MANAGING THE WEAR OF HEAVY CONSTRUCTION EQUIPMENT STEEL TRACK UNDERCARRIAGE BY SOIL SAND CONTENT

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ABSTRACT

Heavy construction equipment owners and managers have few predictive tools that can estimate wear rate of undercarriage track propulsion systems working in various soil types and changing operational conditions. Managing the timely maintenance of these track systems is critical for they represent over half of the non-fuel operating cost of the equipment fleet. Understanding the major influencing factors that impact undercarriage system wear rate can help determine the most economical time to stop a machine for track maintenance thus positively impacting the equipment's return on investment (ROI).

This research analyzed the population of track type dozers in the eastern half of North Carolina, United States of America. This region has markedly different soil types, topography and precipitation amounts making this to be an excellent study canvas. Sand percentage in the soil where the machine is working is thought to be a primary factor influencing the wear rate. In addition, other factors like precipitation, temperature, machine model, machine weight, altitude above sea level, and work type code are also considered and analyzed to determine which of these factors have significance. A regression model is developed that can be used as a predictive model to help manage this high value maintenance wear item.

This research is important because the results can assist machine owners in maximizing the life of the undercarriage system in eastern North Carolina and will result in better machine maintenance decisions. In addition, this research can be utilized to accurately bid construction jobs predicting machine operating expense for each specific job site soil makeup.

PREFACE

Individual concepts of knowledge and understanding are as vast as the countless grains of sand comprising the shoreline. "God gave Solomon wisdom and very great insight, and a breadth of understanding as measureless as the sand on the sea shore" (NIV Study Bible, 2011). This vast body of knowledge is ever changing and evolving and it is my hope that this study contributes one more grain of sand to the expansive landscape of knowledge. Although one grain of sand may seem insignificant, the massive shoreline is comprise of countless unique and individual grains with each adding to the sum.

Like these grains of sand, there is a huge amount of information at the disposal of todays equipment managers and owners. The hope of this research is to provide one more useful tool for equipment managers and owners to use in managing their equipment fleets. As with any new knowledge, this study will be added to and hopefully will strengthen the current body of knowledge that already exists today. This will help make better equipment management decisions and if utilized properly, helping to optimize the utilization and efficiency of today's equipment fleets.

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Gregory Poole Equipment Company is where I have worked for the last 36 years. Here is where my passion for construction equipment was ignited, inspires and continues to evolve. Specifically, I wish to thank Kevin Ray, Lane Crouch, Kevin Hendges, Paul Eberhart, Tracey Haeseker, and Gregory Poole III for their tremendous support.

My parents worked very hard as a welder and as a finish sander in a furniture factory to help me pursue my dreams of a college degree. They taught me how to work hard, follow Jesus Christ and treat others as I would want to be treated. They simply wanted me to have opportunities that they did not have and for that I am most grateful. I love you both.

My wife Kimberly has been my foundation throughout this journey and without her support, I could not have accomplished what I have thus far. Her patience and encouragement has meant so much to me and has allowed me to pursue my passion. Thank you for your love and patience.

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CHAPTER 1

INTRODUCTION

It has been long hypothesized in the equipment management industry that working in sandy soil accelerates the wear rate of the steel track undercarriage. Few scientific field studies have been found regarding this relationship and quantifying it would help in the management of diverse track type equipment fleets. This understanding would provide valuable information creating impetus for more profitable equipment management decisions. Understanding the relationships of the critical operational conditions that impact undercarriage wear rate could assist organizations in the bidding process of large earth moving projects to gain an understanding of true equipment cost depending on the soil types and working conditions.

Background

This research is an extension of previous research performed by this author and Dr. Christopher Kluse. (Rich & Kluse, 2018). In the original study, it was determined that differences in the track system life of heavy construction equipment depends on the geographic location in which the machine was working in the study area. The research analyzed track wear life of two populations of track type machinery where one population resided in the coastal plain area and the other in the western piedmont region of North Carolina. Some interesting characteristics of these two regions is the marked distinction in the geological composition of the soil texutures, topography and precipitation totals. The results of the research determined there is statistical different between the eastern and western populations however, the research did not investigate the causation of this finding. One of the main differences between the two regions is soil composition. The eastern region is in the coastal plains of the state where the soil is composed of a higher percentage of sand while, the western half of the territory is comprised of far less sand with much more silt and clay. This research expands upon the previous study and quantifies the wear rate differences between the regions. Once this relationship is quanitified it is leveraged in designing a tool set to assist equipment managers by accounting for the additional cost of working in very sandy environments or other operational soil conditions.

To fully understand the setting for this research, there are several topics discussed in this background section. A description of track systems on dozers which include the components comprising the track system, track system maintenance and track system measurement are discussed. Understanding the management of track components helps in the understanding of how the different machine operational conditions impacts the undercarriage track systems. There is a general overview of the soils in the study area focusing on the differences in the soil components as one moves from west to east within the study region of eastern North Carolina. Moisture, elevation, and other factors could play a role of an accelerant on undercarriage track bushing wear.

Track System Background

Undercarriage systems on heavy construction equipment propels the machine utilizing a sprocket and chain arrangement that rolls on a foundation of idler wheels and bottom rollers. Figure 1 illustrates the complete undercarriage system of a large track dozer. In addition to propelling the machine forward and reverse, the tracks are designed to turn the machine by reducing the power to one side or even counterrotating to turn quickly. The track system also transfers power into the ground engaging tools such as blades and rippers that performs the work of moving and manipulating the soil. Engine horsepower is transferred from the engine through the power train and into the tracks to push the blade in the front of the machine or to pull a ripper in the rear. The blade arrangement pushes dirt, rocks or tree stumps while the ripper is used to fracture hard dirt or sandstone to make it bladeable. This entire track system is designed to wear together as a system and is considered sacrificial iron which must be either maintained or replaced at wear point intervals.

Figure 1. Heavy Construction Equipment Undercarriage System

The area of concern in this track system is the contact area of the pin and bushing where the sprocket tooth contacts the bushing of the track chain. The pin and busing are part of the link assembly and this assembly is produced by pressing the links, pins and bushings together into the chain shown below. Track shoes are bolted to this chain and this track assembly is then wrapped around the sprockets, rollers and idlers and bolted together at a master link assembly. As the sprocket is turned by the drivetrain of the machine, the track assembly propels the machine in a circular motion as it rolls on the foundation of the rollers and idler assemblies.

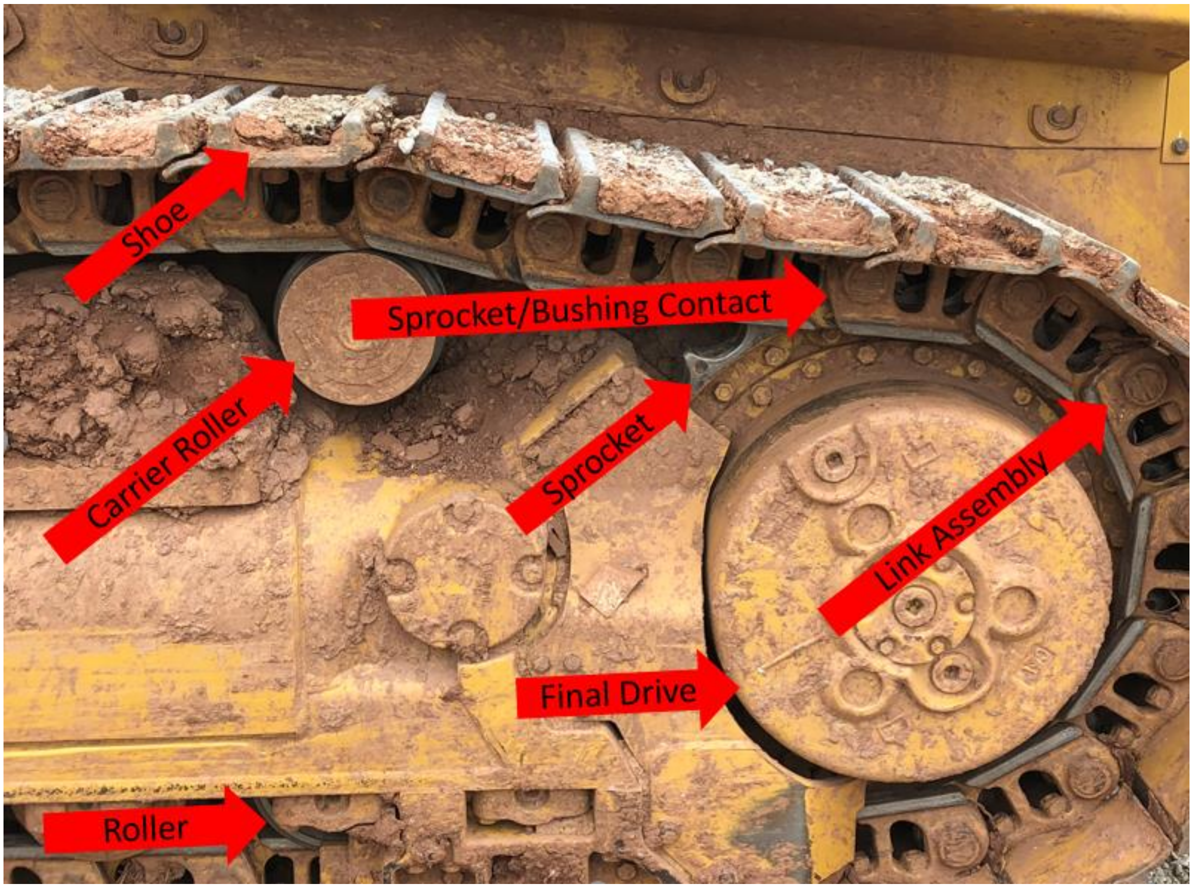

Figure 2. Main Components of Undercarriage System

The components referenced in Figure 2 displays the major components of the undercarriage system with some critical ones defined in the terminology section. Figure 3 illustrates the most critical area for undercarriage management. That is where the sprocket segment, as it rotates around with the final drive movement, contacts the link bushing. Daily maintenance is needed in this area to ensure the tracks are cleaned of excess dirt and mud buildup to prevent unnecessary and premature wear (Nunnally, 2000). Without daily cleaning, dirt packs on top of the track frame as well as inside the track shoe and bushing area of the link assembly creating additional opportunity for dirt to get between the sprocket and bushing contact area.

Figure 3. Sprocket and Bushing Contact Area

If one is to look up into the sprocket area directly where the red arrow is pointing in Figure 3, the contact area where the sprocket and busing areas can be seen. This is where most engine horsepower is transferred to the link assembly resulting in pressures being exerted on the wear surfaces. As the sprocket engages with the bushing, not only are there pressures exerted between the surfaces, there is also sliding between these two metal surfaces which generates the friction for wear to occur. To compound this issue, dirt can become trapped between the sprocket tooth and track bushing acting as an abrasive which can accelerate the wear of the sprocket and bushing surfaces. Figure 4 is a close-up picture of this area where the most critical wear on the undercarriage system occurs. The worn paint on the bushing shows exactly where the sprocket contact patch of the bushing surface is located.

Figure 4. Sprocket and Track Bushing Wear Surfaces

Over time, the sprocket wears into the track bushing surface. This is expected and is part of the sacrificial material that needs to be managed. Normal wear for a bushing surface is shown in Figure 5. One can see how the bushing surface has eroded the once round surface into an oval one where the sprocket contacts the bushing. This wear is acceptable until the bushing diameter reaches a point of 100% worn which is the trigger for the equipment manager to schedule maintenance.

The typical track bushing is cold extruded from low carbon steel. After cold extrusion the bushings are induction heated and carburized for maximum hardness and toughness (Parts Sales Kit, 2005). The actual specifications for other physical property values such as toughness, yield strength and UTS of the bushing steel are proprietary and not available for public disclosure. Matching new sprockets with the new bushing wear surface is critical in matching these hardness levels and the profiles of the new mating surfaces. Keeping old sprocket segments on the machine after a bushing turn can create a pitch mismatch and will also have differences in the hardness levels of the two surfaces.

Figure 5. Normal Bushing Wear

Keeping accurate wear measurements of a dozer track system is one key factor to successful track system management. All components showed in Figure 2 can be measured ultrasonically to determine the percentage of the wear material that has been worn. Technicians gather this information to produce reports that predict how much life is left in the undercarriage system before maintenance is performed. This data is housed in a central data base and has been utilized for this study. Table 1 shows the critical data in the report provided to the machine owner assisting them in undercarriage management. The track bushing with the most wear is on the left-hand side of the machine and currently is at 102% worn at 3,277 hours of operation. This is shown by the yellow highlight. All components of the undercarriage are listed in the complete report. The focus of this study is on the bushing wear percentage as it is the most important component to measure and interpret for bushing maintenance hours can be optimized if managed properly (“Custom Track”, 2013).

Table 1

Track System Wear Report

Model	D6TXL
Manufacturer	Cat
Serial Number	KMR00XXX
Hour Meter	3277

	Left % Worn	Right % Worn	100% Projection Left	100% Projection Right
Track Link	22	25	5891	4905
Track Bushing	102	96	1251	1330
Track Shoe	7	7	18229	18229
Front Idler	48	40	2659	2849
Rear Idler	20	20	4381	4381
Roller 1	30	32	4254	3958
Roller 2	29	30	4421	4388
Roller 3	29	29	4421	4421
Roller 4	22	25	5801	5105

When the track bushing reaches 100% worn, level 1 bushing turn maintenance is required to the link assembly. At this maintenance interval the track assembly is removed from the machine and the track shoes are removed from the link assembly. This isolates the link assembly which is placed on a large press that separates the links from the track bushing. Pressing both links away from the bushing allows for the bushing to be manually rotated 180 degrees from its original press fit position. After the bushing is rotated 180 degrees the links are pressed back together which now exposes a new wear surface to the sprocket. At this maintenance interval the sprocket segments are also replaced to provide a new mating surface for the newly exposed bushing surface to contact. Figure 6 depicts this maintenance process.

Figure 6. Bushing turn Maintenance of Rotating the Track Bushing

If for some reason this bushing turn maintenance is not performed the failure of the link assembly can occur and is shown in Figure 7. If the bushing fails, level one maintenance cannot be performed, and the link assembly must be replaced prematurely creating waste of the remaining sacrificial metal. This reduces the useful life of the track system by approximately one-half equating to thousands of dollars in lost undercarriage value. To optimize the undercarriage track system life, the equipment manager continues to operate the dozer until the critical bushing reaches 100% and then perform maintenance. If maintenance is performed too soon, perfectly good sacrificial metal is wasted as unused wear potential. Conversely, if the maintenance is pushed out too far, the bushing ruptures, and a catastrophic failure as shown in Figure 7 ensues.

Figure 7. Failed Track Bushing Due to Missed Maintenance

After the level one maintenance is completed the track system is now in the run-out stage of its lifecycle. The undercarriage should be operated until the destruction of the tracks occurs. Once the undercarriage is worn beyond operational capacity, the entire undercarriage system is replaced including rollers, track groups, sprockets and idlers. This generates the normal bushing/link replacement interval for complete system replacement. Figure 8 describes the maintenance cycle of a track type undercarriage system and the steps that occur. If the bushing turn maintenance is missed and the bushing fails, the second life of the track system is also forfeited. Therefore, the inspections are critical for accurate forecasting of these maintenance intervals to account for the different input factors that may be affecting the wear rate.

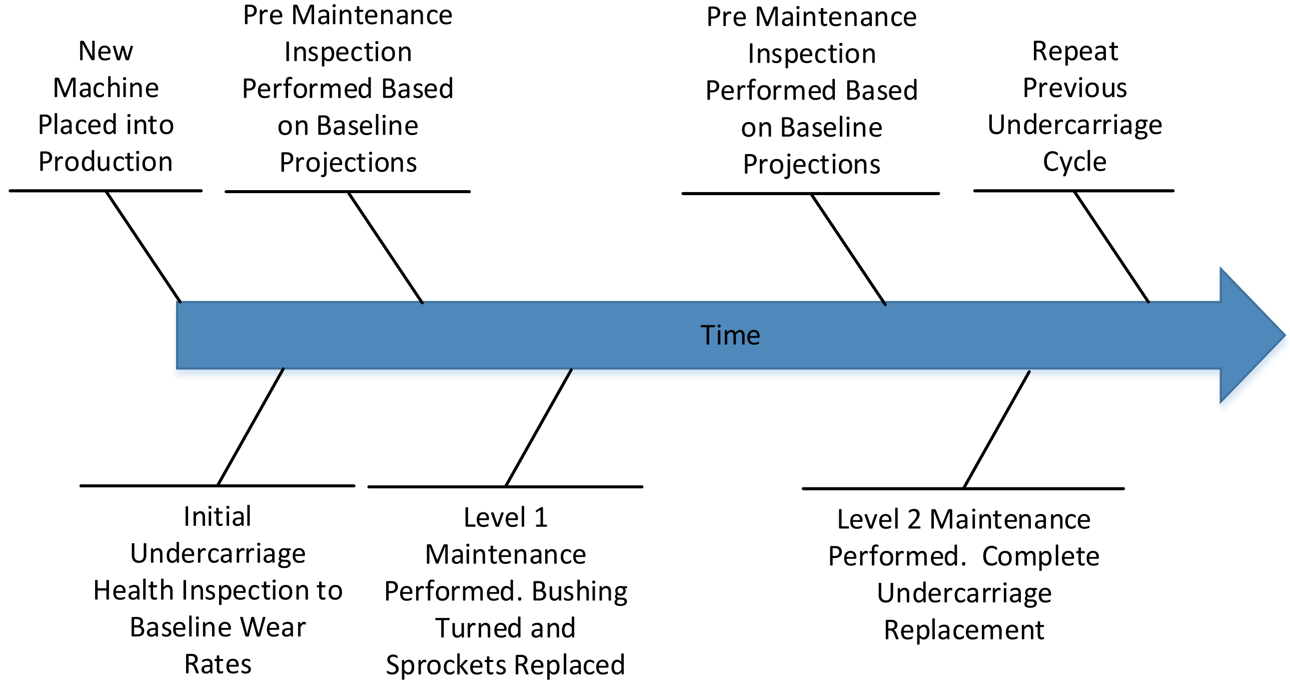

Figure 8. Life Cycle of Track Undercarriage Systems

Input Factors

This study investigates how soil texture impacts the wear rate of the undercarriage components mentioned and explores if higher sand content in the soil accelerates the wear rate. To determine this correlation, one must have a general understanding of soil texture and how the sand content is determined in a soil sample. This is critical in the collection of the data and for the determination of the sand content percentages required. All soils are classified by use of a soil texture. The specific soil texture refers to the makeup and physical characteristics of the soil and specifically is the proportion of three sizes of soil particles being sand (large), silt (medium) and clay (small) (Plaster, 1997). For this research, the proportion of sand in the soil sample is the main input factor to determine the correlation to metal track wear rate. Depending on the proportion of sand, silt and clay, the soil texture could fall within 12 different textural classifications. If the silt and clay soil component proportions are known, the sand percentage can be extrapolated (Davis & Bennett, 1927). This relationship developed by Davis and Bennett is very important in this research for it assists in the determination of the sand percentage in the soil in which the heavy equipment is working.

