that are not usually accounted for in models (Yan et al., 2008).

Many articles optimize military airlift loading procedures and include very specific constraints. One of these constraints dealt with airfield parking and servicing capacity. This technique and constraining process was useful for evaluating what affects load times at different bases and why they might be different (Baker et al., 2002). Simulation methods that deal with the mobility airlift problem mostly encompass the entire flow of cargo and aircraft from the port of embarkation to the port of debarkation. These simulations are very intricate but do not delve into the preciseness of the exact amount of time it takes to load certain individual pieces of cargo. Selinka, Franz, and Stolletz, (2016) address how simulations are used to approximate the time-dependent behavior such as heterogeneous queueing systems (Selinka, Franz, & Stolletz, 2016). This study will not utilize a simulation, but it is an option for future studies.

## **2.4 Hypothesis Development**

This research focuses on the variables selected to create the model in this study. Each cargo characteristic is defined by a hypothesis, starting with the same overall prediction. The specific cargo characteristics outlined in this section are believed to all have an impact on the amount of time it takes to load cargo for airlift. Upon the

completion of this study, the *working ton* will be developed with necessary cargo characteristics for daily use by AMC.

#### ***2.4.1 Cargo Load Type***



**Figure 4: Standard 463L Pallet with Straps & Net**

The cargo load type has three different identifications to include pallet, rolling stock, and loose load. A pallet is used by many different aircraft companies and can easily roll on and off the aircraft. A pallet is accompanied with straps and a net to make sure the cargo positioned on the pallet will stay in place as shown in Figure 4. A pallet is also referred to as a 463L that is 108 inches by 88 inches. The pallet is surrounded by indentions that allow it to be locked into a cargo aircraft's rail system or the military handling equipment used to load the aircraft. The purpose of the pallet and rail system was to increase the upload and download speed of cargo. A pallet that weighs 400 pounds takes the same amount of effort when using a rail system as a pallet weighing

1000 pounds. The same test does not hold true for rolling stock as shown in Figure 5.



**Figure 5: Rolling Stock Prepared for Airlift**

Rolling stock is equipment that can be driven or rolled directly into the aircraft cargo compartment. Most civilian aircraft will not accept rolling stock. The difficulty of rolling stock comes when it is loaded onto an aircraft, it will need to be accompanied with shoring. Shoring is defined by TRANSCOM as the “protection of the conveyance (aircraft) by using materials to respond to floor limitations.” Shoring is often lumber or plywood and can be used to protect the aircraft floor or distribute weight evenly as shown in Figure 6. According to the Defense Transportation Regulation, equipment should be designed to minimize the requirements for shoring to limit the logistics burden during air movement (United States Transportation Command, 2016). The use of shoring can cause the upload of cargo to take longer and require closer attention.



**Figure 6: Shoring for Rolling Stock**

Loose loaded cargo is items that can be walked into the aircraft or placed between other items (United States Transportation Command, 2016). The acceptable weight of loose loaded cargo is one hundred pounds. Due to the simplicity and ease of loading, it is expected to have a negative relationship with load time (Feng, Li, & Shen, 2015; Selinka et al., 2016; Yan et al., 2006). Thus, the first hypotheses are:

**H1a.** A pallet will be positively related to the amount of time it takes to load cargo.

**H1b.** Rolling Stock will be positively related to the amount of time it takes to load cargo

**H1c.** The loose load will be negatively related to the amount of time it takes to load cargo.

#### ***2.4.2 Pallet Positions & Oversize***

A pallet position (PP) is defined as one standard 463L pallet. Pallet trains are made by coupling together two or more pallets so that the cargo can fit efficiently into the aircraft. For example, a T-2 is a two-pallet train as shown in Figure 7; a T-3 is a three-

pallet train, and so on. One reason a pallet train might be utilized is for oversized cargo as shown in Figure 8. Oversize cargo is defined in the Defense Transportation Regulation – Part III as cargo that exceeds 1,000 inches in length, 117 inches in width, and 105 inches height. It requires the use of a C-5 or C-17 aircraft or surface transportation (United States Transportation Command, 2016). In the civilian sector this is typically referred to as bulk cargo, and because of the complexity of loading this type of cargo, it can be very expensive. Typical studies show how this type of cargo is normally associated with surface transportation (Fok et al., 2004; Yan et al., 2006).

**H2a.** The number of pallet positions will be positively related to the amount of time it takes to load cargo.

**H2b.** Oversized cargo will be positively related to the amount of time it takes to load cargo.



**Figure 7: T-2 Pallet Train**



**Figure 8: T-6 Pallet Train**

### ***2.4.3 Hazardous Categories***

Hazardous cargo is regulated in AMC by the Air Force Manual 24-204 *Preparing Hazardous Materials for Military Air Shipments*. This regulation is developed for persons that handle, pack, inspect, and/or prepare hazardous materials for transport as cargo on military-controlled aircraft (Department of the Air Force, 2017). The hazardous category will be identified on the cargo when it arrives at the aerial port, and Table 1: Hazardous Cargo Classification (Department of the Air Force, 2017) shows the different types of hazardous categories/classifications. This information was used to develop the model because it can easily be found on the load plans for each aircraft departure and it would be known ahead of time to include in the *working ton*. AMC experts have said hazardous cargo often affects the loading and preparation of cargo because of difficult documentation and regulations.