Soils in Eastern North Carolina, USA

The location of this field study is performed in the geologically diverse eastern half of North Carolina, USA which is represented in the counties lying roughly east of the 79.79 west latitude. This area for study was chosen for two reasons. The undercarriage reporting for the track type dozers in this study area is readily available in an interactive data base designed to monitor track wear. Secondly, the geology in this area is diverse and changes gradually along a continuum from west to east. As one moves from west to east, the geology changes from one of a metamorphic composition of granite-based soils to one of high sand and silicon-based soils in the coastal plane. Generally, as one moves from west to east, the soils continuum gravitates to proportionally more sand based soil. It is found that soils in the western third of the territory generally has 20-40% sand content and a higher percentage of silt and clay. As one moves west to the central third of the territory there is comingling of soil types that represents a transition zone between the piedmont and coastal plain zones. Here there are streaks of different soil types that have more variability of sand content. As one transitions to the eastern third or coastal plain area the sand content steadily increases to 80-90% with less variability. There are soil types directly on the coast in Dare County that are comprised of 99% sand (Tant & Byrd, 2019).

In studies of soils across eastern North Carolina it is found the "soil samples varied most widely in texture" with sand being the largest in differentiation across the geologic continuum (Lu, Bowman, Rufty & Shi, 2015). This study area provides the researcher with many different soil textures which reflects a very diverse sand percentage. This allows for variability in the determination of the regression model.

Precipitation across this territory is quite diverse with far more precipitation occurring in the eastern half (NOAA, 2019). 2017 annual rainfall data reflects much more precipitation along the coastal areas with lesser amounts as one travels west. One major cause for this higher level of coastal precipitation is tropical storm activity. On average there are 2.27 tropical systems that impact this study area creating spikes in the yearly rainfall averages (“Hurricanes”, 2019). Another factor to this gradient is the on-shore winds that create storm activity during the summer. As warm ocean waters are driven by a typically persistent easterly breeze, this phenomenon can create coastal rain episodes that the piedmont region does not experience. In the summer months, the differences between the land and the ocean waters create a strong eastern sea breeze that increases the precipitation in the coastal plain area of the state (Sims & Raman, 2016). This east to west gradient provides another opportunity to gauge the bushing wear rate to determine if this gradient of moisture differential creates a correlation to faster bushing wear.

As with sand percentages and precipitation, topography tends to mirror the same gradient patterns exemplified in these other two input factors. As one begins at the coast, the topography is very flat with very few undulations. The further one travels west into the piedmont, there are many more gentle rolling hills. This increase in undulation continues to grow until one reaches the high peaks of the mountainous region of the state. There is a line of demarcation where the coastal plain ends and the piedmont begins which closely mirrors the same gradient as sand content and elevation (NCOnemap.gov, 2019). This correlates very closely with the silicon-based soil line and this discovery is the basis of some of the input factor measurements. The rationale in measuring the input factor of terrain by gauging elevation above sea level is due to this predictable gradient. As one moves east to west both the elevation increases as well as the undulation of the terrain.

The machinery that is a part of this analysis is quite diverse in size and the applications in which the equipment is operating. Some of the different types of work performed in this territory consists of landscapers, utility installation and residential job sites which are typically requiring smaller machines to perform the work. Another type of work is the heavy construction projects comprising roadwork and large industrial projects. These projects are typically large earth moving projects that must use the full gambit of machinery models with proportionally more large equipment being used on this type of project. Finally, the mine sites require the largest machines and these machines are operating in very harsh and high impact applications. These mining machines are designed for this type of work and the undercarriages systems are designed to withstand the abuse found in this application. Each of these types of work applications are grouped together in the data base by using a work type code. This is a code that designates the type of work each machine is involve in to discern whether the type of work performed by the machine has any impact on the undercarriage hours per percent worn.

Statement of Problem

Equipment managers and owners have a challenging task in determining track system wear rate when working in unfamiliar locations or in areas with diverse soil textures and other variable operational factors. This makes it difficult to accurately time maintenance intervals and to calculate the true cost of operation of track type equipment. This lack of track wear visibility could cause missed maintenance intervals and erode profitability for a construction job if the extra track wear due to high sand content is not accounted for in the job bid. Therefore a need exists to quantify the impact of these input factors and create a model to aid in the prediction of the wear rate based on these factors.

Statement of Hypotheses

1. The null hypothesis to test is: Is there a correlation between the percent of sand present in soil, elevation above sea level, machine weight, temperature, precipitation and the wear rate of steel track undercarriage systems?

$$H_o: \beta_{\text{sand content}} = \beta_{\text{elevation}} = \beta_{\text{weight}} = \beta_{\text{Temperature}} = \beta_{\text{Precipitation}} = 0$$

$$H_A: \beta_{\text{sand content}} \text{ or } \beta_{\text{elevation}} \text{ or } \beta_{\text{weight}} \text{ or } \beta_{\text{Temperature}} \text{ or } \beta_{\text{Precipitation}} \neq 0$$

2. The null hypothesis to test is: Is there a difference between the model number of the machine and the wear rate of steel track undercarriage systems?

$$H_o: \mu_{\text{Mod 3}} = \mu_{\text{Mod 4}} = \mu_{\text{Mod 5}} = \mu_{\text{Mod 6}} = \mu_{\text{Mod 7}} = \mu_{\text{Mod 8}} = \mu_{\text{Mod 9}}$$

H_A: At least one mean is not equal

3. The null hypothesis to test is: Is there a difference between the machine population groups by work type code and the wear rate of steel track undercarriage systems?

$$H_o: \mu_{\text{Landscape}} = \mu_{\text{General Contracting}} = \mu_{\text{Utilities}} = \mu_{\text{Residential}} = \mu_{\text{Mining}} = \mu_{\text{Landfill}}$$

H_A: At least one mean is different.

Statement of Research Questions

1. Do steel track undercarriage systems hours per percent bushing wear vary depending on the percent of sand present in the soil in which the machine is working?
2. Do steel track undercarriage systems hours per percent bushing wear vary depending on the annual precipitation totals in the location on which the machine is working?
3. Do steel track undercarriage systems hours per percent bushing wear vary depending on the elevation above sea level at the location on which the machine is working?
4. Do steel track undercarriage systems hours per percent wear vary depending on the model number of the machine being investigated?
5. Do steel track undercarriage systems hours per percent bushing wear vary depending on the weight of the machine being investigated?
6. Do steel track undercarriage systems hours per percent bushing wear vary depending on the work type code that is assigned to the customer grouping?
7. Do steel track undercarriage systems hours per percent bushing wear vary depending on the yearly average ambient temperature at the location the machine is working?

Statement of Purpose

The purpose for this research is to develop a regression model that describes the correlation and quantifies the differences between steel track undercarriage wear rate to the sand content in the soil, other significant input factors and their interactions to assist equipment managers better manage undercarriage system cost.

Statement of Need

There are presumptions in the equipment industry that the higher the sand content in the soils the faster the undercarriage on heavy equipment wears. There could be other input factors that affect wear rate as well. The need for research in this topic is to quantify the actual impact of the sand content in soil and other factors have on the wear rate of the steel track undercarriage systems. With this regression equation coupled with other analysis tools, equipment managers can determine the impact of these factors on the rate of wear of the undercarriage system. In addition, the engineers who are bidding on earth moving and construction jobs can utilize these tools to better ascertain the true cost of operating the heavy equipment in the specific soil types and operational conditions in which the machine is working in. Today there could be general allowances made with a lack of quantification of these major input factors in quoting jobs for construction company future work sites. These tools help equipment managers be more precise with their equipment management decisions thus more effeceively managing the cost of machine operation. It also helps the job estimators be more precise in the quoting of their jobs for the high cost of undercarriage system utilization will be better estimated depending on the soil type and other factors at the specific job site location.

Statement of Assumptions

This research adheres to the following assumptions:

1. The machine is used in only one localized area during the research study therefore is working in the same soil type. All efforts were exhausted to ensure that machines that are not domicile to one area are not part of this study.

2. The calculation process of percent worn is consistent throughout the entire make and model spectrum within the study area. A measurement system analysis was performed to validate the measurement data.
3. The soil type classifications developed by the United States Department of Agriculture (USDA) are accurate.
4. The equipment owner primarily works in only one type of business which correlates to an appropriate work type code.

Statement of Limitations

The location in which the machine is operating, and the associated soil type is acquired using the USDA soil survey mapping system using longitude and latitude coordinates provided by a telematic system data feed from the machines. If there are multiple soil types present the soil type closest to the border line used in the data point determination. It is assumed that the soil data in the mapping system is accurate.

There is some localized error in the measurement of terrain however accurately quantifying local terrain differences would be nearly impossible in the field with such a large and physically dispersed population of equipment. A United States Geological Survey (USGS) document stated the accuracy of the USGS mapping system is accurate to an average of plus or minus 2.7 feet (Gesch, Oimoen, & Evans, 2014).

Undercarriage branding, metal composition and metallurgy was not considered part of this research.

There is some localized error in the measurement of annual precipitation rate for the data output is delivered by weather stations. There may be some between station to station variation depending on the location of the GPS coordinates provided due to thunder storms that may bypass any of the gauges in the study area.

Statement of Delimitations

This study focuses only on the eastern half of the state of North Carolina, United States of America since the undercarriage wear data is the accessible for this area only.

This study uses the research data which is comprised of machines whose undercarriage system measurements are currently available. Only machines being monitored by undercarriage reporting and with GPS location hardware and is included in this research.

Statement of Terminology

Steel track undercarriage: The propulsion system for many heavy equipment models of dozers, excavators and loaders designed for heavy duty earthmoving appliations. This proplusion system also transfers horsepower from the engine into the ground engaging tools that are performing the work (Moore, 2010).

Soil texture classifications: The descriptive name given to different soils designating the percent of sand, silt and clay seperates present in the soil makeup (Foth, 1984).

Soil texture triangle: The tool used to classify soil texture when two of the three soil components of sand, silt and clay are known. Conversely, if the soil type is given these three component percentages can be described using this tool. It visually depicts the soil texture reflecting the diffent proportions of sand, silt and clay in the soil sample (Foth, 1984).

Percent worn: The useful life of a track type tractor system that has been worn away with 100% being the maintenance point (“Custom Track”, 2013).

Ground engaging tool: Sacrificial metal on heavy construction or earth moving machinery that contact the soil directly to do work or to propel the machine. Examples are undercarriage systems, ripper shanks, bucket teeth or dozer blades (Finning, 2019).

Service Meter Unit (SMU): Hours of machine operation measured by electronic meter on dash typically used for machine billing and maintenance interval calculation ("Custom Track", 2013).

Track Bushing: The track system component that is pressed into the track links and is the most critical component in determining track maintenance (Moore, 2010).

Hours per % worn: The number of hours the machine operates before one percent of the useful life is removed from the bushing surface.

Soil classification: The name assigned to a soil with a specific soil textural profile based on morphology, origin and developmental factors of the soil sample (Foth, 1984).

Bushing turn or level 1 maintenance: Where only the pins and bushings are turned 180 degrees to expose a new second contact surface for the sprocket segments to drive ("Custom Track", 2013).

Bushing/link replacement or level 2 maintenance: After bushing turn maintenance has been performed the machine's track system is to be ran to destruction and a new track system installed ("Undercarriage", 2013).

CHAPTER 2

REVIEW OF LITERATURE

Equipment Maintenance

There are three types of equipment maintenance cost which include acquisition, operational maintenance and residual cost. Operational maintenance cost has the largest financial impact, is the one that is very controllable, and the cost being researched in this study (Tsimerdonis & Murphree, 1994). Undercarriage components can comprise 50% of this non-fuel operational cost (Kalousdian, 2008). Unfortunately, it has been found that up to one third of the maintenance costs is wasted because of unnecessary or improperly managed (Fan & Fan, 2015). OEM and dealer support in the management of this maintenance cost is increasingly important as new equipment becomes more sophisticated and technically advanced (Caterpillar, 2018). One of the support functions performed by the OEM is to measure the undercarriage track system to determine the rate of wear and the hours of operation until maintenance intervals are reached. To maintain the high performance of earthmoving equipment and to reduce operational maintenance cost, proper and timely maintenance of the track system is required. Understanding when to perform this maintenance and the input factors impacting this timing is critical to minimizing equipment maintenance costs (Schexnayder & David, 2002). It is also found that properly maintained machines hold their value better and can expect higher residual value at the end of the machine's useful life (Lucko, Anderson-Cook & Vorster, 2006). To be profitable in managing an equipment fleet, it is critical to accurately forecast the cost of replacement wear materials and to schedule the downtime rather than repairing after failure (Mitchell, Hildreth, &

Vorster, 2011). Downtime resulting from an unscheduled breakdown of equipment unexpectedly drives additional cost and affects project schedule significantly is one of the most important areas for research on equipment management (Praseryrungruang & Hadikusumo, 2009). Knowing when to schedule the machine's downtime before failure occurs improves operating efficiency and the ROI for the machine owner (Townsend & Badar, 2018). Understanding the factors that drive machine part wear is critical to this management strategy and it is proposed the soil texture and other factors could have a major impact. It has been found that wear rate of certain ground engaging tools and other non-undercarriage track system maintenance wear parts are directly related to the abraisivity of the soil and depending on the material being tested the time to failure could be predicted (Lee, Kim & Young, 2014). Sand crystals are 2-5 times harder than the ground engaging tools attached to the machines therefore are very abrasive (Gharahbagh, Qiu, & Rostami, 2013).

Science of Metal Wear

Metal wear is the result of metal particles being separated from the parent material due to the interacting, fractioning surfaces and extreme pressures being generated at the sprocket/track bushing interface. "In the course of abrasive wear between the surfaces moving on each other, the peaks of the harder material gouges grooves into the softer material, peeling some material, so it is a groove-proceeding process (appearances: craters, scores, scratches, scrape traces)" (Szuchy,2013). The erosion of metals under pressure with sand particles occurs when the impacting particles cause severe localized plastic strain on the parent material. Figure 7 shows the erosion of the track bushing area and the location of this bushing on the undercarriage system and this area of the undercarriage system is the most critical in determining the maintenance interval for the machine. This area of the undercarriage system must be maintained before any other part and is the pace maker for further maintenance intervals. This material removal occurs when the strain to failure of the deformed material is exceeded (Yoganandh, Natarajan & Babu, 2013). The pin and bushing area of the undercarriage system is one critical area on the undercarriage system where this metal wear occurs and is the first major maintenance opportunity required by the OEM. There are tremendous loading and pressures exerted in the sprocket and bushing area of the undercarriage system for much of the engine horsepower is being transferred there. The greater the pressure the greater the wear impact generated by the detachment of metal layer and cracks generated by these higher loads (Kamalpreet & Pandey, 2013).

In laboratory studies of metal wear, there are many studies where the introduction of sand into the experimentation resulted in much higher wear rate. During these tests "a further increase in sand content caused a greater mechanical damage" and "the critical ranges of sand here proposed are related to the effects of increasing the sand content" (Flores, Neville, Kapur & Gnanavelu, 2011). In addition to the amount of sand introduced into the experimentation, the type of sand also creates differences in the wear rate of metals. The metals being tested were "abraded by two types of abrasive sand (alumina and silica) in three different grain sizes" with the two types having vastly different granular hardness (Kasparova, Zahalka, Houdkova & Ctibor, 2010). The size of the sand particle also impacted the rate of wear which "may be due to higher embeddability of particles in one of the rubbing surfaces, and additionally the separation and elimination of worn surfaces. We noticed that the average value of friction coefficient increases with increasing sand particle size "(Ramadan, 2016). Heavy equipment can operate in other material besides soils. Working in fly ash, organic muck soil or coal can produce a radically different wear rate and should be considered during the field study of this research (Nikhilesh, Dash, Mishra, Patra & Mahapatra, 2010). The laboratory studies seem to correlate sand with accelerated wear rate with particle size and physical harness being a significant characteristic.

The material makeup and heat treatment of the steel comprising the undercarriage system is critical in weathering the severe impact of sand introduction into the system. “Due to its properties of high hardness, good toughness and high wear resistance, steel is widely used in applications such as mine and rock crushing, etc. which involve impact and abrasion” (Dumrudkarn & Muangjunburee, 2015). “Both hardness and toughness play the important roles in wear resistance” and in some applications where impacts are severe, tough buffering layers are often needed to prevent breakage (Srikarun & Muangjunburee, 2015). The choice of steel in undercarriage is an important input factor where “amorphous steel has better wear resistance than traditional crystalline steels and a good linear correlation was found between wear resistance and microhardness (Ji, Shan, Chen & Wang, 2016). One critical factor to consider here could be the choice of undercarriage brands which uses many different types of steel configurations in their undercarriage link design. Metallurgical properties of undercarriage systems may be different between manufacturers and should be a concern for the most profitable operation of the heavy equipment fleet.

Past Wear Mitigating Technology

To help mitigate wear to the bushing surface there have been some technological innovation utilizing creative application of some of the metallurgical principles discussed. Wear resistant material has been infused into the bushing structure to help the impact of the metal to metal contact of the segment and bushing surface (Haslett & Blunier, 1975). Another approach to help mitigate this wear is to employ a metallizing process to spray a hardened coating onto the bushing area to “improve abrasion and galling resistance” (Anderton, Chuong, Dremann, Holt & Shankwitz, 2000). To remove the movement component of friction a revolving bushing was invented in 1963. This prevents the bushing from sliding down the face of the sprocket contact surface thus reducing sliding movement and reducing the wear rate (Zeller, 1965). This invention was very simplistic and impractical until 1970 when a more advanced and producible derivation of this idea was employed. This idea replaced the sleeve to make the bushing rotate about the pin (Boggs & Dadds, 1970). Many of these innovations seem to be the breakthrough ideas to revolutionize track undercarriage management but this type of track was initially not reliable in the field. These early technological innovations were all designed to reduce abrasive friction in the bushing and sprocket area. This technology continues to develop and in the future, a bushing design could remove “much of the friction, and the wear out of the track chain” by using this rotating bushing technology (Stewart, 2010). It has been found that the standard undercarriage is reliable and is by far the overwhelming track system used in the market today (Moore, 2013). As technology continues to evolve and advance, this premise may and probably will change in future tractor designs.

Eastern North Carolina Soil Structure

The study area of this research is the eastern half of North Carolina and the geological makeup of the soils are quite diverse. “North Carolina is a state of diverse geography, ranging from sandy barrier islands on the Atlantic coast to the rugged Appalachian Mountains on its western border” (Williams, 2018). The diverse geography results in equally diverse ecosystems each comprised of a broad range of soil types and textures within the state. These three physiographic regions are named the mountain, piedmont and coastal plain regions. Within these three regions of North Carolina there are over 400 different types of soil, though certain soil types are more common to the state. The different types of soils found in the research territory depends primarily on the underlying rock substrate and geological conditions that are present in the specific region. Other factors that play a role are drainage, climate, vegetation and historical attributes of the land (UNC, 2018). Each soil type contains a different percent of sand, clay and silt content thus defining the textural composition of the soil type classification. The physiographic regions being studied in this research is the eastern half of the piedmont and the coastal plain regions of the state.

One of the largest factors driving the soil diversity is the gradient of sand percentages present in the soils in the two regions of this research study. In the piedmont area of the state the land mass is composed of soil types and textures comprised largely of clay containing a lower percentage of sand and silt. The piedmont is resting on a metamorphic base of granite rock and the resulting soils reflect this parent material (UNC-1, 2018). Almost all the piedmont region soils are ultisols, with light upper layers and a reddish sub-soil which is the result of erosion of the granite and other metamorphic rock formations from hilly outcrops and underlying rock formations (UNC-1, 2018).

The coastal plain area of the research zone was undersea for millions of years and a limestone base was formed during this time with much silicate sand being created. In some temperate regions formed by limestone, calcite and dolomite may dominate the soil. In other temperate regions quartz dominates the resistant inherited mineral (Rowell, 1994). This limestone produced lands along the coastal plains that are diverse and very rich with high quality agriculture lands. “These soils can vary tremendously, particularly in texture, which depends on exactly how the parent material was deposited when this region was under the ocean at the edge of the continent and consists of gently rolling land with a rather sandy soil" (UNC-1,2018). The resulting geological composition of the soil types range from low levels of sand in the piedmont with much higher concentration of sand in the soil types of the coastal plain regions of the state and this geological diverse area is the focus of this research study.

Soils throughout the research territory are classified by soil texture. Soil textural classes represent the proportion of sand, silt and clay that is present in the soil determined by lab testing. Sand is technically defined by silica groupings with very course sand separates having a diameter from 2 to 1 mm. The smallest sand classification is that of very fine sand which measures between 0.10 and 0.05 mm. Anything between 0.05 and 0.002 mm is considered silt and separates with diameter less than 0.002 is considered clay particles (Foth, 1984). If the percentage of two of the soil components are known then the other can be calculated using the textural triangle (Ease, Sauer, Razvi, Walker & Bratz, 2015). In using the textural triangle, if one knows the soil textural classification, the researcher can determine the percent of sand in the soil in which the piece of heavy equipment is working.

Impact of Moisture on Metal Wear

In laboratory studies, adding moisture to the abrasive sand types has a "significant impact" to the abrasivity impacting the wear components (Gharahbagh, Qiu & Rostami, 2014). Beyond laboratory studies, the premise of moisture in the soil increasing wear permeates into the field studies of tunneling equipment. From these tunneling machinery studies it was concluded that the "water content is a crucial factor in tool wear as well as shear resistance, especially in soils with higher mineral hardness" (Mirmehrabi, Ghafoori & Lashkaripour, 2016). If adding moisture as an input factor to laboratory and field studies increases the metal wear rate then the addition of moisture to the operating conditions of construction equipment undercarriage should increase wear as well. It has long been hypothesized that working in high moisture soils could impact the wear rate of the track systems. Some track manufacturers state that working on "wet job sites" can increase track wear (West-Trak, 2019). In John Deere's Undercarriage Wear and Care Guide, they talk about how working in wet conditions is not conducive to long track life (Deere, 2019). If this is case, the use of rain fall totals may be a significant input factor measurement for this study to determine the impact of the soil moisture. Precipitation is "the dominant source for soil moisture" and "precipitation has the most direct and important influence on the estimation of soil moisture" in modeling studies (Liu, Reichle, Bindlish, Cosh, Crow, De Jeu, De Lannoy, Huffman & Jackson, 2011). If such correlations exist the annual precipitation measurements across the study area should be a good measure of soil moisture.

There is a gradient of increased rainfall as one goes from east to west or from the coastal plain to the piedmont regions. This precipitation variation across the study area can be attributable to several factors. It was also found that in the case of the coastal plain area of North Carolina, certain interactions between the sea breeze and the thermally driven local circulation creates higher rainfall amounts in the coastal plain. It has been found that "much of the precipitation that falls in the coastal region can be attributed to locally driven convection process" (Sims & Raman, 2016). This is one reason for the precipitation gradient being present for as the sea breeze blows across the increasingly elevated land mass, rising air and precipitation are produced. Tropical cyclones are another reason the coastal plain area has an increased precipitation totals compared to the piedmont region. Tropical cyclones are attributable to between 10-15% of the total rainfall totals in the coastal plain region of the state of which the piedmont is often spared this additional rain (Nogueira & Keim, 2011). With hurricane landfalls, the amount of rain produced by each storm is very unpredictable but most of the rains fall in the coastal areas (Kehoe, Raman & Boyles, 2010)

Topography

Topography is another input factor of the track bushing area that could have impact to wear rate. As tractors navigate across undulated terrain or are constantly working on sloped ground, additional torsional loads are placed on the bushing area. Deere states that working on slopes or depression will “accelerate wear on the inside track contact surface. Working in depressions will put loads on the outside bushing ends” (Deere, 2019). Deere does not however discuss the impact on the wear rate of the bushing surface. Caterpillar states that working uphill increases the weight load on the sprocket/busing area which increases the pressures on the forward drive side of the bushing. Working on a downhill slope shifts weight to the idler and front rollers creating more extreme pressures there. Also noted by Caterpillar that working on side slopes, depressions and crowns has greater impacts the roller flanges and idler surfaces with no mention of the bushing surface (“Work”, 2019). As with the sand content and moisture in the soil, the terrain varies quiet differently on ironically the same gradient. From east to west the topography is quite different.

Other Peer Reviewed Studies

In many studies on heavy equipment maintenance, undercarriage track systems are often not included in the analysis due to the variability in their wear rate. “These expendables can wear at greatly different rates depending upon a wide variety of factors” (Mitchell, Hildreth, &Vorster, 2011). There has been one notable and well performed study found that investigates specifically the wear of top carrier rollers in a pit mining environment. The study used a Weibull analysis to predict the mean time to failure (MTTF) of this non-load bearing component between three populations of dozers. These three dozer fleets were in three different mine sites with different quartz percentages in the material being mined. It was found that there was a linear relationship between this quartz content and the MTTF of the carrier roller (Djuric & Milisavljevic, 2016). The Djuric & Milisavljevic study differs from this study in that:

-The carrier roller does not trigger level one or two track system maintenance as the track bushing does. If a carrier roller fails between a bushing turn or level two maintenance interval, the roller is simply and comparatively quickly replaced. Track bushing wear, on the other hand, is widely used by equipment managers as the bell weather for bushing turn and bushing/link replacement windows which can result in much longer unplanned downtime if not properly managed.

-The carrier roller, although it supports the track group weight between the idler and sprocket, does not have the extreme forces placed upon it by the sprocket as the track bushing does. Targeting the bushing helps better predict the entire system maintenance interval for the machine when compared to the carrier roller replacement thus bringing more value to the machine maintenance decision process.

-The diversification of the machines used in this study was vastly different. Rather than a high population of one machine model in three separate geologically diverse locations, this study investigates a wide array of machinery models of various sizes across a much wider continuum of geological variation of sand content. This approach better simulates a typical diverse machine fleet by having multiple machine models over a wider and varied geologic landscape.

Elverman also discussed in a trade magazine article that he found that working in abrasive materials in the oil sands area of Canada can reduce steel undercarriage life from 14,000 hours to 3,000 and the abrasiveness impacts not only tracks but other sacrificial metal containing areas of the machine (Elverman, 2004). This reinforces Djuric & Milisavljevic' s work in a different machine application.

These studies argue the presence of a cause and effect relationship of sand between the soil and the accelerated wear on undercarriage and other heavy equipment maintenance items. Both studies mentioned focused specifically at certain job sites with like machine populations and one soil type or one specific component of the machine for replacement. This study investigates variable sand content's impact on the entire replacement management strategy of the entire undercarriage system throughout a wide study area. This approach should be more applicable to strategic decisions on machine fleets using the regression equation that is developed through this research.

Research Method

This study is a quantitative correlational study of several machine operational input factors and how they impact the wear rate of the undercarriage system. This study evaluates "an interrelated set of constructs (or variables) formed into propositions or hypotheses, that specify the relationship among variables" (Creswell, 2014). The quantitative inquiry begins with a specific plan which includes a set of hypotheses. The research seeks facts and causes to disprove these hypotheses which can and does include ex post facto data (Roberts, 2010). In this study there are seven variables of either continuous or categorical data types which are the input factors. Quantitative data are said to be objective, which indicates that the behaviors and in this case the correlational relationship are easily classified or quantified by the researcher (Gliner & Morgan, 2000). For the study to be correlational, one needs to determine if there is a statistical relationship between the variables. (Terrell, 2016). The correlational aspect of this quantitative study looks at how these seven factors impact the dependent factor of hours per percent of bushing wear. Variables are related to answer research questions or to make some type of prediction the researcher wishes to show in the form of a hypothesis (Creswell, 2014). When one is interested in the relationship between two or more variables, one asks if the input factor statistically impacts the dependent variable. In most quantitative research, the relationships may have been already established and the hypotheses deal more with the investigation of which variables are significant, and to what extent, in a scientific way (Walker, 1997). The quantitative correlative analysis of this data satisfies the requirements of such a study and the correlation determination impacts many stakeholders in the equipment management space.

CHAPTER 3

RESEARCH METHODOLOGY

This quantitative correlational research study utilizes multiple data sources and technologies to determine the relationship between seven input factors on track bushing wear rate in the eastern half of the state of North Carolina. The seven independent variable factors for this study are listed in Table 2. Each input factor is analyzed to determine its significance on the output or dependent variable which is hours per % bushing wear.

Table 2

Independent and Dependent Variables

Input Factor	Variable	Data Type
Sand Percentage	Independent	Continuous
Machine Model	Independent	Categorical
Machine Weight	Independent	Continuous
Annual Precipitation	Independent	Continuous
Mean Average Temperature	Independent	Continuous
Elevation Above Sea Level	Independent	Continuous
Marketing Code	Independent	Categorical
Hours Per % Worn	Dependent	Continuous

For each machine, it is important to determine the transiency of each machine being considered to ensure it does not perform work in multiple geographic locations. High transiency places the machine in different soil strata and other job specific differences for extended periods of time creating location to location variation that would influence the results of the study. The equipment contained in the undercarriage report data base comprises machines that are being systematically monitored for undercarriage wear. The process shown in Figure 9 must be followed to make these determinations. Each machine inspection identified represents one data point in the research study. It is not required that the same order is followed but to reduce variation in the study the data point determination process is followed.

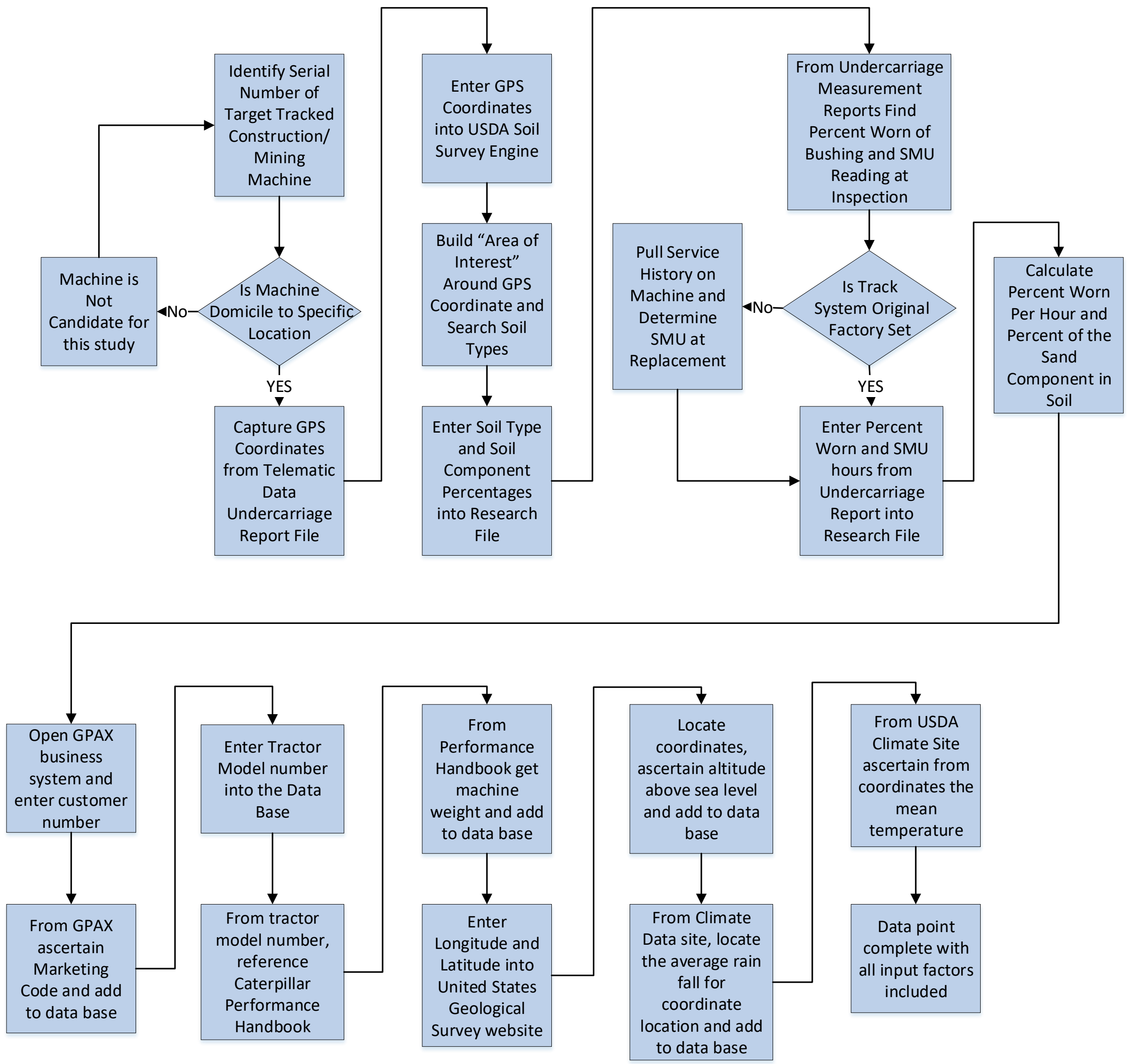

Figure 9. Process of Determining each Machine Data Point

Once the machine localization has been determined, the next step is to pinpoint the machine's exact physical location using latitude and longitude coordinates provided by the telematics when the undercarriage wear report was generated. This file is downloaded from an undercarriage report management file system which is the data base that produces the reporting found in Table 1. Included in this file are dealer telematic location data files which provide longitude and latitude coordinates to locate the exact position of the individual construction equipment units at the time of wear report inspection (Gregory Poole, 2019). This location data is automatically captured for machines equipped with telematic technology. When an undercarriage inspection is performed, the telematic system pings the machine to retrieve and capture its exact coordinates. Construction equipment equipped with telematic functionality produces the automated location updates and can be tracked along with the undercarriage report data. The location coordinate data is transmitted to the web portal to 5 decimal places. GPS technology today can detect geographic differences up to 80 mm (Gorski, Breuer, Konopka & Napieraj, 2019) however, the telematics used on the study targets are accurate to about 1 meter which is adequate for this study's needs. The telematic output is visualized onto a map with pins representing the exact location of the machine being measured. If one were to click the location pin, the undercarriage report would be shown. The precise location of the machine is critical in determining the corresponding map location on the soil map to determine the soil type.

High hour machines that may have had the original undercarriage system replaced at a prior maintenance interval require additional investigation. This requires delving into the equipment service history file to determine when the machine's original undercarriage was replaced. The service meter unit (SMU) reading from the last major maintenance is the new starting point of reference from which the current undercarriage wear percentage is calculated. Once these high hour machines are identified, the rate of undercarriage wear is calculated for each data point from the updated SMU reading. This requires dividing the number of hours derived from the above investigation by the percent worn on the undercarriage. This produces a wear rate measure of operating hours per one percent of undercarriage wear which is the output factor of our research. If this connection to an earlier repair cannot be made, the machine is then removed from consideration for the true hours of operation cannot be accurately determined.

The undercarriage wear report data set is a historical record of undercarriage inspection results. These results are gathered and documented by highly experienced and trained undercarriage specialists employed by heavy equipment dealership customer support staff who understand the undercarriage systems. These specialists utilize ultrasonic tools to gauge the critical measurements of the wear surfaces of the undercarriage components and these measurements are captured into a web portal. The wear charts built into the portal tool convert the measurements of the wear surfaces into percent worn calculation. The percent worn represents the percent of the sacrificial metal that has been worn off the components where 100% represents the maintenance interval of the track system. Figure 10 shows the actual measuring process of the track components.

Figure 10. Physical Measurement of Undercarriage Components

The information gleaned from this data is used to assist equipment managers and owners in managing this very expensive part of the track type piece of construction equipment. As mentioned earlier, properly timing the service of the equipment wear components are critical in achieving optimized ROI that the large investment each piece of equipment represents (Townsend, Badar & Szekerces, 2015). The flat file generated from this detailed inspection is extensive and is the foundation for the web portal that marries the telematic tracking to the undercarriage report information. Only certain value-added fields are extracted for this analysis. The fields captured include the machine serial number, county, GPS coordinates, measurement of left and right-hand bushings, percent worn of both the left and right-hand bushings, measurement of left and right-hand links, percent worn of left and right-hand links, customer name, SMU reading, and work type code. The most critical of these data fields are the SMU, bushing percent worn, and the GPS coordinates.

Now that the precise location of the construction equipment target is identified and the undercarriage wear report is generated, the research needs to acquire the soil textural data for the final piece of required data. The GPS coordinates of the machine is used to search the soil survey data base to determine the soil texture. From this data, the percent of sand, silt, and clay can be determined. The United States Department of Agriculture Natural Resources Conservation Service soil survey data has meticulous records on soil types and textures throughout the country based on field research of coring the soils and measuring the texture in a fine grid pattern (Soil Survey Staff, 2019). The latitude and longitude are entered into the search engine of the web portal and the location of the machine is denoted by an orange box with the plus sign in the middle. Surrounding the target in a green square is the area of interest (AOI). Within this AOI one can see the different soil classifications of the soil in the AOI. A data box displays the percent of each soil classification that comprises the AOI. The researcher now determines which soil classification the target resides in to determine the percent of sand, silt and clay. The search engine also displays how the soil types are shown down to a granular detail of study area. The different colors on the map designates the different soil types in the AOI.

The search engine delivers the soil classification name in which the machine is working. For example, the search engine results tell the researcher the machine is working in a ChA or Chapanoke Silt Loam soil classification. Knowing this, one can further query the data set to determine the percent clay classification of 18.5%, the percent silt of 42.8% and percent sand of 38.7%. The sand percent is the input factor needed to correlate to the undercarriage wear rate and is entered into the data table as the independent variable.

The next input variable is the work type code for the machine and corresponding machine owner. This work type code compartmentalizes the large customer data file into like business groupings. For example, all landscaping companies are placed in the landscape group. This input factor allows this study to determine if the type of work a machine performs impacts the bushing wear rate. This input factor is a categorical factor that needs to be analyzed using ANOVA to determine significance. To gather this code, there must be an inquiry performed in the dealer's business system to determine this code for each machine. This requires the customer number of the machine owner being entered into the system and the resulting code entered into the data base. The codes include mining, heavy construction, landscaping, utility and residential customer groups.