**H3.** Cargo hazardous classifications will positively affect the amount of time it takes to load cargo.

**Table 1: Hazardous Cargo Classification (Department of the Air Force, 2017)**

HAZARD CLASS/ DIVISION NUMBER	HAZARD CLASS/ DIVISION NAME	HAZARD CLASS/ DIVISION NUMBER	HAZARD CLASS/ DIVISION NAME
1.1	Explosives (with mass explosion hazard)	4.1	Flammable solid
1.2	Explosives (with a projection hazard)	4.2	Spontaneously combustible material
1.3	Explosives (with predominately a fire hazard)	4.3	Dangerous when wet material
1.4	Explosives (with no significant blast hazard)	5.1	Oxidizer
1.5	Very insensitive explosives; blasting agents	5.2	Organic peroxide
1.6	Extremely insensitive detonating substances	6.1	Poisonous (toxic) material
2.1	Flammable gas	6.2	Infectious substances (etiologic agents)
2.2	Nonflammable gas	7	Radioactive material
2.3	Poisonous gas	8	Corrosive material
3	Flammable liquid	9	Miscellaneous hazardous material

#### ***2.4.4 Classified Cargo***

A classified piece of cargo can add complexity to the cargo load. A DD Form 1387-2, as seen in Figure 9, needs to be visible from all sides of the cargo that requires protective service or other special services (Department of the Air Force, 2017; United States Transportation Command, 2016). One special service could be the requirement of an armed guard or constant surveillance. Cargo, with particular special handling codes, is locked in vaults at night and require additional documentation and certification as shown in Figure 10.

**H4.** Classified cargo will positively affect the amount of time it takes to prepare and load cargo.

SPECIAL HANDLING DATA/CERTIFICATION		
1. ITEM NOMENCLATURE	2. NET QUANTITY PER PACKAGE	3. TRANSPORTATION CONTROL NO.
	4. CONSIGNMENT GROSS WEIGHT	5. DESTINATION
6. SUPPLEMENTAL INFORMATION		
This is to certify that the above named material is properly classified, described, packaged, marked and labeled, and in proper condition for transportation according to the applicable regulations of the Dept of Transportation. THIS IS A U.S. DEPARTMENT OF DEFENSE SHIPMENT! (Complete applicable blocks below)		
7. DTR REFERENCE		
8. HANDLING INSTRUCTIONS		
9. ADDRESS OF SHIPPER		10. TYPED NAME, SIGNATURE AND DATE

DD FORM 1387-2, NOV 2004      PREVIOUS EDITION IS OBSOLETE.      Form Approved OMI 0188

**Figure 9: Classified Form (United States Transportation Command)**



**Figure 10: Classified Vault at Travis, AFB**

## 2.5 Summary

This chapter laid out the supporting literature and framework for developing a model to represent a *working ton*. As seen in the reviewed research, it is imperative to understand the different types of cargo characteristics that will be utilized to develop this model. The study will test all four hypotheses outlined in this section. Chapter III describes the data collection, research methods, and provides additional information on variables used to create the *working ton*.

### **III. Methodology**

#### **3.1 Overview**

Chapter III illustrates the methodology and clarifies the specific type of data used in this research. The first section provides a background on the data synchronization and cleaning of the data. The next part details the steps taken throughout each phase, including the development of variables as well as the analysis process. The understanding gained throughout this chapter provides the readers with a background for the *working ton* development discussed in Chapters IV and V.

#### **3.2 Data Synchronization**

One database called Global Air Transportation Execution System (GATES) was used to gather needed information for this study. GATES provides a plethora of information to the Air Force and DoD partners about specific load characteristics on aircraft throughout the world. GATES is a system used by aerial port members to track passenger and cargo uploads and downloads. This system records cargo movement, per mission, identification numbers into and out of individual airports. Known delays for aircraft departures are documented in GATES, and will only be accounted for if the mission delay involves cargo upload. This system tracks where cargo is currently, where it came from, and where it is going.

The GATES system is used to pull information about how much cargo was uploaded into specific aircraft with specific mission numbers. Data was pulled from August 2017 through October 2017 on C-17 aircraft departures only. The first step in data cleaning was excluding all of the aircraft departures that did not originate at that

base. This accounts for aircraft arriving with previous cargo already on-loaded. This study only uses originating aircraft to be sure that off-load times do not influence the load times. The next critical part of cleaning the data is to exclude all aircraft that did not have anything loaded at the origin. This took out over half of the data points because a large number of AMC aircraft is contracted at an AMC location, but there is no cargo originating from that location. There were also a large number of data points with less than one short ton of cargo. These data points were excluded because they did not have a load plan associated with the flights to analyze cargo characteristics. Table 2 below shows the number of usable data points after each iteration of data cleaning.

Approximately 88% of the data was unusable.

**Table 2: Data Cleaning Process**

	Original Departures	Exclude Non-Originating	Exclude No Cargo Load	Exclude < 1 Short Ton	Total Departures
<b>Joint Base McGuire</b>	630	379	294	210	92
<b>Joint Base McChord</b>	214	193	156	129	66
<b>Travis, AFB</b>	2461	627	275	186	161
<b>Dover, AFB</b>	176	144	138	117	75

The remaining 394 data points were utilized for this study and Table 2 shows the number of aircraft that originated at each location. After cleaning the data, this study needed specific cargo characteristics for each load. The only way to obtain this information is to look up, by mission number, each departure. Then, by using the load plan, the exact specific cargo characters were determined. The information from GATES chosen includes: short tons on-loaded, pallet positions on-loaded, loose stock, palletized cargo, rolling stock, standard cargo, pallet trains of size 2, 3, 4, 5, and 6, total cargo, hazardous cargo classifications, and special handling codes (classified).

Data collection was almost complete after gathering all the information out of GATES. However, this study also needed load start and load complete times to determine exactly how long it took to load individual aircraft. Unfortunately, this information was not available in GATES and HQ AMC had to pull a schedule of events for each of those mission numbers to determine load time. Supplementary pruning is also accomplished based on actual loading times. It was observed that six data points had extremely low loading times but a significant amount of cargo on-loaded. According to AMC, this was because the schedule of events where loading times are recorded is not always completed and is not checked upon departure, so human error plays a factor.