Machine model and machine weight are two input factors that are very interrelated. The model numbers being investigated designates the size of the machinery being studied. The smallest machine to be investigated is a model 3 dozer which is the smallest and lightest weight machine in the territory. Conversely, the model 9 dozer is an extremely large and heavy machine that is on the other end of this continuum. In addition to the actual weight of the machine, the larger the model number, the higher the horsepower ratings of the engines. Although the bushing size increases proportionately with model number, there is much more horsepower being transferred through the bushing as the machine is propelled and work is being performed. Machine model is a categorical variable and weight is the continuous factor. These two variables help to evaluate if equipment weight and model categories have any bearing on the rate of bushing wear. The machine model is gathered from the undercarriage report. Once the machine model is known, the weight can be determined by referencing auction search engines which monitors and captures machine weights for a wide array of equipment models ("Construction Equipment Guide", 2019), (Performance Information, 2019).

As one moves from west to east across the study territory, the topography of the state of North Carolina moves from very hilly to almost flat. One way to measure this change is topography is to identify the elevation above sea level where each machine is working. The higher the elevation, in the case of North Carolina, the more undulation in the landscape (USGS-1, 2019). This is exemplified by how the slope of the land increases from east to west. There is naturally a high correlation between the elevation above sea level and slope increase as one moves from east to west (NC One Map, 2019). The elevation in the most eastern part of the figure is in most locations virtually at sea level. As one moves from east to west the transition occurs indicating the increasing in the elevation above sea level (NC One Map, 2019). With the increase in elevation mirroring the slope gradient increase, the elevation above sea level could be a good continuous measure for the undulation of slope change across the study area.

The question here would be if this undulation has any impact on the bushing wear rate. To determine this input factor, one needs to enter the longitude and latitude coordinates into the United States Geological Survey website to pinpoint the contour mapping functionality *(USGS, 2019).* The results show a blue dot inside the blue circle of the figure representing the output of the longitude and latitude query into the site. By interpolating the values of the contour lines that surround the blue dot, one can determine through interpolation the elevation above sea level. In this example, this machine is working in an area with 28 feet elevation. This machine is working near the coastal areas thus very close to sea level. The closer the lines are together the greater the slope in the landscape. In this example the lines are very far apart denoting a very flat landscape.

There is of course a component of error in this measurement. The United States Geological Survey performed as study of vertical accuracy between data points being measured. In this study there were 1,068 data point pairs compared and the relative vertical accuracy was a negligible 0.81 meters or 2.7 feet (Gesch, Oimoen, & Evans, 2014). It should also be noted that localized variation in the terrain as it also changes as the machinery moves about on the job. This measure of elevation correlates to the changes in topography undulation as jobs progress.

The next two factors to measure are both climatological in nature and can be found from the same data source. The first is mean annual rainfall and second is the mean annual temperature where the machine is working. To collect these input factors, one needs to access the well respected and location rich US Climate Data network (US Climate Data, 2019). This search engine produces both the annual mean values for temperature and precipitation depending very near the location, to the nearest community, where the machine is working. This search engine produces an average rainfall to the closest weather station nearest the machine's GPS coordinates. The deliverable from each query adds to the data set where the average precipitation and temperature can be calculated.

When considering the temperature average in this study there is a factor of error present. One of the main concerns with temperature variation is the location of the temperature instruments with regards to the location of the job site. In this ex post facto data study, real time measurements at the jobsite was not available to acquire. For example, if the closest thermometer is located 25 miles from the jobsite, there may be some differences between the measured temperature at the weather station and the actual temperatures as the jobsite. Another factor could be the jobsite being in a low-lying area when compared to the location of the thermometer. This would tend to reflect a slightly lower temperature reading at the jobsite.

Precipitation measurement also has a component of error and the reasons are very similar to the temperature discussion above. Again, there is some negligible between station variation due to the instrument measurement systems which is present to some extent with all instruments. The larger and more impactful component to any precipitation measurement error in this research is due to the randomness of intense thunderstorms that can travel across eastern North Carolina. For example, an intense storm travels over the jobsite but bypasses the rain gauge. This common phenomena understates the precipitation at the jobsite. Another cause for this is the randomness of the rain bands of tropical systems. The random travel of these bands can create great variation that may be missed by any precipitation gathering system unless it is located at each jobsite. The research design produces a data table that is shown in Table 3 that is populated with representative hypothetical data to show how the data fields is laid out. The data is then analyzed using Minitab.

Table 3

Representative Data Set to be Used in Analysis

Hours per % Bushing Wear	% Sand	Market Code	Rainfall	Elevation	Weight	Temperature	Model
39.4	50.1	Landscape	4.30	35	15984	64.5	3
42.8	31.9	Mining	3.81	58	369865	62.5	9
45.7	26.4	GCI	4.06	458	89254	60.8	5
18.4	91.5	Landscape	3.74	389	16734	59.6	3
24.8	73.3	GCI	4.19	603	98235	59.5	8
45.3	36.6	GCI	3.83	23	88348	63.7	6
50.3	46.8	Landscape	4.39	3	17873	62.5	4

One tool to be used to test the significance of the input factors in Table 1 is a regression model for regression analysis has proven accurate in predicting equipment maintenance over medium range planning horizons (Bayzid, Mohamed & Al-Hussein, 2016). ANOVA is utilized to determine the significance of the categorical variables. The data sources used consist of undercarriage wear reports (Gregory Poole, 2019), the United States Department of Agriculture Natural Resources Conservation Service soil survey data (Soil Survey Staff, 2019), the National Geographic Survey website and the National Oceanic and Atmospheric Administration website. These resources are utilized to build the data set where the statistical tools is employed.

The dependent variable in this research study reflects the hours it takes to wear one percent of sacrificial metal lift off the bushing surface. This is calculated by dividing the number of SMU in which the bushing is in operation by the percent worn from the undercarriage condition report. For all categorical input variables, an ANOVA analysis is performed to determine if there are significant differences between the categorical groupings in the hours of operation per percent worn. For the input factors of machine model and work type code ANOVA is the analysis tool of choice. For the remainder of the continuous input factors of weight, elevation, temperature and precipitation and percent sand, a multiple regression analysis is performed. As it is determined a factor is insignificant at an alpha value of 0.05, the factor is removed from the model and further iterations of the analysis is performed until only significant factors are included.

This study acquires data points for the entire population sample of machines in the study area meeting the domicile and other criteria. There were 353 data points generated across the continuum of the research territory. This produces a robust model for this territory using an alpha value of 0.05. Having this large sample size helps to mitigate common noise factors that permeates the research space. Much of the noise and uncontrollable input factors is common throughout the study area. One example is having multiple operators on the same machine on the same jobsite. For example, when multiple operators are used, this occurrence typically occurs across a generalized area of eastern half of North Carolina and not on just job site.

To validate data accuracy from the undercarriage reporting, a Gage Repeatability and Reproducibility analysis is performed specifically focusing on the bushing diameter measurement of the track specialist creating the undercarriage wear reports. The bushing is the most critical component of the components measured and is used to derive the dependent variable of this research. The gage study calculates the variation components based on standard deviation of the different measurements by different people (Cepova, Kovacikova, Cep, Klaput & Mizera, 2018).

The matrix for this gauge study required 10 bushings be measured three different times by three different technicians (AIAG, 2010). Three replicates of the matrix comprise the study producing 90 data points in the study. The study is performed during a one-day event on 10 various track bushings of various percent worn percentages to represent the full range of the bushing measurement spec limit. Each of the ten selected bushings were marked 1-10 with a paint pen for measurement traceability. Three certified track specialists were chosen appraisers to perform the measurements of the 10 marked bushings and the measurements were kept confidential until the completion of the study. The measurements were entered into Minitab utilizing the Gage R&R Study (Crossed) functionality. This study validates the measurement system is robust enough in that no more than 10% of the total variation in the bushing measurements is due to the measurement system (AIAG, 2010).

CHAPTER 4

DATA ANALYSIS

Research data was gathered per the instructions described in the Chapter 3 research methods which utilizes various data collection sources. The foundational data for this research is derived from the undercarriage inspection report data base which is interrogated using a sequel query. The query results produced 1765 report lines representing 1072 different serial numbered track type tractors. The most critical information pulled from this data set is machine model number, bushing wear percentages, GPS coordinates and hour meter readings. The GPS coordinates were used to pull additional data from other web-based sources while the hour meter reading and bushing wear was used to calculate the dependent output of hours per percent bushing wear.

Continuous Input Factor Data Analysis

Undercarriage Inspection Report Data

After the undercarriage report data was acquired, the process shown in Figure 9 was followed to determine if each machine report represented would be a candidate for this study. The first requirement stated the machine must be domicile within the territory being studied for a complete track maintenance cycle. If the machine was a transient machine and only on a jobsite for a partial maintenance interval, it was removed from the study data set. The issue with a transient machine being in the study is the variability of the soil the machine would be exposed to. If a machine moved from place to place periodically, the soil and other input variables would contain unwanted variability. After completing the domicile machine evaluation there were 1117 undercarriage reports remaining representing 297 machines. Most of these domicile machines have multiple inspections performed for they were localized machines within the study territory and their undercarriage health is being closely monitored. Other issues found were SMU missing, bushing percentage missing or GPS coordinates not being found in the data base. After these reports were removed from consideration there was 353 usable data points available for the study.

For each of the 353 study data points, all 7 input factor data were acquired through the various methods noted in the research method. For each input factor there is an overview of the descriptive statistics generated, the null hypothesis is restated, and the statistical analysis is provided to determine the acceptance of the null hypothesis. Once all continuous input factor data is acquired, the first analysis to be performed is a multiple regression analysis to determine input factor significance. The two categorical input factors are then summarized and tested using ANOVA. The first input factor to be discussed is the percent of sand content in the soil.

Input Factor Sand

The sand percentage in the soil was determined by utilizing the longitude and latitude location of the machine being investigated. These coordinates were entered into the USDA soil survey website to determine the sand content in the soil where the machine is working (Soil Survey Staff, 2019). All 353 input readings for the percent of sand in the soil is displayed in the histogram in Figure 11. It appears the bulk of the readings fall between the 50 and 75 percent marks by the high concentration of data points in the center of the graph. The center section of the graph represents many of the readings in the southern and northern piedmont area. There is large histogram bar at the 95% mark representing a large population of machines along the coastal areas. Another interesting concentration of data points is at 15% and 30-35% which represents many of the machines in the high clay areas of the central piedmont.

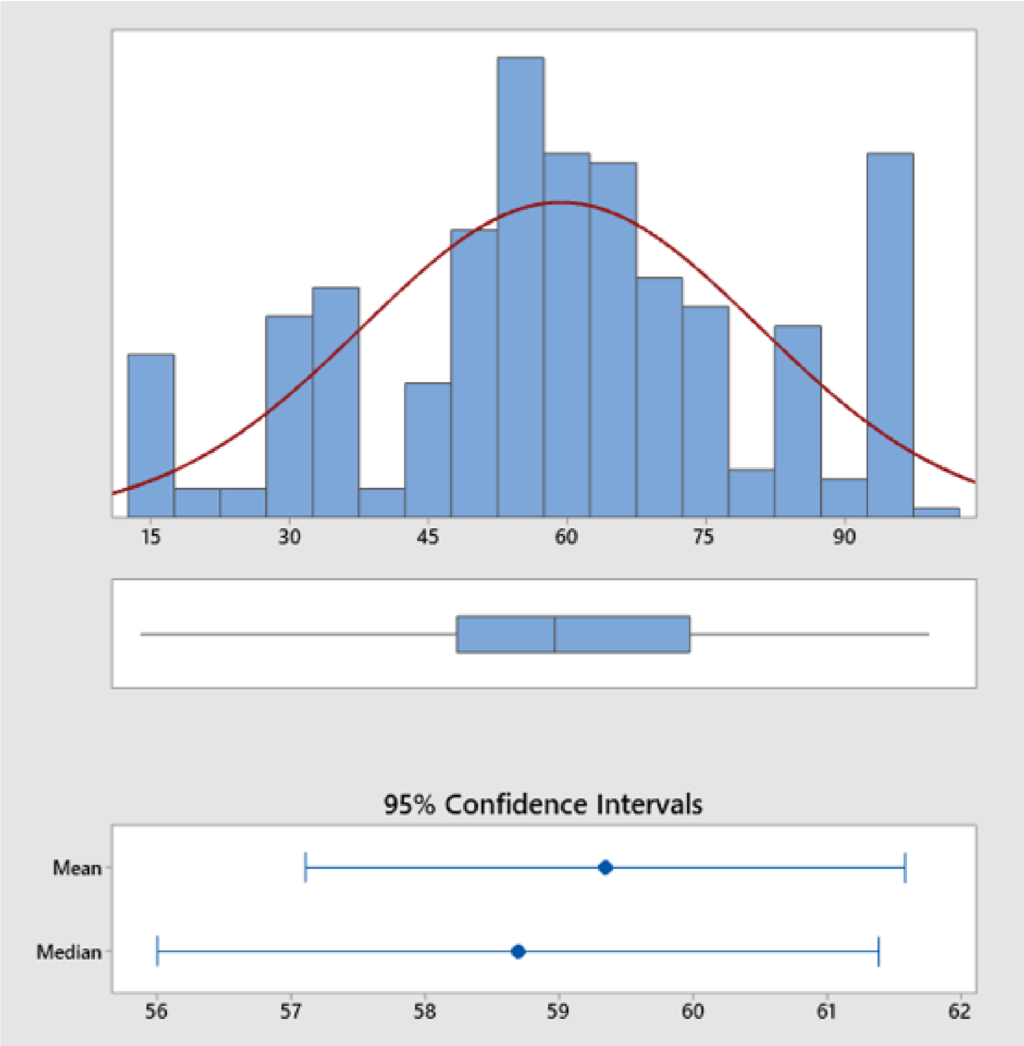

Figure 11. Graphical Summary of Percent Sand Content in Soil

Table 4 documents the descriptive statistics of the data from this input factor. The data is not normal having a low AD p-value and has a mean of 59.349. The standard deviation is rather large at 21.408 which dovetails with the expectations of the wide gradient of sand content as one moves from west to east in this study area. The spread between the minimum of 13.9% and a maximum of 99.10% is also expected for the same reasons. The data reinforces the soil sand content gradient exists from west to east with the soil in the upper piedmont areas are very low in sand content while on the outer banks the soil is almost pure sand (Tant & Byrd, 2019).

Table 4.

Descriptive Statistics for Sand Content

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
59.349	21.408	458.321	353	13.90	58.700	99.10	-0.117	<0.005

Input Factor Elevation Above Sea Level

The next input factor to consider is the elevation above sea level where the machine being investigated is working. The longitude and latitude of the machine's location is entered into the USGS topographic map website (USGS-1. 2019). The elevation is determined by interpolating between the elevation contour lines and is measured in feet. Once the elevation is determined it is logged into the data set with the corresponding machine inspection. The data shown in Figure 12 shows data that is skewed to the right with a large proportion of the data points at less than 100 feet above sea level. This is understandable considering the high level of development that is occurring in the eastern half of the territory and consequently where a high number of machines are now located. The machines along the coastal area are naturally at a lower elevation and the terrain is extremely flat. Another interesting observation is the gradient up to about 900 feet above sea level which represents the machines between the coastal plain and the western edge of the study area. The western areas of the study area have a much more undulated and hillier terrain as shown by the data. There are only two outliers which one would expect due to the gradual increase in elevation across the territory and there are no excessively high elevations in the piedmont area. These two outliers were in the most north west corner of the territory where the rolling hills become more elevated compared to the rest of the territory.

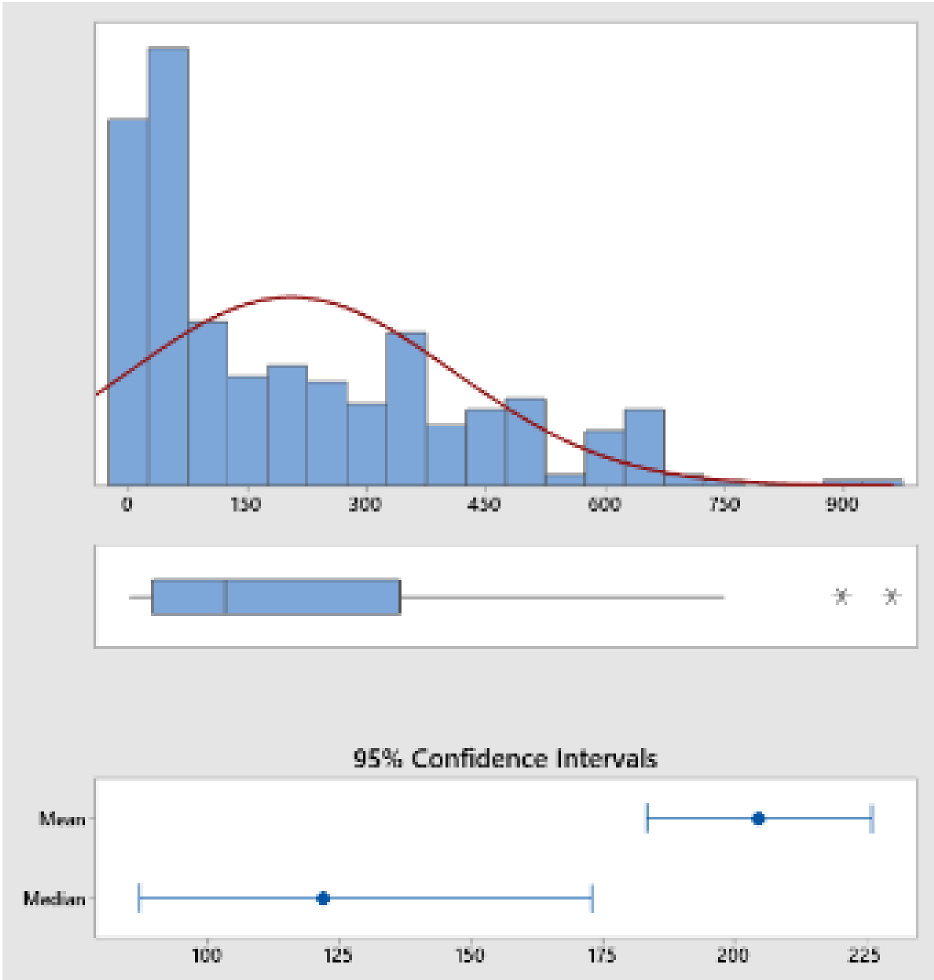

Figure 12. Graphical Summary for Elevation Above Sea Level

The minimum elevation in Table 5 is noted at 2 feet above sea level which is not unexpected for there are beach renourishing projects and residential developers working directly on the seashore performing beach renourishment. There are also many low-lying and swampy areas that are very near sea level with elevations in the single digits.

Table 5

Descriptive Statistics for Elevation

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
204.84	204.07	41664.28	353	2.00	122.00	963	0.9967	<0.005

Input Factor Machine Weight

The next continuous input factor is the weight of the machine in pounds. Based on the model number, the weight of the machine is entered into the data set. Figure 13 shows the distribution of the weights of the machines in the study. This distribution is skewed to the right slightly which is expected due to the majority of the machines being in the small to mid-sized dozer range. There are a few large dozers having much heavier operating weights resulting in the number of outliers. If machine arrangements have been modified, there may be some error in the weight data results. For example, if a straight blade is retrofitted with a KG Blade or a winch added, the weight of the machine being analyzed would be understated. Typically, this is an anomaly but needs to be mentioned for accuracy.

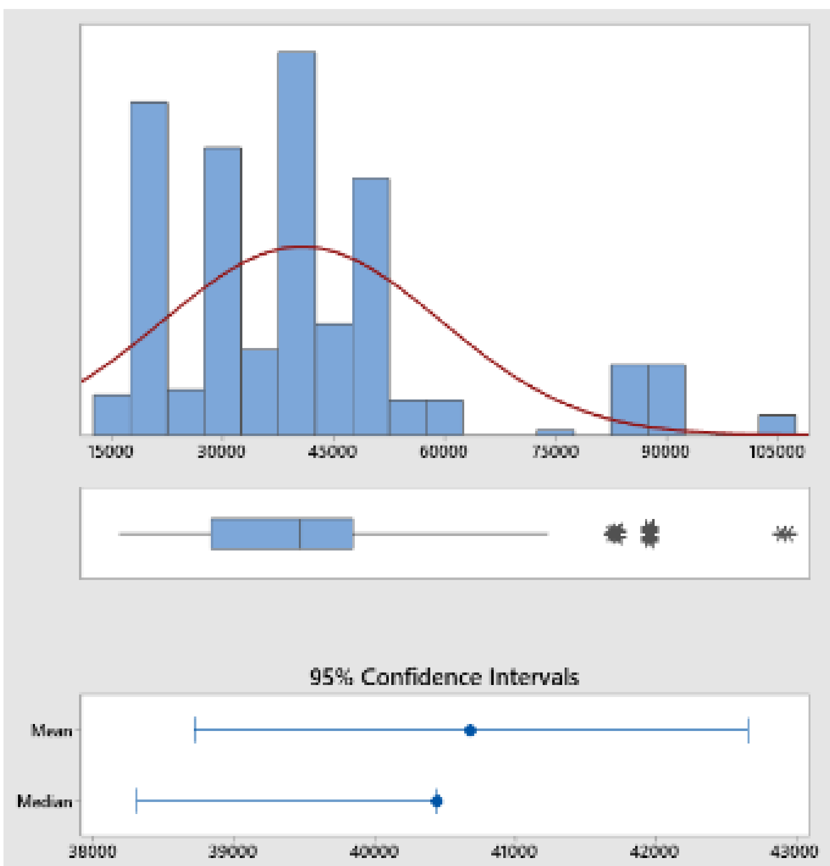

Figure 13. Graphical Summary of Machine Weight.

The machine weights range from 16,103 to the maximum of 106,618 pounds. The standard deviation of 18,825 reflects the diversity of the machine population with a wide range of machines from the smallest to some of the largest dozers in the world. The Anderson Darling p-value is <0.005 meaning the data for this data category is not normally distributed.

Table 6

Descriptive Statistics for Weight

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
40687	18825	354395275	353	16103	40446	106618	1.304	<0.005

Independent Input Factor Precipitation

Annual precipitation is an input factor to be considered in this research, for it is shown that adding moisture to laboratory tests increases metal wear rate (Gharahbagh, Qiu & Rostami, 2014). It will be interesting to determine if this premise holds true with precipitation in the field. To acquire the yearly precipitation averages, the location where the machine was working was matched to the nearest weather station in the US Climate Data network (US Climate Data, 2019). The data from this station is then queried and the average annual precipitation is recorded in inches. The histogram in Figure 14 reflects a large grouping between 45 and 50 inches per year which is reflective of most of the inland regions of the study area. The large spikes between 56 and 59 inches per year are along the coastal counties which typically receive more precipitation due to storms and the sea breeze generated precipitation during the summer months (Sims & Raman, 2016), (Nogueira & Keim, 2011). It should be noted that histogram bars between 56 and 59 inches all are statistical outliers when considering the entire study area’s rainfall totals. For each of the 353 machine inspections entries, the precipitation is added to the data set for analysis.

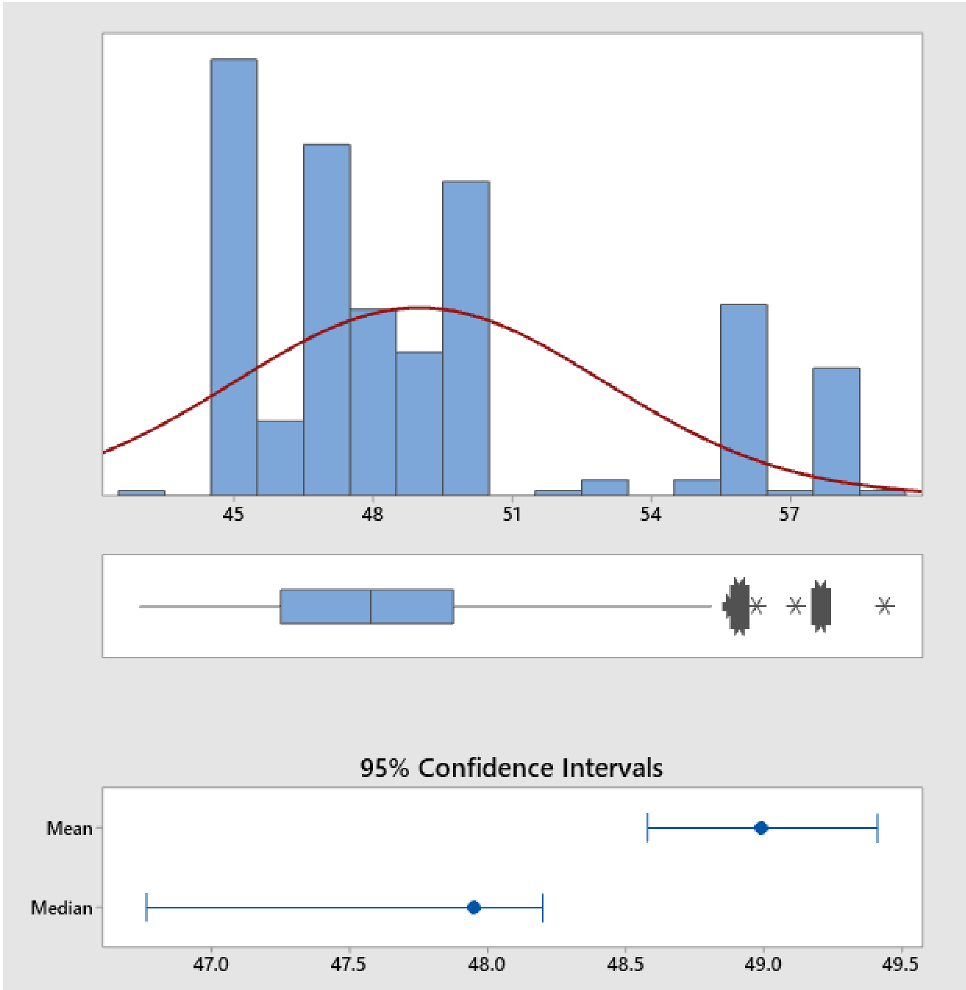

Figure 14. Graphical Summary for Average Annual Precipitation.

Table 7 reflects the descriptive statistics for precipitation. The minimum value is 42.96 inches which is in north west corner of the piedmont and a maximum of 59.06 inches which is in the central coastal area very near the coastline.

Table 7

Descriptive Statistics Precipitation

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
48.997	3.985	15.880	353	42.960	47.950	59.060	1.087	<0.005

Temperature Impact

Average annual temperature is an input factor in this analysis. The data for temperature is gathered at the same time the precipitation data is collected from the same website (US Climate Data, 2019). For each of the machine inspection entries the average annual temperature was entered in to the data base. Figure 15 displays a data set that is slightly skewed to the right with a negative skewness value and a large histogram bar at the 61-degree mark which includes the mean value.

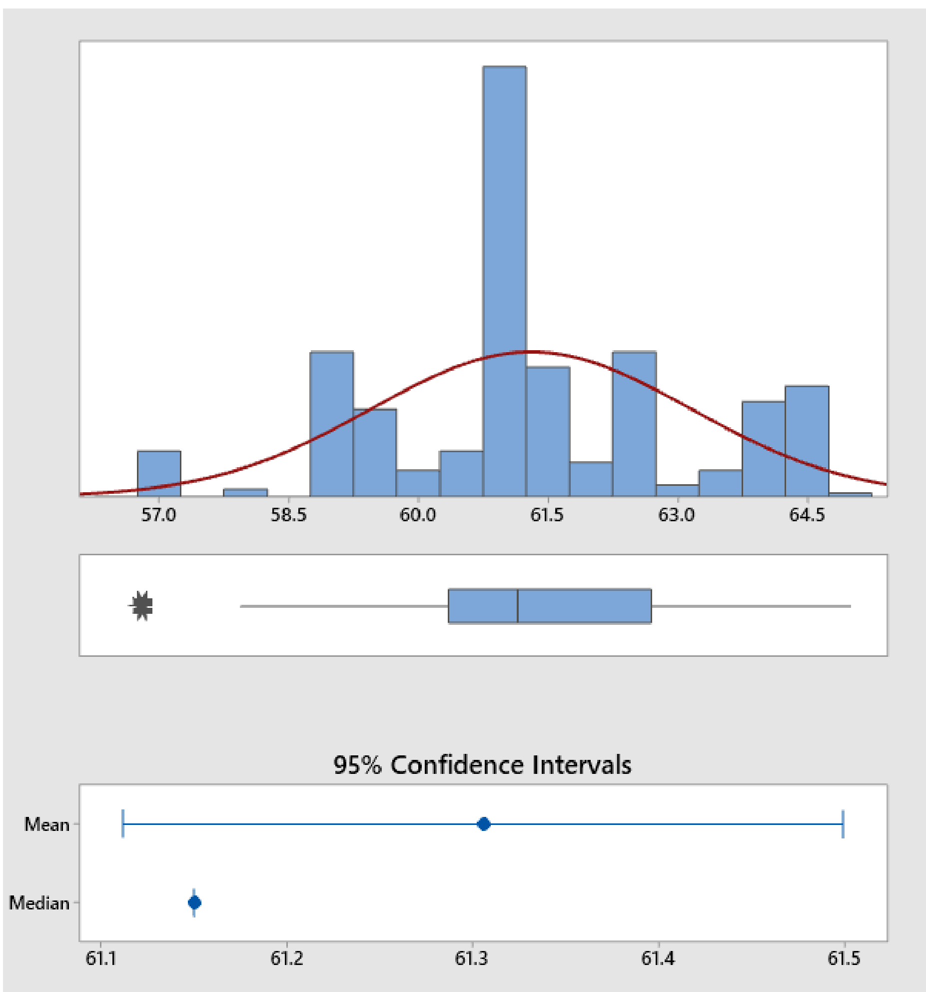

Figure 15. Graphical Summary of Average Annual Temperature.

From Table 8, the minimum value of 56.75 came from the northern border of the study area while the maximum shows a value of 65.0 from the southernmost border location in the area. The standard deviation is rather small at 1.851 degrees F and the data set is very slightly negatively or left skewed.

Table 8

Descriptive Statistics Temperature

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
61.306	1.851	3.426	353	56.750	61.150	65.000	-0.0192	<0.005

Dependent Variable Hours Per Percent Worn

The first five factors described thus far are the independent variables for the regression analysis of significance. The dependent variable is derived from the number hours of machine operation required to wear one percent of wear metal off the track bushing. To calculate this, the undercarriage wear report for all 353 machines are compiled and the hours of operation on the bushing is divided by the percent worn off the track bushing. This measure reflects a rate of track wear and the bushing is used to predict maintenance intervals (“Custom Track”, 2013). The goal of this preliminary regression analysis is to determine if either sand content in the soil, machine elevation, machine weight, annual precipitation and annual temperature are significantly correlated to the rate of track bushing wear. Figure 16 reflects the wear rate distribution for the 353 machines in this study. There seems to be a rather normally shaped histogram with larger distribution category bars on the lower end of the wear rate range. The median is slightly larger than the mean and is slightly right skewed.

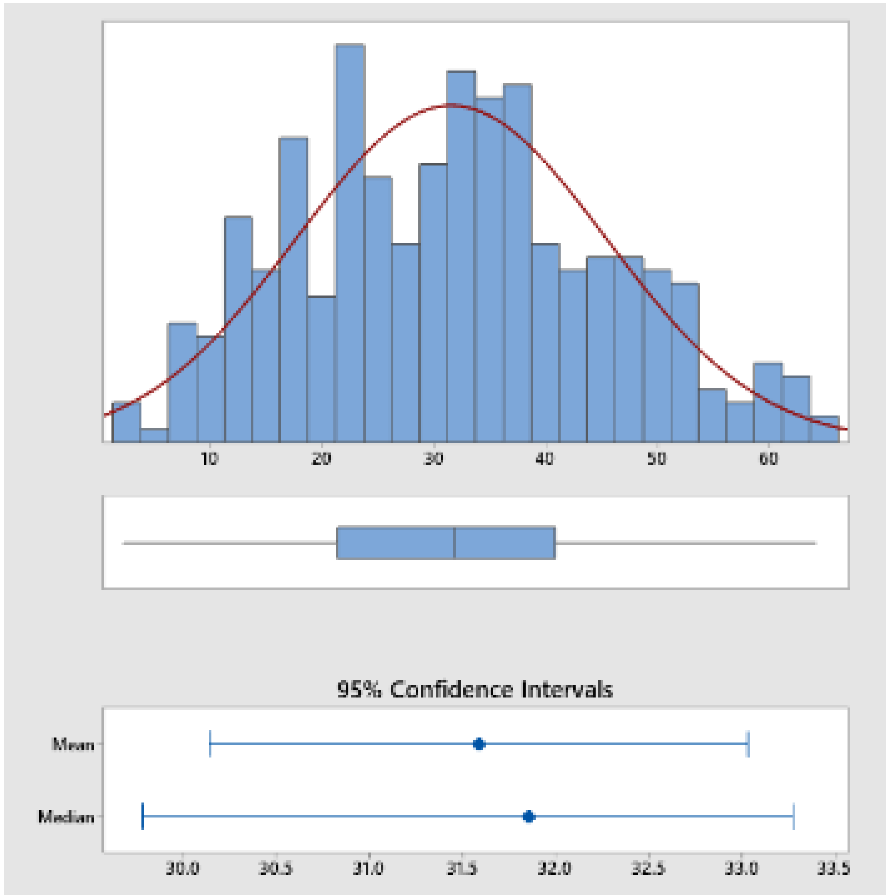

Figure 16. Graphical Summary for Dependent Variable of Hours per Percent Worn.

Table 9 reflects the minimum value of a very low 2.225 hr/% worn while working in the most southeastern coastal counties. The maximum value was 64.25 hr/% worn from the clay fields of central piedmont where clay bricks are manufactured. The mean value is 31.587 and the data is slightly right skewed.

Table 9

Descriptive Statistics for Dependent Variable Hours Per Percent Worn

Mean	St Dev	Variance	N	Min	Med	Max	Skewness	AD-P value
31.587	13.844	191.650	353	2.225	31.857	64.250	0.1915	0.021

Initial Regression Analysis

Now that the data for the first hypothesis test has been compiled, a multiple regression analysis can be performed to determine the significance of the factors. This preliminary analysis is used to identify any insignificant factors so they can be removed from the final model to be assembled. The null hypothesis to test is: Is there a correlation between the percent of sand present in soil, elevation above sea level, machine weight, average temperature and average precipitation to the wear rate of steel track undercarriage systems?

$$H_o: \beta_{sand\ content} = \beta_{elevation} = \beta_{weight} = \beta_{Temperature} = \beta_{Precipitation} = 0$$

$$H_A: \beta_{sand\ content} \text{ or } \beta_{elevation} \text{ or } \beta_{weight} \text{ or } \beta_{Temperature} \text{ or } \beta_{Precipitation} \neq 0$$

The regression analysis first determines if there are any input variables that are significantly correlated to the output dependent variable and designates those variables of significance at an alpha value of 0.05. Table 10 reflects the output of the initial regression analysis. Only the p-value for sand content in the soil shows a significantly low p-value of 0.000 with a corresponding high F-value of 235.18. Knowing there is one significant input value, the null hypothesis can be rejected and the alternate accepted that the $\beta_{sand\ content}$ is greater than zero.

Table 10

Regression of Hours vs Sand %, Elevation, Precipitation, Temperature and Machine Weight

Source	DF	Adj SS	Adj MS	F-Value	P-Value	S	R-sq	R-sq Adj
Regression	5	34071.6	6814.3	70.82	0.000	9.809	50.51%	49.79%
Sand	1	22629.8	22629.8	235.18	0.000			
Weight	1	25.5	25.5	0.26	0.607			
Elevation	1	15.6	15.6	0.16	0.687			
Precipitation	1	71.7	71.7	0.75	0.388			
Temperature	1	7.9	7.9	0.08	0.775			
Error	346	33389.2	96.2					
Lack of Fit	329	32658.1	99.3	2.44	0.014			
Pure Error	18	731.0	40.6					
Total	352	67460.7						

Table 10 Cont.

Regression of Hours vs Sand %, Elevation, Precipitation, Temperature and Machine Weight Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	57.3	25.3	2.27	0.024	
Elevation	0.00133	0.00331	0.40	0.687	1.67
Weight	0.000014	0.000028	0.51	0.607	1.01
Sand	-0.4452	0.0290	-15.34	0.000	1.41
Precipitation	-0.186	0.216	-0.86	0.388	2.70
Temperature	0.146	0.511	0.29	0.775	3.28

The R-squared value is 50.51% for this model which states that 50.51% of the variability in the dependent variable can be explained by the input variables in this model. This value is not exceedingly high but is an acceptable value for significance consideration.

Figure 17 displays a fitted line plot graphically describing the relationship of the significant variable of sand content in the soil to the dependent variable of hours per percent bushing wear. The relationship is a negative one for as the percent of sand in the soil increases, the hours per percent worn decreases. This negative relationship is graphically depicted by the red fitted plot line in the center of the data points. The prediction interval represented by the purple dotted line is used to predict where the next data point calculated by the regression model can be expected to fall. There are several data points outside the prediction interval that seem to be evenly distributed both above and below the prediction line. There are some soil types that are prevalent in the study area. These appear as vertical lines on the fitted line plot where multiple machine inspections occur in the same soil type. In most cases there is rather even distribution of inspection results both above and below the regression line.