Exploratory analysis was accomplished based on delay categories and delay descriptions. Delay categories were assigned a specific type of delay to that departure. Examples include logistics, operations, higher headquarters, and air transportation. After analyzing all the data points, it was determined that this information was not as useful as originally planned. This was due to the same delay descriptions recycled and used

without details. There were four delay descriptions that outlined cargo loading time exceeded or additional shoring/tie-down required. The specific details as to what piece of cargo required additional up-load time or attention could not be determined so this information did not prove to be as useful, and delay codes were not taken into consideration for this study.

### **3.3 Regression**

Linear regression is a commonly used statistical technique to analyze a relationship between variables. There are three different types of data collection techniques: a retrospective study based on historical data, an observational study, and a designed experiment. The historical data collection method was used in this analysis, and that leads to a retrospective study. There are a number of ways to deal with historical data, but the one used for this study was the idea of training data and test data. Training data is a set of data used to discover potentially predictive relationships while test data is a set used to evaluate the predictive capability of the model. Data splitting was used because all data points are historical and there are three months of data with many points (Azen & Budescu, 2009; James, Witten, Hastie, & Tibshirani, 2013). Two months of data to include August and September was used to train the model and this included 273 departures. The third month with 121 departures was used to validate and test the model.

Multiple linear regression was a focus for this study because many different variables were regressed onto the dependent variable. In this study, the dependent variable was calculated by taking the loading complete time and subtracting the loading start time. This gave an overall loading time for each departure, which determined if

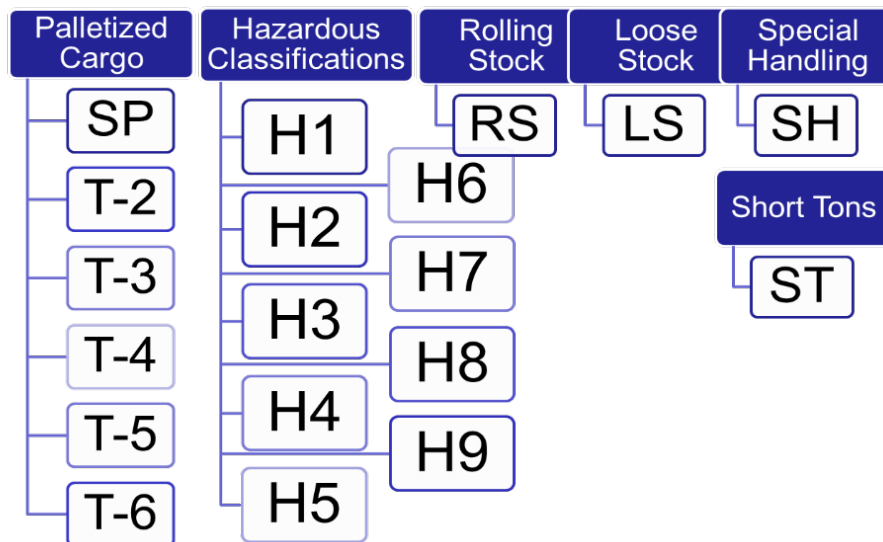
there was a positive or negative relationship. Multiple linear regression uses the method of least squares to determine the regression coefficients just as simple linear regression (James et al., 2013; Montgomery, Peck, & Vining, 2012). There are many methods to find the best possible regression equation, and there are advantages to all of them. Some of the ways to measure and determine the best fit and build the model are by using the coefficient of determination ( $R^2$ ) and adjusted  $R^2$  (James et al., 2013; Montgomery et al., 2012).

### **3.4 Variable Selection**

Variable selection and model building are integral to this analysis. This study utilized nineteen factors to include varying types of cargo off-loaded at each location and the specific cargo characteristics. This study included loose stock, rolling stock, palletized cargo, and pallet trains that can consist of two to six pallets tied together as one pallet (T2, T3, T4, T5, T6), special handling codes, and hazardous cargo classifications. Each one of these types of cargo is given an equivalent pallet position in the GATES load plan. This means that for a certain type of cargo, e.g., a trailer as rolling stock taking up two pallet positions (T2) on an aircraft, it is counted as the number of pallet positions occupied on the plane. Weight was initially used, but due to the variance in weight per pallet position, a number of pallet positions better-explained load times. For example, it takes the same time, manpower, and equipment to push a pallet that weighs 200 pounds as it does to push one that weighs 2000 pounds. The hazardous categories can add up to include hundreds of different types, as was shown in Table 2. For simplicity, this study

grouped hazardous categories into numbers only from one to nine. If a piece of cargo was classified as 4.2, it was used as a four for the remainder of this study.

The labels used for the actual columns in the EXCEL database, that was fed into JMP® Statistical Software include the following: LOAD\_TIME (load start-load complete), LS (loose stock), RS (rolling stock), PC (palletized cargo), T2, T3, T4, T5, T6 (pallet-trains), SH (special handling), H9, H8, H7, H6, H5, H4, H3, H2, H1 (hazardous categories), and finally total short tons loaded into the aircraft (ST). Figure 11 shows the factors chosen for this study.



**Figure 11: Factors Chosen**

### 3.5 Model Development

Once the data was cleaned and set-up for this study it was transferred into JMP® for a stepwise regression. Stepwise regression breaks down into three specific areas: forward selection, backward elimination, and stepwise regression. Forward regression starts with zero factors in the model. One factor was added to the model at a time. The

first factor selected for entry is the one with the largest simple correlation with the response variable. The second factor picked for entry is the one with the largest correlation with the response after adjusting for the effect of the first factor. This continues until the next factor with the largest correlation does not surpass the specified significance level that was set at a p-value of .01 to enter (James et al., 2013; Montgomery et al., 2012).