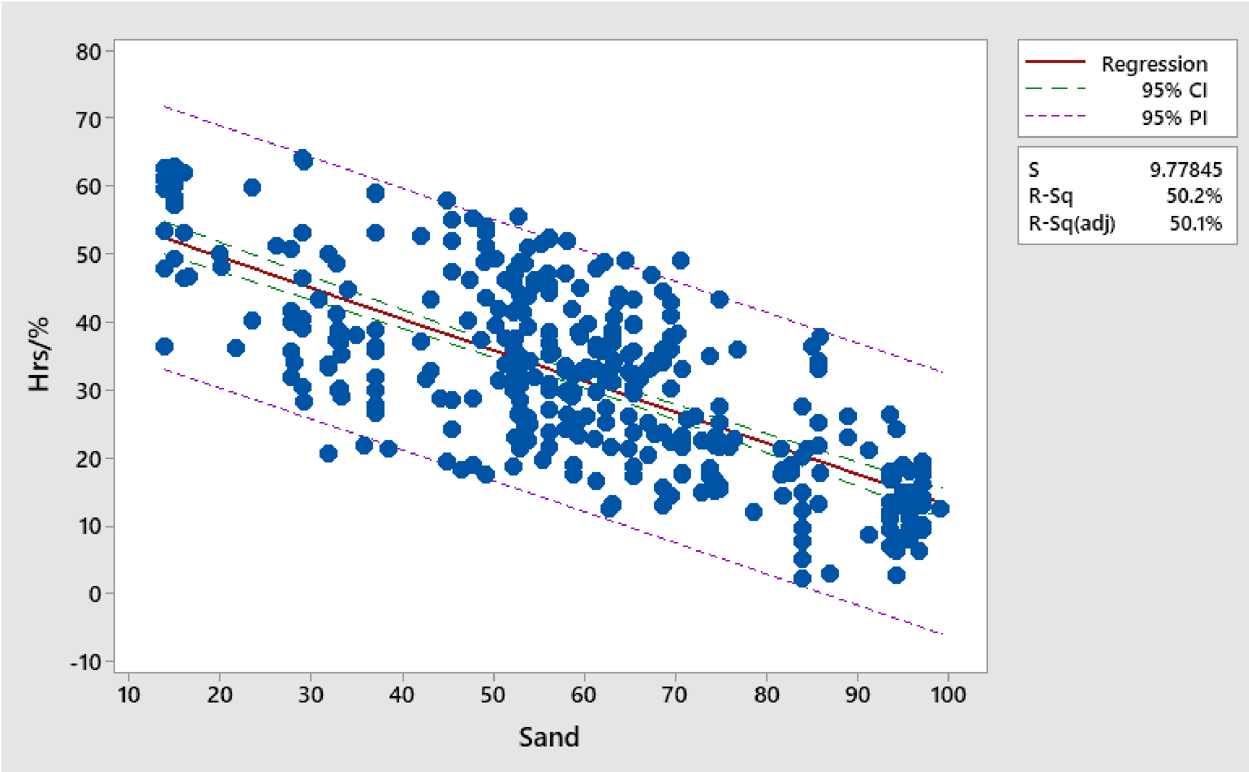

Figure 17. Fitted Line Plot of Hours per % Worn vs Sand Percent.

To express this regression model including the insignificant variables, the equation would read:

Hours / % = 57.3 – 0.4452 Sand + 0.000014 Weight + 0.00133 Elevation

– 0.186 Precipitation + 0.146 Temperature

The 57.3 value in the equation denotes where the red regression line in Figure 17 intersects with the y axis of the dependent variable. The other values explain the constant value of impact each of the input variables has on the output variable Y and due to the insignificance shown in the high p-values, only the sand constant is of any great impact as a multiplier.

Figure 18 displays the standardized effects plot for the multiple regression. The line of significance is drawn through the 1.97 value and only factor C or sand has a significant value of 15.336 and is the only factor that has a standardized effect greater than the critical value of 1.97.

This means only sand is statistically significant in impacting the output variable. This also means the other values are insignificant and can be removed from the model.

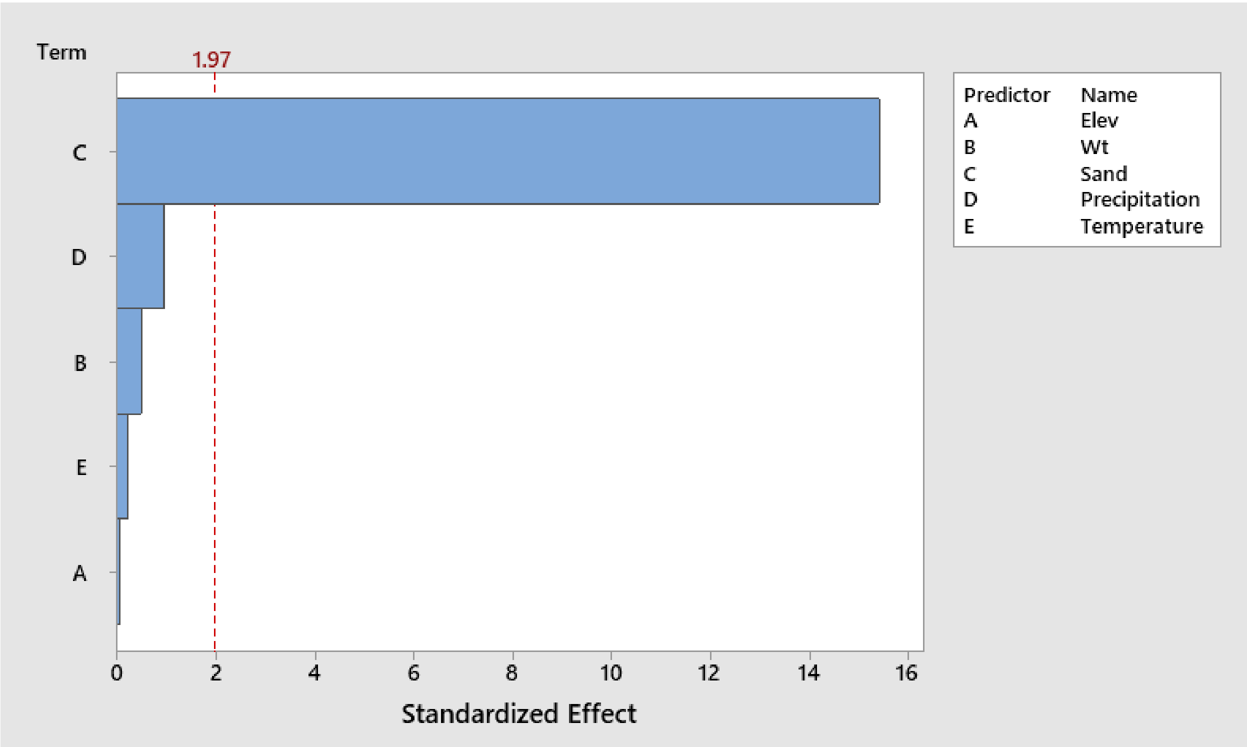

Figure 18. Pareto of Standardized Effects.

Figure 19 is a display of the residuals 4 pack and the residuals look randomly distributed with the residual points aligning rather nicely with the normal residual plot line. There are a couple of data points on the tails of the normal probability plot that are of concern but for most of the data points, the residuals look random and evenly distributed.

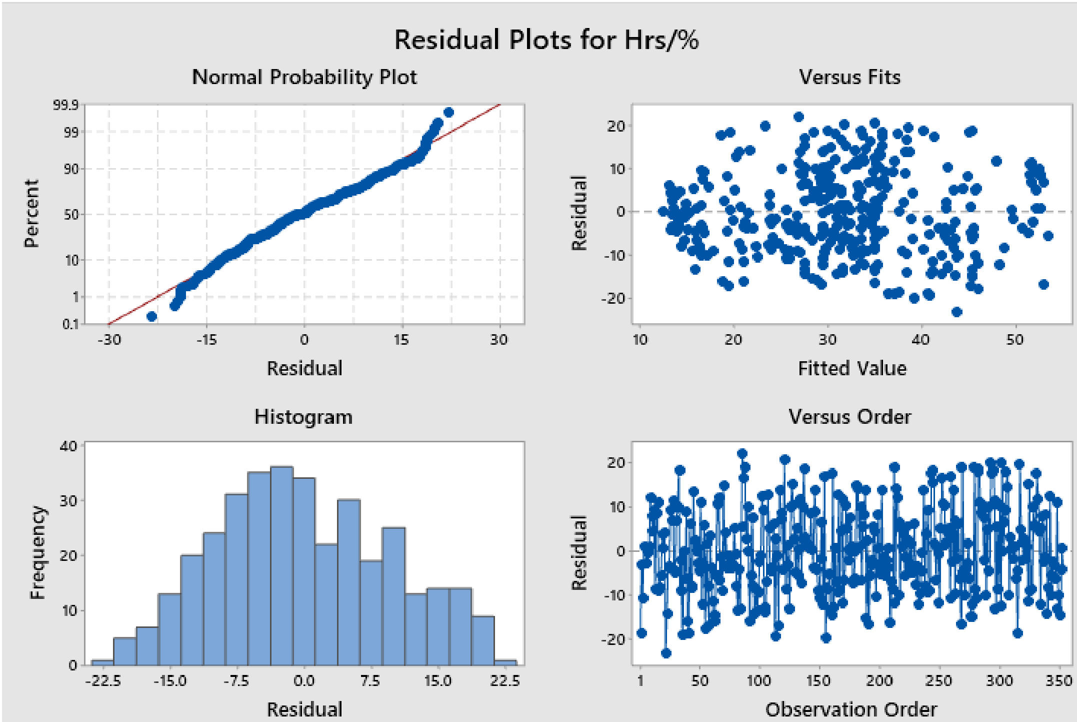

Figure 19. Residual 4 Pack of Initial Regression.

Non-Linear Analysis of Precipitation

Given the strong and vast amount of literature discussion on the effect of moisture on metal wear rates, it seems prudent to perform a non-linear analysis on the input factor of precipitation. A quadratic regression analysis was performed on this input factor to determine if there was significance in using this model configuration. Table 11 displays the results of this analysis. Note that the p-value of 0.00 showing precipitation as a significant value using quadratic regression.

Table 11

Non-Linear Quadratic Regression Analysis of Precipitation

Source	DF	SS	MS	F-Value	P-Value	R-sq	R-sq Adj
Regression	2	8143.2	4071.58	24.24	0.00	12.20%	11.70%
Error	349	58611.9	167.94				
Total	351	66755.1					

Figure 20 displays the fitted line plot for this quadratic regression as well as the equation of: **Hours / % Worn - -145.3 + 8.056 Precipitation – 0.09015 Precipitation^2.** This figure also shows a R square value of only 12.20% which is a low value.

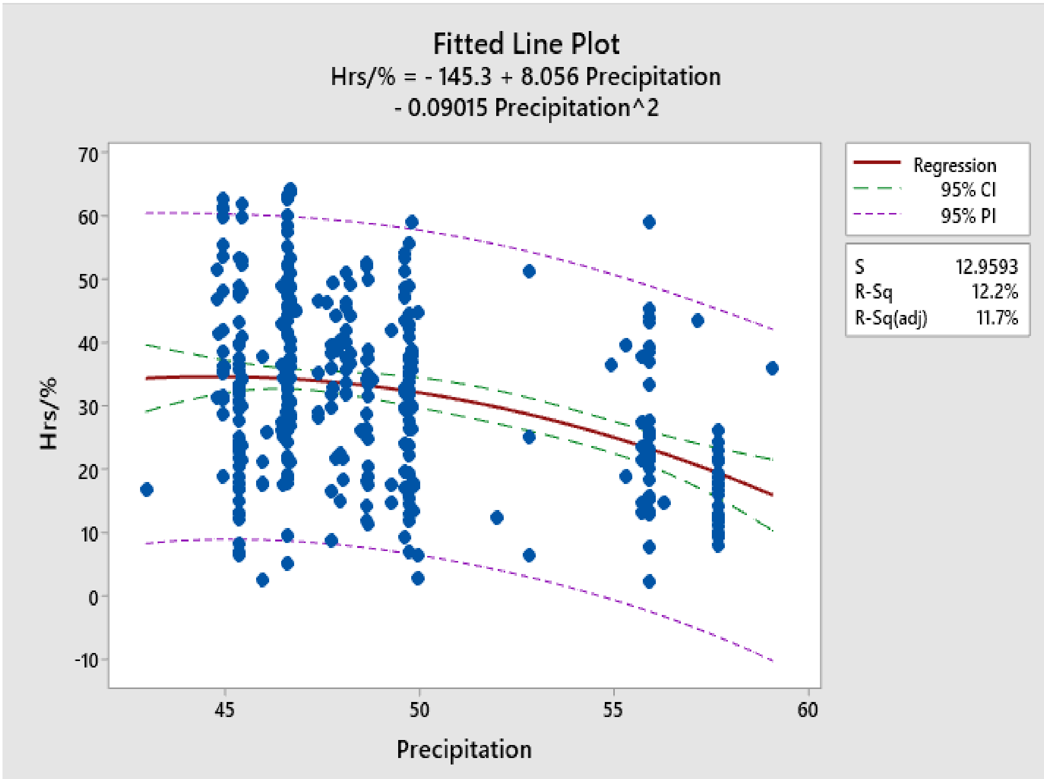

Figure 20. Non-Linear Quadratic Regression Analysis of Precipitation

In addition to the low R square value of 12.20% there are residuals that are not random nor are they symmetrical about the residual value of 0. Figure 21 displays the residual 4 pack of this analysis. Looking at the versus graph, one sees where the residuals are not random at all with most of the residual values congregating between the 32 and 35 fitted value. These residuals are problematic for having an acceptable model.

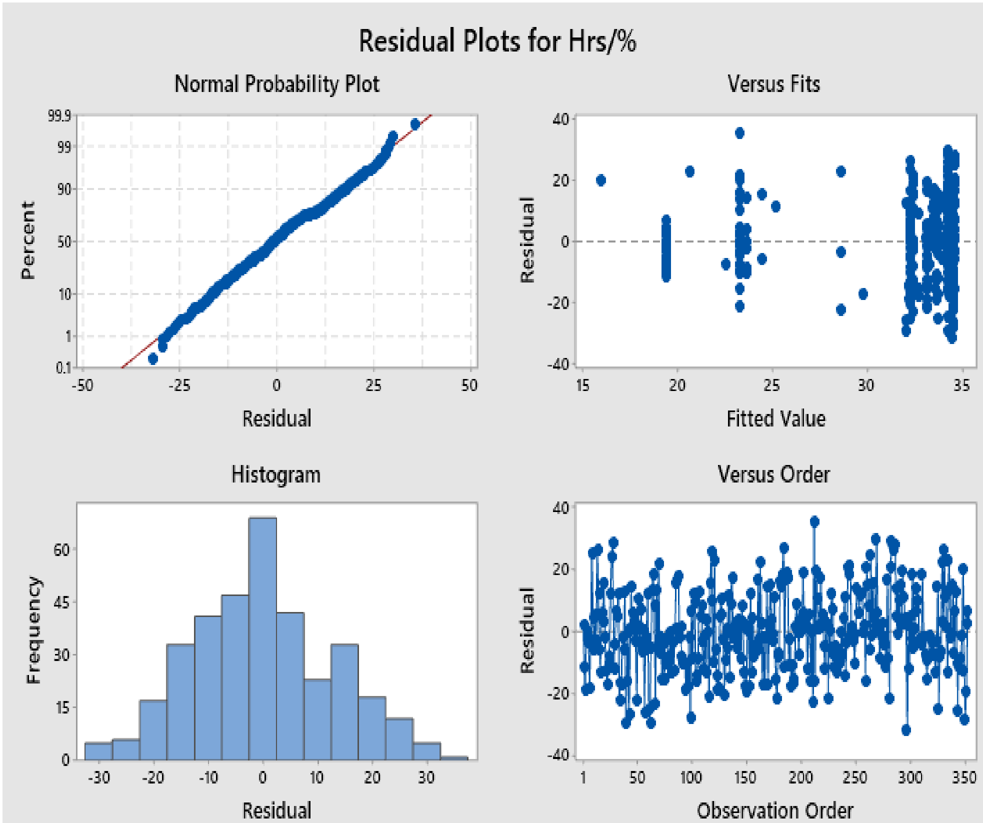

Figure 21. Residuals for Quadratic Regression Analysis for Precipitation.

Even though the p-value for this quadratic regression is 0.00, the low R square value and the problematic distribution of the residuals will confirm the removal of this input factor from further consideration in this study. Future study of this input factor would be recommended possibly using moisture in the soil as a dependent variable.

Categorical Factor Data Analysis

Input Variable Machine Model

Now that the continuous variables have been considered for significance, the categorical variables should be as well. The first to be considered is the machine model number. There are 7 models to consider with model 3 being the smallest and model 9 the largest in physical size.

An ANOVA was performed to compare the categorical input factor of model to the output of hours per percent bushing wear. The first output is reflected in the confidence interval for the mean shown in Figure 22. All confidence intervals overlap with the variability in the number of machines in each group being reflective in the width of the individual model's graph. Many more of model 6 were present in the analysis than model 9's. This graphic would lead to the conclusion that model number does not impact the hours per percent worn output.

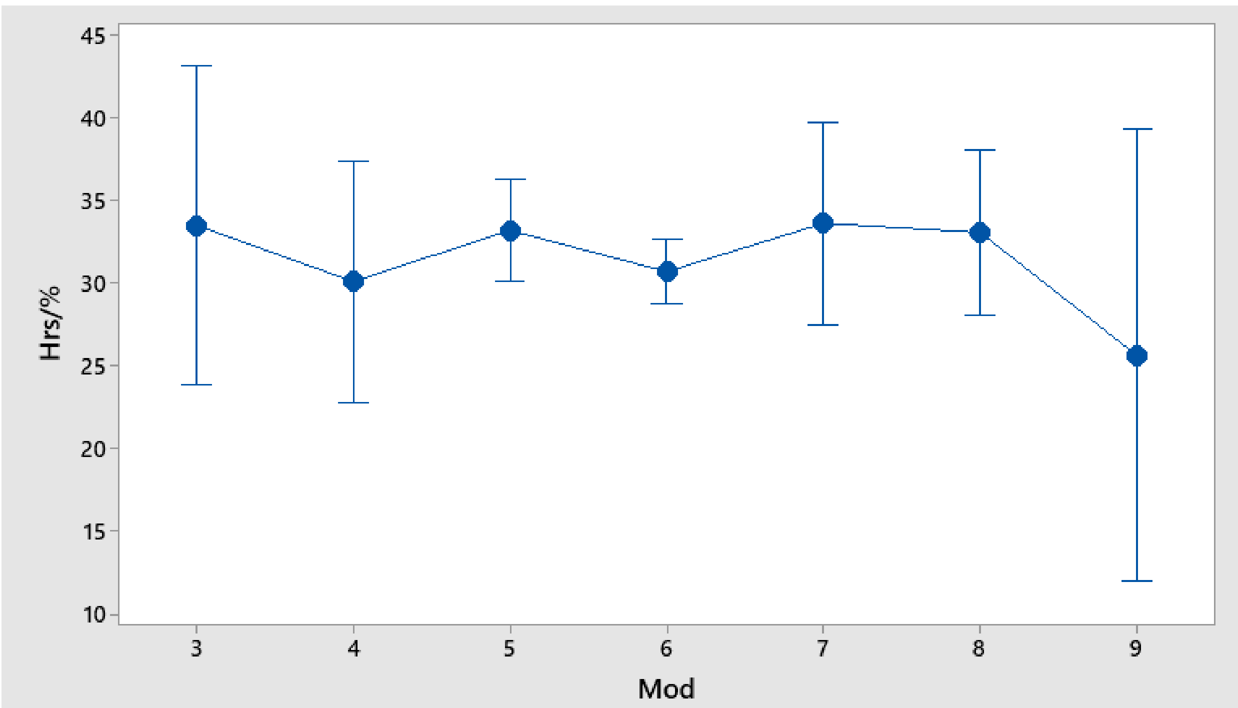

Figure 22. 95% Confidence Interval for Mean of Hours per Percent Worn by Machine Model.

The boxplot in Figure 23 provides additional graphic representation of the spread of the same data shown in Figure 22. Models 3-8 share many of the same graphical attributes with model 9 seemingly having slightly different dispersion in the overall values than the other models and the mean slightly lower. It should be noted that models 3 and 9 had by far the lowest number of data points for consideration.

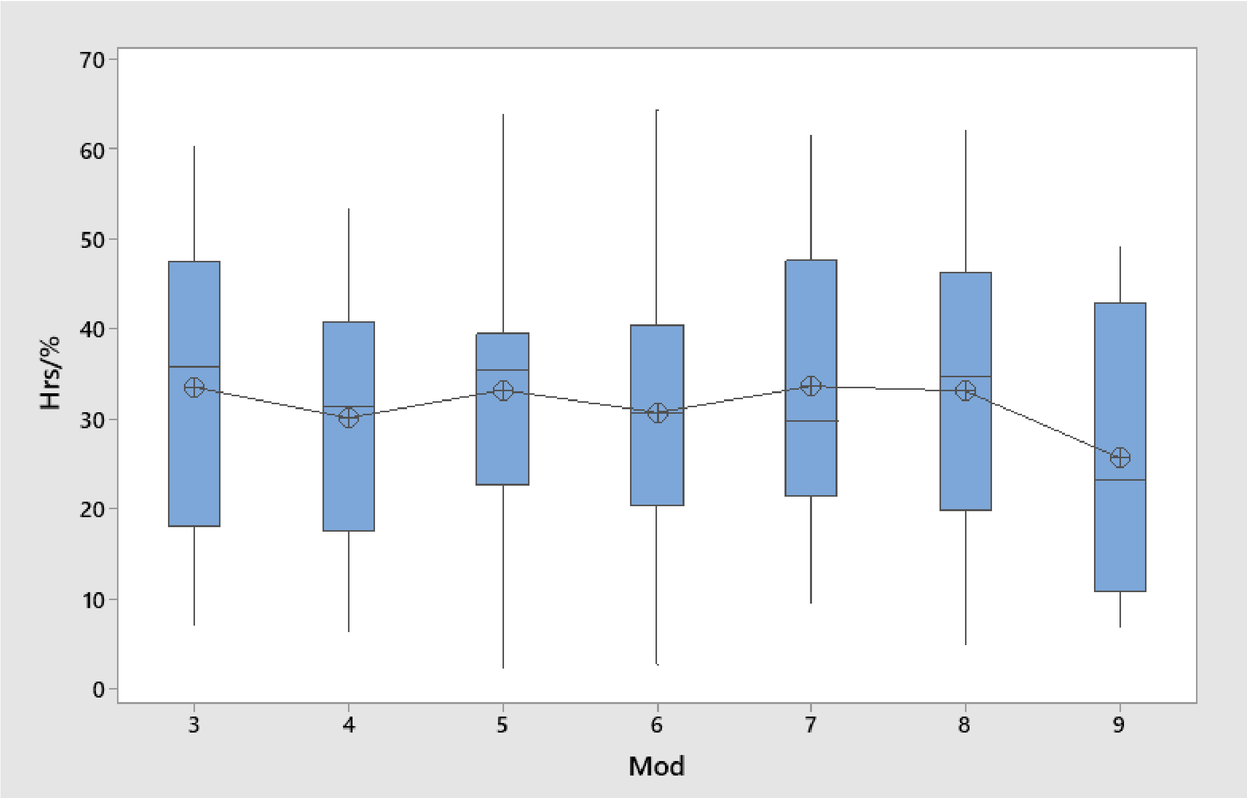

Figure 23. Box Plot of Hours Per Percent Worn By Machine Model.

Figure 24 displays the distribution of machines in this study by model. There are by far more model 6 in the data set than any other model with the next model 5 being less than half of the model 6 total. This is reflective of the model mix in the study territory for there are by far more model 6's in the territory than any other machine model. The low number of models 9, 3, and 4 making this analysis of model less robust than if all machine models were represented by a large n value. In the case of 9, 3, and 4, there is simply not that many of these machines in the study territory to measure.

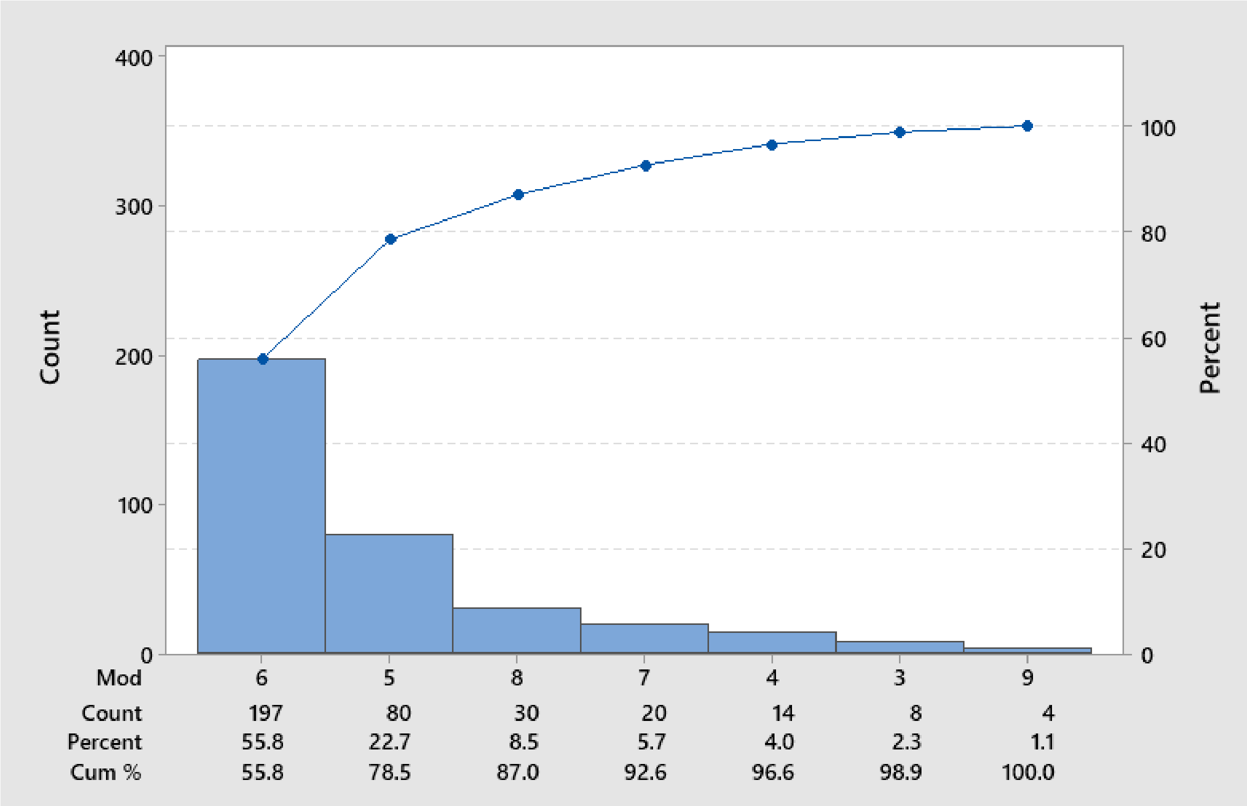

Figure 24. Pareto Chart of Machine Model Count.

For this statistical analysis, the null hypothesis to test is: Is there a difference between the model number of the machine and the wear rate of steel track undercarriage systems?

$$H_o: \mu_{\text{Mod 3}} = \mu_{\text{Mod 4}} = \mu_{\text{Mod 5}} = \mu_{\text{Mod 6}} = \mu_{\text{Mod 7}} = \mu_{\text{Mod 8}} = \mu_{\text{Mod 9}}$$

H_A: At least one mean is not equal

Table 12 reflects the 0.717 p-value result of this test and as Figure 22 would suggest, there is no significant difference in the mean output value for any of the model numbers. It makes no statistical difference which model grouping is being considered, for there is a very low probability that the model number impacts the wear rate of the undercarriage system. The R-squared value is 1.06% meaning there is very little dependent variable output impact due to model number.

Table 12

Anova of Hours per Percent Worn by Machine Model

Source	DF	Adj SS	Adj MS	F-Value	P-Value	R-sq	R-sq Adj
Model	6	714.1	119.0	0.62	0.717	1.06%	0.00%
Error	346	66746.6	192.9				
Total	352	67460.7					

Input Variable Work Code

The next categorical variable to be analyzed for significance is the work code. The work code is a marketing code identifying the type of work a customer generally performs. Marketing departments use these codes to target like industry customer groups with programs specifically geared for customers in the different industries. The equipment is used for different tasks between these groups with some applications being more extreme than others. Figure 25 shows the confidence interval for the mean for the 6 customer groupings in this study. From the visual interpretation of this graph, none of the confidence intervals overlap. Grouping “heavy” has the smallest variability of all groups and landfill application having the greatest.

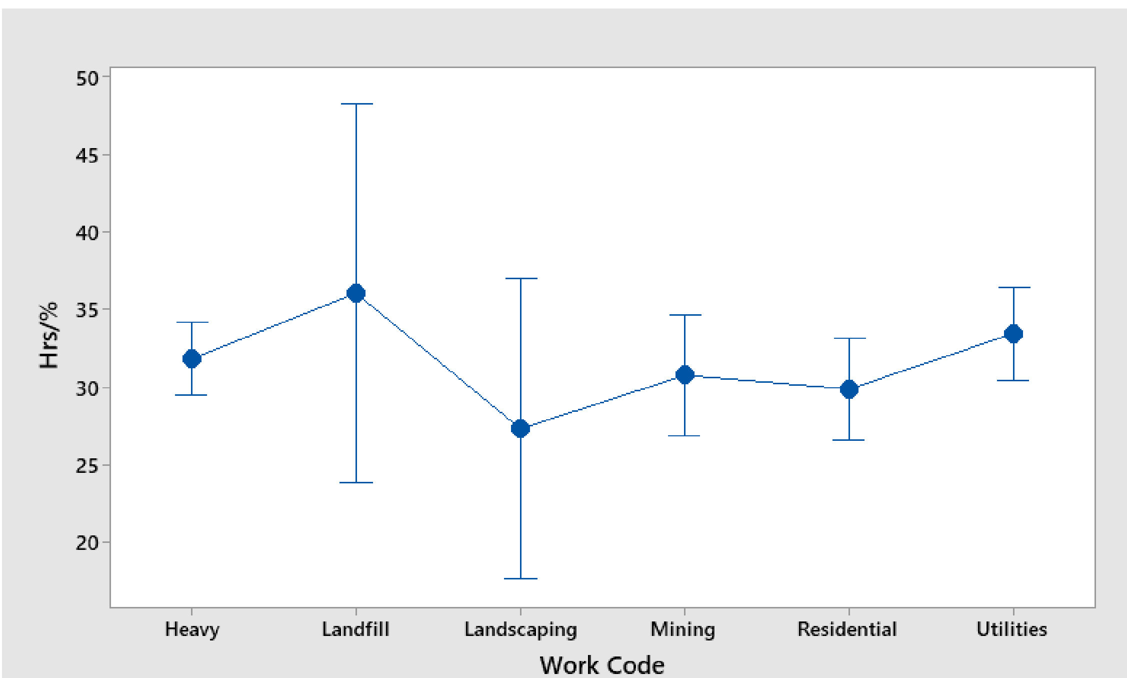

Figure 25. Confidence Interval of the Mean for Hours Per Percent Worn by Work Code

The boxplots of work code in Figure 26 shows similar distribution of hour/percent worn output values for all but landfill and landscaping work codes. It should be noted that the groupings of landfill and landscaping have low n values in the data set which may be driving these graphical differences in variation.

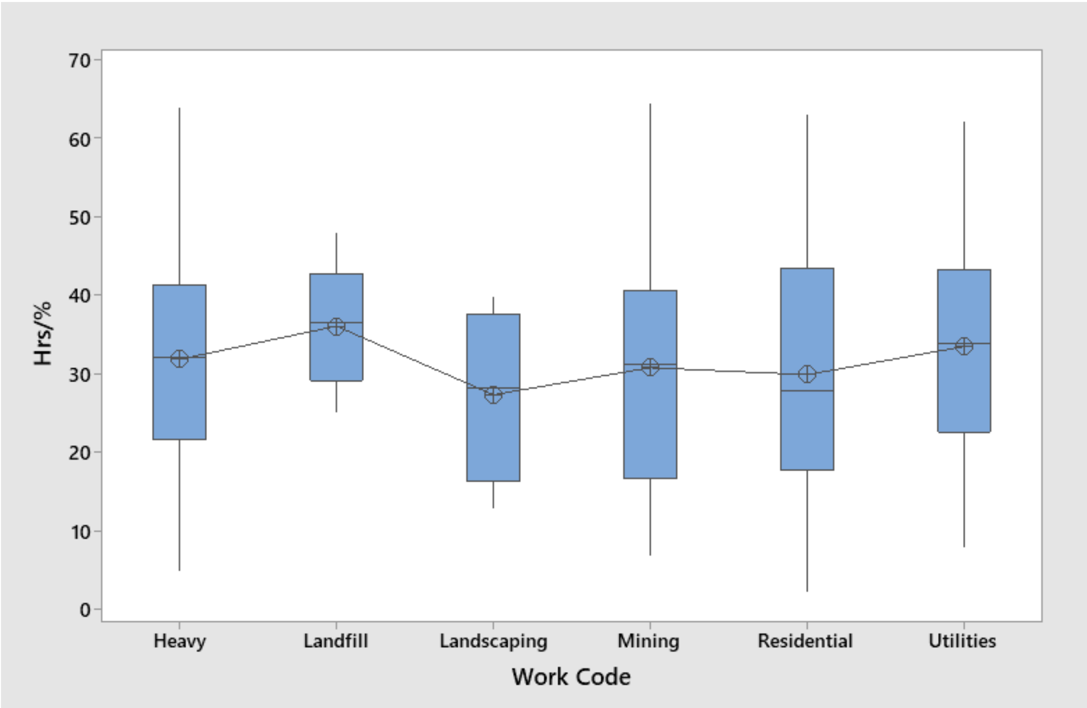

Figure 26. Box Plot of Hours per Percent Worn by Work Code.

Figure 27 graphically displays the distribution of undercarriage reports by work code. Heavy by far has the most machine data points represented with 138 followed by residential having numerous with 98 machine inspections being represented. Landscaping and landfill machinery are on the small end of this spectrum with only 8 and 6 undercarriage inspections respectively. There is a large population of landscaping machines in the territory however, landscaping customers have smaller jobs and move frequently. Many of the landscape machines are considered as transient which unfortunately removes them for inclusion in this. With regards to landfill machines, there is simply a small population of them in the territory. Figure 27 graphically depicts the type of work being undertaken in this study area for there is much heavy road work and large commercial construction projects underway. The customers performing this type of work are the heavy customers.

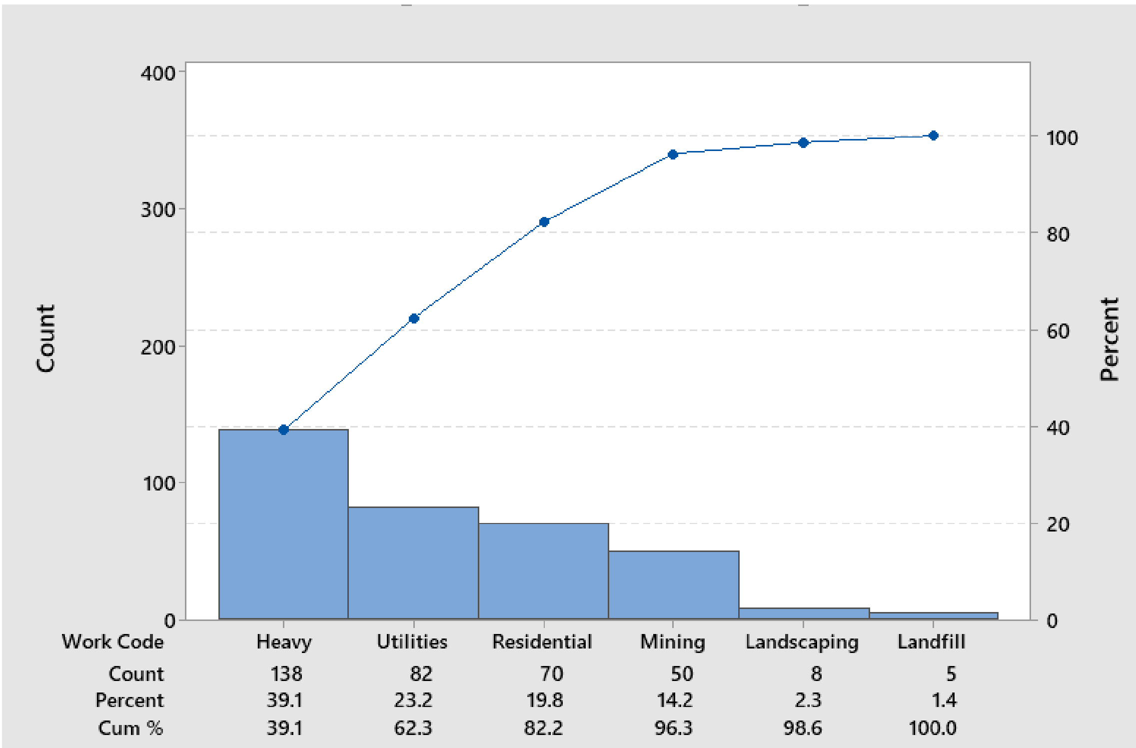

Figure 27. Pareto Chart of Work Code Count.

The null hypothesis to test is: Is there a difference between the machine population groups by work type code and the wear rate of steel track undercarriage systems?

$$H_o: \mu_{\text{Landscape}} = \mu_{\text{Heavy}} = \mu_{\text{Utilities}} = \mu_{\text{Residential}} = \mu_{\text{Mining}} = \mu_{\text{Landfill}}$$

H_A: At least one mean is different.

The result of this categorical analysis shown in Table 13 returns a high p value which tells us to reject the null and that there is no difference in undercarriage wear rate means between the different work groups. With a R squared percentage for this analysis is 1.16%, the variability of the output mean value is negligible between the different type of work being performed by your study machine population. The mean values of the wear rate between work types are statistically the same.