Backward elimination uses the p-value thresholds as well. It is computed for each factor as if it were the last variable to enter the model. This continues until one factor's p-value is not below the specified p-value for elimination which was .05 in this case. Stepwise regression combines both of these methods using .01 p-value for including and .05 p-value for eliminating from the model. The statistical software utilized a mixed stepwise regression to account for both forward and backward elimination (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012).

The Y variable chosen in this study was the load complete time subtracted from the load start time to have an overall load time. Next, the nineteen remaining factors were selected and used to determine significance. The model was run with p-value thresholds of 0.1 for the probability to enter and 0.05 for the probability to leave. Mixed stepwise was coded and run in the JMP® Statistical Software to determine predictive variables.

### **3.5 Model Accuracy**

Validation of the model was accomplished to determine significance. To validate the data for our model we had to test three assumptions: normality, homoscedasticity

(constant variance), and independence of the residuals. For all assumptions, where relevant, we used an alpha of .05.

To check for normally distributed errors, the residuals were plotted in the statistical software and observed. This gives a picture of the distribution where normality can be detected. The Shapiro-Wilk test was used to test for normality as well and validate the histogram of residuals (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012). In this analysis, an alpha of .05 was used, and in the Shapiro-Wilk test, a p-value above .05 is desired.

The next step was to plot the residuals vs. fitted (or predicted) values. The model is correct, and the assumption holds true if the residuals do not follow any pattern. The magnitude of the residuals versus predicted values should be relatively constant across the observations, and the average value of the residuals should also be approximately zero. This can be seen in the statistical software with residuals by the predicted plot (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012).

Next, a test for independence was completed. Since the data collected for this analysis was observational time series rather than experimental, we could not use the Durbin-Watson test statistic. Instead, we sought to assess independence visually from the runs plots output in JMP®. If there is no observable trend in the runs plot, it will be concluded that the model maintained the assumption of independence.

Finally, a series of three diagnostics analyzing the variance inflation factors (VIF), Cook's distance, and the studentized residuals was completed. These three diagnostics allow for quantifying the severity of multicollinearity, estimating the influence of any single data point, and identifying outliers in the residuals, respectively.

The VIF provides a measure of the correlation between each of the independent variables in the regression model. A high VIF score for any one variable indicated that variable was highly correlated to at least one other variable, a condition known as multicollinearity. To identify and potentially check influential data points for validity, Cook's D was plotted for each data point in the model. Cook's D measures the estimated p-value change of the regression parameters when each observation is either included or excluded. For Cook's D, data points above .5 are determined to be influential and would need to be assessed for validity or excluded from the model. The third and final diagnostic for this model was to analyze the studentized distribution of the residuals to identify outliers. An outlier was defined as any data point falling more than three standard deviations away from the mean. For each 100 data points, there should be no more than one outlier (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012).

### **3.6 Summary**

This chapter summarizes the mixed stepwise regression used for model development. It also identified each of the variables used and determined the dependent variable. The statistical techniques in this chapter are applied to the model and results are presented in Chapter IV. The following chapter will outline effects and have further details that will then be used to create the *working ton*.

## IV. Analysis and Results

### 4.1 Overview

This chapter describes the results found and analysis conducted for the model. Stepwise regression was completed followed by the validation of the model for accuracy. Then, the outliers and multicollinearity were considered before determining what variables would be included in the *working ton*. Finally, a new unit of measure is created and will be validated at Travis, AFB during an exercise from January 29<sup>th</sup> through February 2<sup>nd</sup> of 2018. The final *working ton* excel tool can be found in Appendix A.

### 4.2 Analysis

Stepwise regression was conducted in the statistical software JMP® to create the model for this study. Stepwise regression was used to screen for predictive variables. A significance level of  $\alpha = .1$  was used as the threshold for variable selection as the stepwise regression was strictly exploratory. The step history for the stepwise regression model in Table 3 shows that eight variables were identified as predictive, and the model was initially created with these variables (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012).

As would be expected, the overall analysis of variance (ANOVA) identified that at least one variable in our model is predictive ( $p < .0001$ ). Based on an experiment-wise error rate of  $\alpha = .05$  and using the Bonferroni correction method, we removed the least significant variables and reran the model until all variables fell below the calculated comparison-wise error rate. Eight variables were identified as significant at a comparison-wise error rate of .006 ( $\alpha_c = .05/8$ ) with all p-values below .007. The final

model is shown in Table 4 (Azen & Budescu, 2009; James et al., 2013; Montgomery et al., 2012).

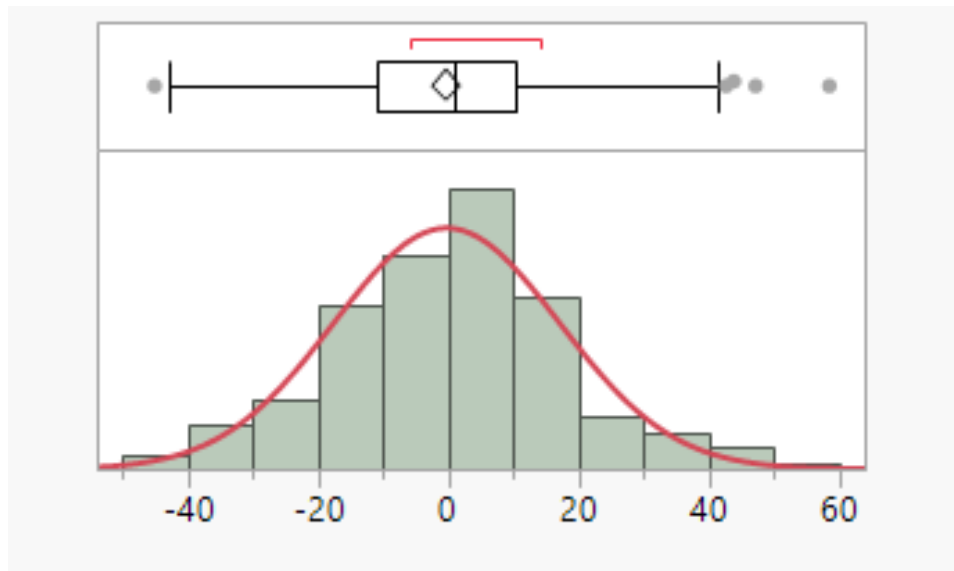
**Table 3: Stepwise Regression Step History**

Step	Parameter	Action	“Sig Prob”	R <sup>2</sup>
1	Short Tons	Entered	0.0000	0.5554
2	Hazard Cat 1	Entered	0.0000	0.6793
3	Pallet Train 6	Entered	0.0002	0.6952
4	Rolling Stock	Entered	0.0009	0.7075
5	Pallet Train 2	Entered	0.0003	0.7215
6	Hazard Cat 2	Entered	0.0010	0.7326
7	Pallet Train 5	Entered	0.0024	0.7418
8	Pallet Train 4	Entered	0.0028	0.7504
9	Hazard Cat 8	Entered	0.0747	0.7534
10	Hazard Cat 8	Removed	0.0747	0.7504

**Table 4: Model Parameters**

Term	Estimate	Prob> t	VIF
Intercept	39.6771	< 0.0001	
Short Tons	2.0460	< 0.0001	1.3217
Hazard Cat 1	2.8942	< 0.0001	1.2565
Hazard Cat 2	2.0597	0.0004	1.1250
Pallet Train 2	1.8099	< 0.0001	1.0695
Pallet Train 4	1.9386	0.0028	1.0575
Pallet Train 5	3.4247	0.0009	1.0431
Pallet Train 6	2.7945	< 0.0001	1.1472
Rolling Stock	2.7641	< 0.0001	1.2153

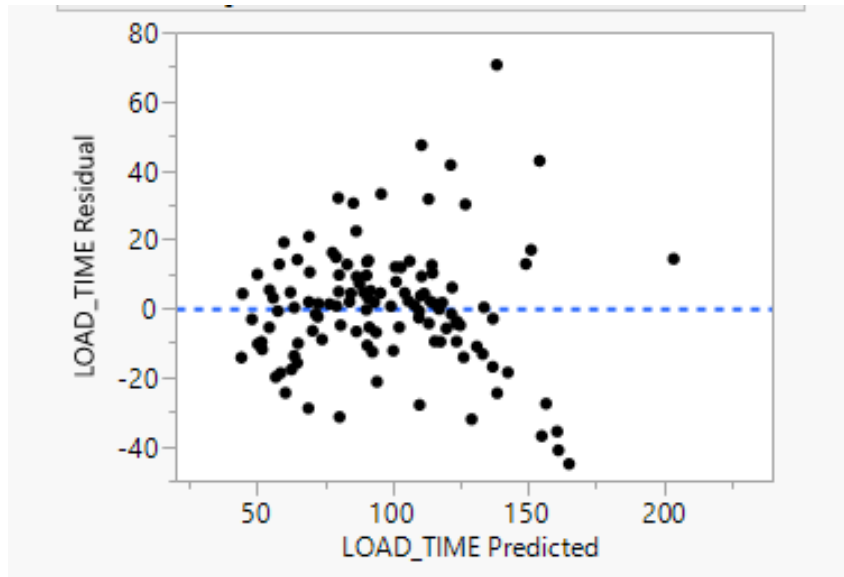
To validate the data for this model prior to analyzing the results, three assumption tests were performed: normality, homoscedasticity (constant variance), and independence of the residuals. For all assumptions, where relevant, an alpha of .05 was used. The first assumption tested was normality where the distribution of residuals was used along with the Shapiro-Wilks test. This identified a major outlier, and it also did not have a p-value greater than .05, so the data point was reexamined. It was determined that the data point in question had a major delay code that resulted in a seventy-hour delay from headquarters. It was deemed necessary to exclude this data point and re-run and test for normality. After excluding that data point, normality was visually apparent as seen in Figure 12 along with passing the Shapiro-Wilks test having a p-value of 0.1274.



**Figure 12: Distribution of Residuals**

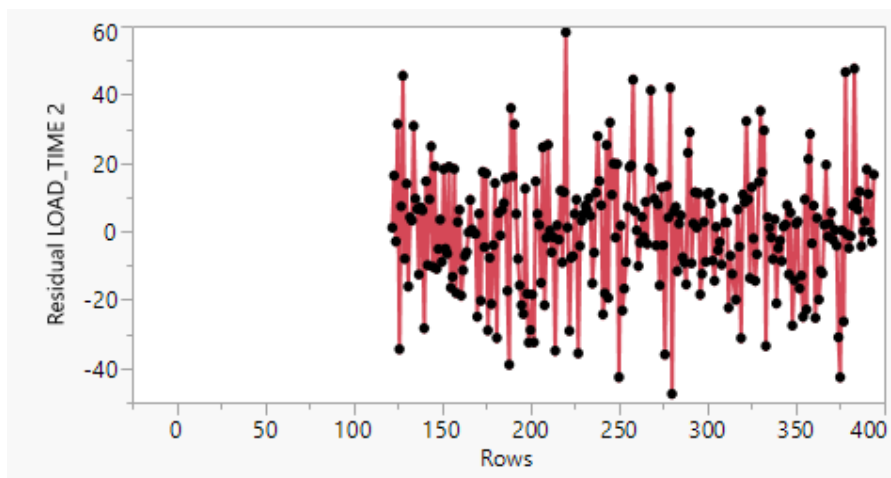
The next test for constant variance was determined by using the residuals by the predicted plot. It showed all the data points in a horizontal band around zero as seen in

Figure 13 to show variances of error terms are equal. It did not form a any particular pattern that would raise concern.



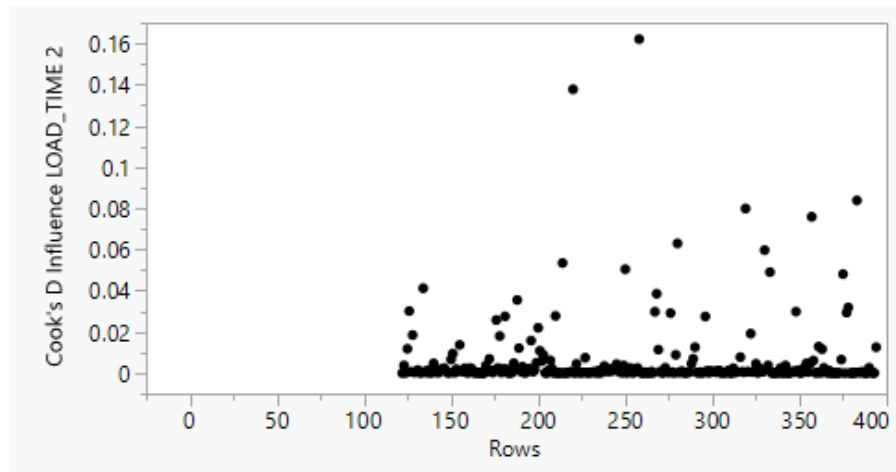
**Figure 13: Residuals by Predicted Plot**

The final test was for the independence of the residuals. There is no observable trend in the runs plot shown in Figure 14. It was concluded that the model maintained the assumption of independence.



**Figure 14: Runs Plot of Residuals**

Next, a series of three diagnostics analyzing the VIF scores, Cook's distance, and the studentized residuals was determined to be important in model validation. These three diagnostics allow us to quantify the severity of multicollinearity, estimate the influence of any single data point, and identify outliers in the residuals. The model parameter estimates from Table 4 include each variable's VIF score. In this model, a VIF score of 5 or higher indicates multicollinearity. Multicollinearity occurs when two or more factors in multiple regression are highly correlated. This can cause the inferences based on the regression model to be flawed or misleading. Based on the VIF scores shown, multicollinearity was not determined to be a concern. Cook's D was analyzed next and each point in our model falls below the value of .5 as shown in Figure 15. There do not appear to be any outliers, as all data points are on the same scale. Therefore, we concluded that we do not need to assess any data points for validity or exclude any data points from this model.



**Figure 15: Cooks Distance**

Upon initial review of the studentized residuals, there are a few outliers in this data. Outliers are extreme observations. These points have residuals that are much larger

than others. Typically they are three to four standard deviations from the mean (Montgomery et al., 2012). The residuals in each scenario are analyzed and standard deviations between three and four are considered. These points are not representative of the rest of the data and could have serious effects on the regression model. If no error was found and the point is just unusual, then it should be kept in the model (Montgomery et al., 2012). For this study, the outliers were left in the model because each of them had a delay code on the departure that could affect the load time.

The summary of fit for our multiple regression models is shown in Table 5. The coefficient of determination ( $R^2$ ) indicated that 68% of the variability, in the amount of time it takes to load an aircraft, can be explained by this model. The adjusted  $R^2$ , which accounts for the number of explanatory variables, is slightly lower since there are eight variables in the model. The mean of response identifies the average load time around ninety-four minutes or just a little over an hour and a half. The Root Mean Square Error (RMSE) identifies how concentrated the data is around the line of best fit. This RMSE does not raise concern because our dependent variable ranges from thirty to two hundred-eighteen.

**Table 5: Multiple Regression Summary of Fit**

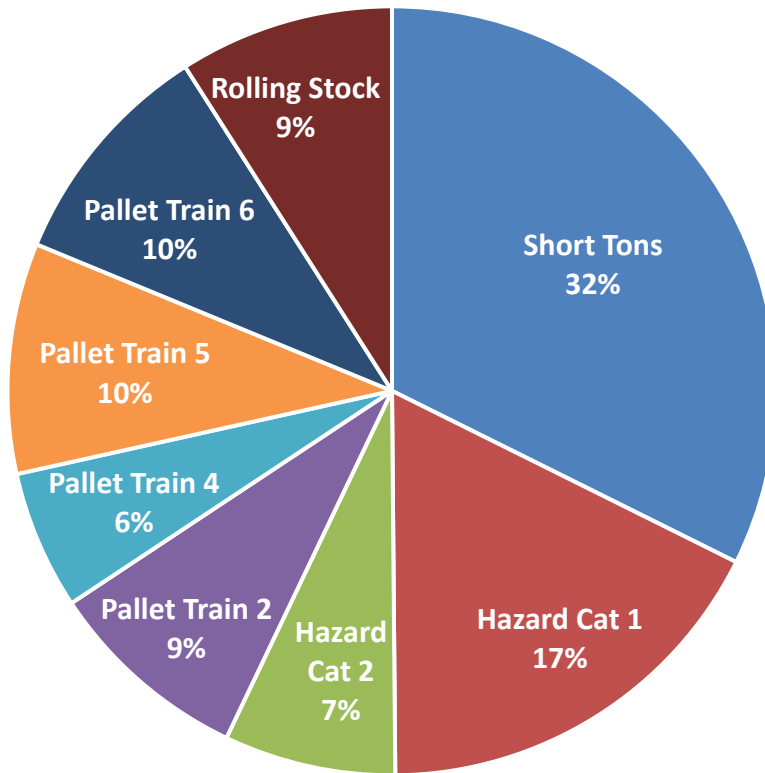
<b><math>R^2</math></b>	0.6799
<b>Adjusted <math>R^2</math></b>	0.6571
<b>Root Mean Square Error</b>	23.7664
<b>Mean of Response</b>	93.57

The final model built to determine the characteristics of the *working ton* is given by the below equation.

$$\begin{aligned} \text{Load Time} = & 39.6771 + 2.0460(\text{Short Tons}) \\ & + 2.8942(\text{Haz Cat 1}) + 2.0597(\text{Haz Cat 2}) \\ & + 1.8099(\text{Pallet Train 2}) + 1.9386(\text{Pallet Train 4}) \\ & + 3.4247(\text{Pallet Train 5}) + 2.7945(\text{Pallet Train 6}) \\ & + 2.76416(\text{Rolling Stock}) \end{aligned}$$

### 4.3 Define Working Ton

The *working ton* was defined using the stepwise regression model standardized betas. The standardized betas refer to how many standard deviations the load time will change per standard deviation increase in each explanatory variable. It was calculated by converting each independent variable to Z-scores for standardization. Using a standardized beta coefficient means the variables can be easily compared to each other. The absolute values of these coefficients indicate the relative strength of the effect of each variable to the dependent variable. Figure 16 is a pie chart of the standardized betas after placing each of them over the variable effect. Short tons and hazard category one are shown to be the most significant variables, having the greatest effect on the amount of time it takes to load an aircraft.



**Figure 16: Percentage Effect of Each Characteristic**

To validate the *working ton*, an excel tool was developed for ease of use. The *working ton* tool was tested and used on seven departing aircraft at Travis, AFB. The tool outputs a *working ton* for each aircraft load, based on pallet positions for specific cargo characteristics, and overall short tons. This will assist decision makers at AMC who are allocating resources to each aircraft. The tool is shown in Table 6 with a *working ton* of 113. The specific aircraft load time is shown with mission number 1 in Table 7 as 118 minutes.

**Table 6: Working Ton Tool**

Aircraft:		C17			
<b>Cargo Type</b>	<b>Pallet Positions</b>	<b>Cargo Type</b>	<b>Intercept</b>	<b>Working Ton</b>	<b>113.516</b>
Short Tons	20.36	Short Tons	2.046	41.65656	
Haz Cat 1	4	Haz Cat 1	2.8942	11.5768	
Haz Cat 2	2	Haz Cat 2	2.0597	4.1194	
Pallet Train 2	3	Pallet Train 2	1.8099	5.4297	
Pallet Train 4	0	Pallet Train 4	1.9386	0	
Pallet Train 5	0	Pallet Train 5	3.4247	0	
Pallet Train 6	0	Pallet Train 6	2.7945	0	
Rolling Stock	4	Rolling Stock	2.7641	11.0564	

**Table 7: Travis, AFB Results**

<b>Mission #</b>	<b>Short Ton</b>	<b>Load Time</b>	<b>Working Ton</b>	<b>Potentially Save</b>
1	20.63	118 mins	113	37 mins
2	27.23	102 mins	110	40 mins
3	28.26	125 mins	105	45 mins
4	31.21	97 mins	96	54 mins
5	20.64	84 mins	92	58 mins
6	18.27	68 mins	81	69 mins
7	22.1	73 mins	79	71 mins

**4.5 Results**

The percentage effects and p-values of each characteristic answer the hypotheses developed for this study in Table 8. Hypothesis one breaks cargo load type out by pallet, rolling stock, and loose load. The model for this study identified rolling stock as having a strong relationship with the amount of time it takes to load an aircraft. A standard pallet and loose load cargo were not included in the model and had no statistically significant

relationship with load time. Rolling stock positively affected the load time and had a variable effect of 9%.

**NOT SUPPORTED H1a.** A pallet will be positively related to the amount of time it takes to load cargo.

**NOT SUPPORTED H1b.** Rolling Stock will be positively related to the amount of time it takes to load cargo

**SUPPORTED H1c.** The loose load will be negatively related to the amount of time it takes to load cargo.

Hypothesis two breaks cargo load type out by a number of pallet positions. Pallet positions had an overall thirty-five percent effect on the load time based on standardized betas. Pallet train two through six, except three, had a strong positive relationship with the amount of time it takes to load an aircraft. Each hypothesis was supported, and the p-value details are outlined in Table 8 along with the variable effect.

**SUPPORTED H2a.** The number of pallet positions will be positively related to the amount of time it takes to load cargo.

**SUPPORTED H2b.** Oversized cargo will be positively related to the amount of time it takes to load cargo.

Hypothesis three breaks cargo type out by hazardous category. Hazardous categories affected the overall load time by twenty-four percent. This was split between hazardous category one and two. Each relationship was positive to show that load time increases. Hazardous category one had the largest impact of all the independent variables besides short ton. This was because this level of hazardous cargo needed to be loaded in a different location away from other aircraft for safety reasons.

**SUPPORTED H3.** Cargo hazardous classifications will positively affect the amount of time it takes to load cargo.

Classified and special handling cargo did not appear in the final model and did not affect the overall load time. The aerial port experts explain this might be because a high number of classified cargo was palletized in a standard pallet. It is located in a vault and does require more documentation, but it was not statically significant enough to appear in the final model.

**NOT SUPPORTED H4.** Classified cargo will positively affect the amount of time it takes to load cargo.

**Table 8: Hypotheses Details**

<b>Hypotheses</b>	<b>P-Value</b>	<b>Standardized Beta</b>	<b>Variable Effect</b>	<b>Outcome</b>
H1a	None	None	None	Not Supported
H1b	None	None	None	Not Supported
H1c	$P < 0.0001$	0.1478	9%	Supported
H2a / T-2	$P < 0.0001$	0.1407	9%	Supported
H2a / T-4	$P = 0.0028$	0.0953	6%	Supported
H2b / T-5	$P = 0.0009$	0.1058	10%	Supported
H2b / T-6	$P < 0.0001$	0.1585	10%	Supported
H3 / Haz Cat 1	$P < 0.0001$	0.2864	17%	Supported
H3 / Haz Cat 2	$P = 0.0004$	0.1180	7%	Supported
H4	None	None	None	Not Supported

## 4.6 Conclusion

Chapter IV detailed how the data was analyzed, created the model and validated the model. This section also defined the *working ton* created for future use within AMC. This chapter outlined the results for each individual hypothesis and stated whether they were supported or not. Chapter V will offer further conclusions and recommendations for what could be done with these results, as well as future research opportunities to supplement the *working ton* development.

## V. Conclusion and Recommendations

### 5.1 Overview

This study defined and created a new unit of measure called the *working ton*. The model has been created and validated. Chapter V outlines the impact and future research opportunities for developing the *working ton*. This chapter goes over a real-world implementation at Travis, AFB and compares seven missions with the *working ton* output.

### 5.2 Future Research

Based on the conclusions, this research suggests both short-term and long-term future research. In the short term, verification of the results from this research needs to occur by gathering data on every AMC base. There were only four bases utilized in this study and looking at more bases within AMC could change the *working ton* model. Additional bases outside AMC may also have a much different impact on the model. Comparing load times for AMC bases and non-AMC bases could potentially change the *working ton* output. This research topic was scoped down to a small selection of Air Force aircraft. The research could be expanded to other aircraft to determine if the type of aircraft affects the load time. The C-5 and C-130 are commonly used to transport cargo, and the same study could be completed with these aircraft.

Long-term research could focus on change management. How will units and the air transportation community actively accept the *working ton*? There are some entities and key players that are involved in cargo preparation and loading. Is it useful to other

key players involved in the cargo transportation process? The creation of a new unit of measure will take time to integrate into the culture and computer systems.

### **5.3 Implications**

Utilizing the *working ton* could have a large impact on future operations. Currently, AMC utilizes a standard of four hours before aircraft departure for load times no matter what cargo characteristics are in the load. The Air Force can include cargo characteristics that are already measured to predict load time better while saving manpower and resources. The data is already collected, and the information is available before departure for compiling a load plan. The implementation of the *working ton* does not require additional data collection or a burden on day-to-day operations.

To determine the current impact, a model was run only using short tons as the independent variable to predict load time as the dependent variable. The results were compared with the model created for this study in Table 9 to find a 250% increase in the variability explained. The  $R^2$  was improved by over forty percent using the *working ton*, and reduced RMSE errors from thirty-four to twenty-three. All of these cargo characteristics are already used in daily operations and can have a potentially major impact on AMC's ability to predict work-levels to save money and improve future mission timelines.

**Table 9: Short Tons vs. Working Ton Model**

	<b>Only Short Tons</b>	<b>Working Ton Model</b>
<b>R<sup>2</sup></b>	0.2675	0.6799
<b>Adjusted R<sup>2</sup></b>	0.2614	0.6571
<b>RMSE</b>	34.88	23.766

The excel tool created and shown in Chapter IV was tested on seven departing aircraft from Travis, AFB. The cargo characteristics were determined before arrival at the aerial port, and the conclusions were accurate. The excel tool predicted three working tons over the load time and four working tons under the load time. Each aircraft does have to be loaded completely one hour and thirty minutes prior to departure, but if the working ton were being used to determine load time, it would have saved a little over six hours of manpower waiting on departures. This was an average of thirty percent savings in time per aircraft.

#### **5.4 Conclusion**

This model can be used by AMC to increase the efficiency of cargo load times by providing greater fidelity on different load-types other than just their weight. The *working ton* also can impact the entire Air Force by providing reliability when preparing for deployments and exercises. The bottom line is that AMC needs a better unit of measure to determine aircraft load times. Utilizing the short ton metric leads to inadequate forecasting times for aircraft loading, which leads to delayed missions. The

root of the problem is that the metric used does not provide enough fidelity for accurate forecasts, and in essence, all tons of cargo are not created equal concerning loading.

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<b>14. ABSTRACT</b> United States Transportation Command (TRANSCOM) along with Air Mobility Command (AMC) provide airlift assets that accomplish thousands of missions around the world every week for cargo distribution. The current unit of measure is a short ton, which is the primary metric used in decision making. However, the short ton measurement does not adequately predict the amount of work necessary to properly prepare different cargo types for airlift. Utilizing the short ton metric leads to inadequate forecasting times for cargo preparation and aircraft loading, which leads to delayed missions. The root of the problem is that the metric used does not provide enough fidelity for accurate forecasts, and in essence, all tons of cargo moved are not created equal concerning preparation and loading. For example, a ton of hazardous material takes more preparation than a ton of standard cargo. This research utilizes a stepwise regression model that accounts for the different cargo types, such as loose stock, palletized cargo, rolling stock, standard cargo, pallet trains of size 2, 3, 4, 5, and 6, hazardous cargo classifications, and special handling codes (classified). This model can be used by AMC to increase the efficiency of planning for cargo preparation and cargo load times by providing greater fidelity on different load-types than just their weight. Seven of the cargo characteristics are found to be statistically significant and are validated with split data and implementation at Travis, AFB. This analysis has led to a new metric called the <i>working ton</i> . The <i>working ton</i> metric is created utilizing the stepwise regression model's standardized betas. The values of these coefficients indicate the relative effect of each variable. Hazard category one and the standard pallet are shown to be the most significant variables, having the greatest effect on the amount of time it takes to load an aircraft. This research proposes a new metric for AMC and TRANSCOM to use that will significantly aid in their ability to predict work-levels and improve future mission timelines.					
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