Table 13

Anova of Hours per Percent Worn by Machine Work Code

Source	DF	Adj SS	Adj MS	F-Value	P-Value	R-sq	R-sq Adj
Work Code	5	781.9	156.4	0.81	0.540	1.16%	0.00%
Error	347	66678.8	192.2				
Total	352	67460.7					

Final Analysis of Significant Factors

Now that the significance of all variables is known, the final regression analysis of the lone significant variable can be performed. Sand percentage of the soil in which the machine is working in is the only significant variable found. The insignificant variables are removed from the analysis and only sand is run in the regression study of this continuous variable. Table 14 illustrates the results of the analysis. The R squared adjusted value is now 50.11% which tells us that 50.11% of the variation seen in the track wear rate can be attributable to the percent of sand in the soil in which the machine is working. The remaining variation is attributable to other factors that are not included in this initial regression model. Some of the additional factors that could impact the wear rate could be operator, track adjustment, materials packing on the bushing or sprocket segment and possibly other unknown factors. Further research will need to be performed in order to determine what percent if any these possible factors could add to the R square value. The p-value is 0.000 with a very high F value of 354.52. Sand is a significant factor in the rate of wear of steel track undercarriage systems.

Table 14

Regression of Hours vs Sand Percent

Source	DF	Adj SS	Adj MS	F-Value	P-Value	S	R-sq	R-sq Adj
Regression	1	33899	33898.8	354.52	0.000	9.778	50.25%	50.11%
Sand	1	33899	33898.8	354.52	0.000			
Error	351	33562	95.6					
Lack of Fit	128	12628	98.7	1.05	0.370			
Pure Error	223	20934	93.9					
Total	352	67461						

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	58.79	1.54	38.28	0.00	
Sand	-0.4584	0.0243	-18.83	0.00	1.00

Figure 28 shows a similar graph as shown in Figure 18 except the insignificant variables have removed. The critical value is still the same at 1.97 however the sand standardized effect is now 18.829 with the insignificant variables removed. The value if the standardized effect of sand only is far above the critical value of 1.97 validating the significance of the variable on the response variable.

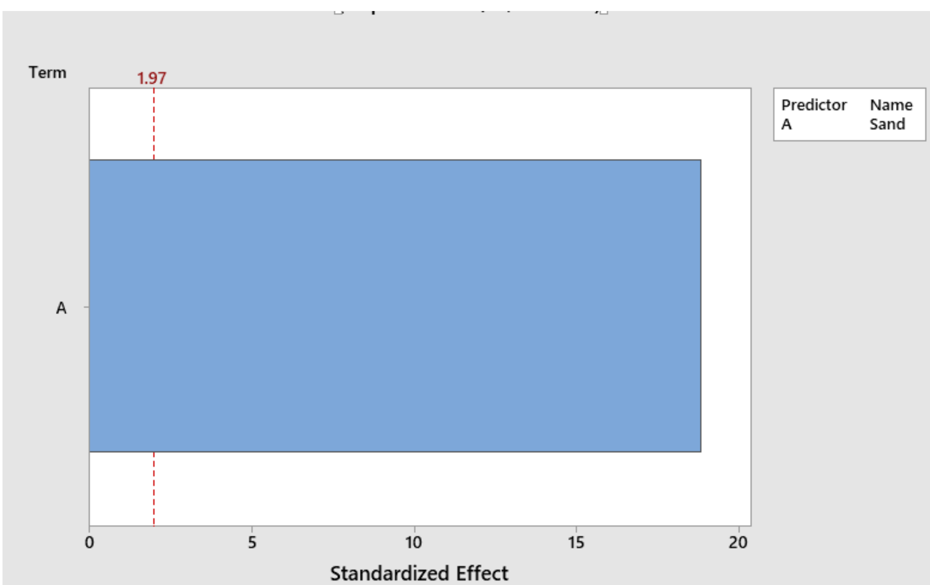

Figure 28. Pareto of Standardized Effects.

Figure 29 illustrates the residuals 4 pack of the final regression analysis. The residuals look randomly distributed and the residual points align rather nicely with the normal residual plot line. There are a couple of data points that are of concern but for most of the data points, the residuals look random and evenly distributed.

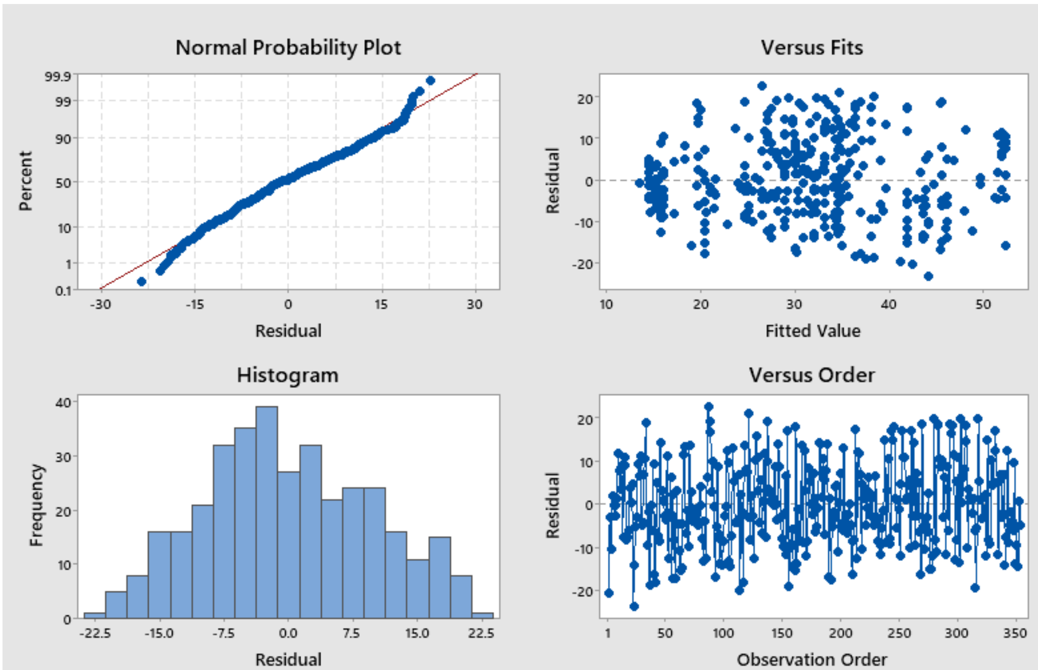

Figure 29. Residual 4 Pack of Final Regression Analysis.

The equation derived to describe the sand percentage to the rear rate can be expressed in the following equation:

Hours of Machine Operation / 1 % Bushing Wear = 58.79 - 0.4584*Sand

The equation states when sand percent is entered into the equation, it is multiplied by -0.4584 and subtracted from the Y intercept of 58.79. The results reflect the hours per percent worn off the track bushing which can be used as a tool to predict track wear in the eastern North Carolina study territory. Stated another way, for every 0.4584 increase in sand percentage, one could expect the rate of undercarriage wear will decrease by 1 hour per percent worn.

CHAPTER 5

INTREPRETATION AND RECOMMENDATIONS

Interpretation of Input Variables

Elevation

The input factor of elevation reflects the elevation above sea level at the GPS coordinate location where the undercarriage inspection occurred. Figure 12 displays the distribution of these elevations for the 353 machine inspections performed. The most interesting thing about this histogram is the largest bar representing 0 to 25 feet above sea level. There are 67 machines working at this elevation and 147 machines working from 0 to 75 feet if the first and second bars are summed. The coastal plain is very flat for many miles inland with most all the land being less than 75 feet above sea level. Much of the coastal machine fleet population falls within this 0 to 75 feet elevation and is reflected in the histogram. Where this flat topography changes and more undulation begins is the beginning of the piedmont region and closely mirrors the sand and metamorphic soil composition changeover (NCOnemap.gov, 2019). Once this changeover occurs, there is a gradual increase in elevation which is evident in the consistent increase in elevation from 75 to about 550 feet above sea level. These higher elevations were seen in undercarriage reports from the western most portions of the study area. The machine population dwindles at greater than 600 feet due the lower machine population in the western most part of territory which is very rural and economically less vibrant than the eastern areas. When this input factor was considered in the multiple regression, the p-value was 0.687 therefore, elevation did not impact the track system wear rate in the machines whose tracks were measured. This input factor is insignificant to our regression model and is removed from the final regression model. The insignificance could be a result of the measurement chosen for this input factor. In this study area when elevation increases so does the average slope. However, this now appears to be a correlation that may be missing some localized variation of topography. For example, if a machine elevation is well above the level ground of the coastal plains, the localized topography could be flat or undulated depending on the localized terrain. A more accurate measurement of this factor could be the actual slope of the ground at the job site. This would be a more granular measure that would incorporate any localized terrain undulations that a GPS coordinate derived elevation value would not deliver. Slope calculations would have to be captured at the time of each undercarriage measurement. There is also a possibility there could be within jobsite slope variation which would also allow bias to creep into this input factor measurement and this could change over time. Job sites can be extremely flat after much of the dirt transfer has occurred or extremely steep in topography when sloping operations on exit ramps or other highly sloped areas are occurring.

Machine Weight

The input factor of weight reflects machine weight based on the model number and special configurations the machine may have. It does not include any additional dirt that may have accumulated on the track roller frames or any other customer added attachment or guarding. The histogram in Figure 13 shows the distribution of these machine weights. Although the weight is a continuous measure, it appears that this distribution follows model designations. The four large bars reflect models 4, 5, 6 and 7 which has the largest population in this study area. Within each of these models, there are different machine configurations that impacts the weight but does not elevate the weight of the machine up to the next model number weight category.

For example, the model 6 dozer could have an extra-long track roller frame which adds weight to the base model weight or different types of blades can be on the same model machine. This explains the differences in the within model weights and the small bars between the larger ones. The very large machines are shown in the 90,000 and 105,000 pound bars. There are only 20 of these machines in the machine population and are shown as outliers due to their extremely large weight values. Machine weight was another regression factor that was statistically insignificant with a p-value of 0.607 therefore, machine weight does not significantly impact the track system wear rate in the machines whose tracks were measured. This input factor is insignificant to our regression model and will consequently be removed from the final regression model. One possible reason for the insignificance of this factor could be the proportional sizing of the undercarriage to fit the machine size and weight. Larger machines have proportionally larger undercarriage systems. With this undercarriage size proportionality, the rate of wear appears very close to the same no matter the machine size. There is more wear metal removed from a larger machine but the rate of that wear to the stated service intervals doesn't seem impacted by the weight of the machine.

Precipitation

The input factor for precipitation reflects the annual precipitation at the nearest weather station to where the machine undercarriage inspection was performed. Figure 14 shows the distribution of the precipitation totals for the machine population inspection GPS coordinates. This shows some interesting results that validates the higher coastal precipitation of the coastal plain due to both tropical systems and the on-shore wind generated precipitation (Sims & Ramon, 2016). With the average precipitation being 48.997 inches and a standard deviation of 3.985. Most all the coastal machines are located areas where precipitation totals are statistical outliers shown by the asterisks in the box plot. There is a large gap between 49 and 55 inches and the outliers easily show where the coastal machines are located. The p-value of 0.388 reflects that precipitation did not impact the track system wear rate in the machines whose tracks were measured. This input factor is insignificant to our regression model and is removed from the final regression model. This insignificance could be due to multiple reasons. There could be between weather station variation that could be creating bias. For example, if a small but potent thunderstorm travels through a jobsite, the measurement of this precipitation could go unmeasured by the nearby weather station not in the storm's path. This would create errors in the measurement outcome. In addition, there is some variation in precipitation annual totals between the coastal plain areas and the piedmont, but is this difference enough drive significance? The minimum value is 42.96 and the maximum is 59.06 which is only 16.1 inches. Another possible reason for insignificance could be the measure itself. Different results may have been achieved if average moisture content of the soil could be measured rather than precipitation totals. Much like topography, this measurement would have to be proactively measured over time to gain a better understanding of the average soil moisture the undercarriage is experiencing. This approach also considers the different soil hydraulic conductivity through the soil with sandy soil dissipating moisture much faster than clay soils (Rowell, 1994), (Jarvis, Koestel, Messing, Moeys, & Landahl, 2013).

Temperature

The input factor for temperature reflects the average annual temperature at the weather station nearest to the GPS coordinates of the track inspection location. Figure 15 displays the distribution of the 353 data points and there is a very large bar about the mean of 61.31. One interesting fact to glean here is the small range of the temperature readings with only an 8.25

degrees difference between the most north west and highest elevation and the most south east and lowest elevation data point. Temperature was another regression factor that was statistically insignificant with a p-value of 0.775. This small temperature range may be one reason this input factor was statistically insignificant. Temperature does not impact the track system wear rate in the machines whose tracks were measured. This input factor is insignificant to our regression model and is removed from the final regression model. One possible reason for this insignificance is the small range of the yearly average temperature variation. The maximum temperature reading was 56.75 and the maximum being 65.0. This represents a differential of 8.25 degrees Fahrenheit in temperature variation between the extreme inspection points in the study territory. This may not be enough temperature variation to make a difference in the bushing wear rate.

Machine Model

Machine model is a categorical input variable that represents the model designation of each machine. Figure 23 shows a graphical display of the hours per percent worn by machine model. There is very little difference in the box plots and is reflected by the one-way ANOVA p value of 0.717 and an R Square Adjusted value of 1.06%. The undercarriage for each model is designed proportionally to the size and weight of the machine. Smaller machines have proportionally smaller undercarriage systems than larger ones and explains one reason why the rate of wear are essentially the same. There is no statistical difference in the wear rate of steel track undercarriage systems when comparing model numbers in this study. This insignificance could be due to the same reasons as the weigh factor discussion. As the model number increases so does the weight and the proportional undercarriage size. Much like machine weight the machine model does not seem to impact the rate of wear.

Work Code

Work code is a marketing code given to all customers that describes the type of work the customer performs and each track report was tagged with this customer work code. Figure 26 displays the rate of track wear by customer work code and the graphical evidence shows very little differences in the wear rate. A one-way ANOVA was performed, and the p value was 0.540 with an R Square Adjusted value of 1.16%. Based on these results, it does not matter which type of work is performed for the track system wear rate was statistically the same. This may not hold true for power train, hydraulic systems or structural framework but for track wear there was no difference noted here. This does not reflect any crossover jobs that the customer may have. For example, there is nothing to tell the researcher if the utility contractor performs a residential job. This may create some undetectable bias in this measurement.

Sand Content

The input factor of sand content reflects the percentage of sand in the soil where the undercarriage inspection was performed based on longitude and latitude coordinates from the instrument telematics. The histogram in Figure 11 displays the distribution of the percent of sand data points for all 353 soil percentage readings from each of the qualifying undercarriage reports. The mean of 59.35% sand is not unexpected for most of the machine population are concentrated in the central Research Triangle area of the state which is in the center of the study territory. This region represents the transition zone in the geological gradient containing a mixture of sand and clay soils. There is currently much residential and road construction occurring in this area therefore, the high concentration of machines in the 53% to 68% sand zone is not surprising. Another interesting observation is the histogram bar spike at the highest end of the sand scale. This is representative of the machines working on the coast working in greater than 90% sand content soils. Currently, there is an economic boom along the coastal plain and especially directly on the coastline. In addition, there is much beach renourishment occurring with a large population of dozers being used to complete this work. The data set looks almost trimodal with a population from the 15 to 40% range, the largest at the 45 to 75% range and the third representing sand percentages of greater than 75%. This aligns nicely with the description of the geological gradient of increasing sand content from west to east in the research study area (Tant & Byrd, 2019), (Lu, Bowman, Rufty & Shi, 2015). The sand regression input factor shows to be statistically significant with a p-value of 0.000 and is included in the final regression analysis equation.

Final Regression Equation

It was found the two categorical factors of machine model and work code were insignificant to the steel track wear rate in our study. It was also found that the continuous data input factors of machine weight, elevation, precipitation and temperature were also insignificant to track wear rate of the machines studied. After the removal of these insignificant factors sand content remains the sole significant factor. The removal of all the insignificant factors only impacted the R squared value by 0.26% so the insignificant factors were contributing very little to the variation in wear rate. Simplifying the regression equation to only the significant factor leaves the equation:

Hours of Machine Operation / 1 % Bushing Wear = 58.79 - 0.4584 Sand

This equation provides a tool for the equipment manager to help predict undercarriage wear. If the manager knows the type of soil the machine is working, she/he can more accurately predict track bushing wear rate. Being able to better predict wear rate helps the manager to better optimize the operational cost of steel track undercarriage systems and ultimately creating more profit for the equipment fleet owner.

Scenario of Equation Application

A hypothetical construction company is based out of and typically works in the central piedmont of the study area. The equipment owner has been quoting jobs in this area for many years and consistently realizes high profit margins in most of the jobs completed. The sand content in the soil in this localized area was consistently a very low 18%. Hypothetical construction manages their maintenance very well and as a result enjoyed long undercarriage life. By using the equation and entering 18% sand content into the equation, the hours per percent worn can easily be calculated.

Hours per 1% Bushing Wear = 58.79- (0.4584*18) = 50.54 Hours per Percent Worn

Knowing this hourly wear rate, we can now estimate the life of a steel track undercarriage for his machines to be:

2 * (50.54 Hours per Percent Bushing Wear*100%) = 10,108 Hour Undercarriage Life

The 2 multiplier is used for the level one and level two maintenance intervals wears out two bushing surfaces if managed properly. The equipment manager for hypothetical construction was accustomed to this hourly rate of 50.54 hours per percent worn and the job estimator used this known cost in calculating the job bids. For a typical model 6 machine the undercarriage level one maintenance and level 2 maintenance replacement cost are typically $40,000.00 US dollars. Now the cost per hour for the undercarriage system can be calculated:

($40,000) / 10,108 Hours = $3.95 Dollars per Hour

Hypothetical construction was asked to bid on a job on the eastern edge of the study territory where the sand content was 98%. The equipment manager knows that the hours per percent bushing wear needed to be recalculated for the sand content is different and is stated in the equation:

Hours per 1% Bushing Wear = 58.79- (0.4584*98) = 13.86 Hours

Instead of 50.54 hours per percent bushing wear, the same machine working in sand rich soils only achieves 13.86 hours per percent bushing wear. This is a 364% difference and has major impact on the equipment operating cost. The same model 6 machine will now only achieve an undercarriage life of 2,772.

2 * (13.86 Hours per Percent Bushing Wear*100%) = 2,772 Hour Undercarriage Life

Factoring in the same undercarriage estimated cost of $40,000.00 US dollars the following cost per hour can be calculated:

($40,000) / 2772 Hours = $14.43 Dollars per Hour

If this awarded job located in a sandy soil area would have required 16,500 model 6 dozer hours of operation to accomplish. If this cost was not factored into the job bid the impact to profitability would have been:

16,500 hours * ($14.43 – $3.95) = $172,920.00

Understanding the sand content in the soil and accounting for it in this job bidding example could have either added $172,920.00 dollars to the bottom line or would be realized as a loss if the increased wear rate of the undercarriage was not accounted for. In addition to the dollar savings, moving from the clay soil jobsites to sandy soil jobs accelerates the level one maintenance intervals. If this difference in maintenance interval hours is not accounted for the bushing would be ran past service interval prohibiting the service to be completed. The level one service interval hour meter reading in the clay soil would be at 5,104 hours while the sand-based soil service interval would be at only 1,386. The regression equation can help predict the level one maintenance interval to ensure the service interval is not missed. Understanding and accounting for the sand content in the soil is very important for profitability and sustainability of construction companies.

Research Question Answers

1. Do steel track undercarriage systems hours per percent wear vary depending on the percent of sand present in the soil in which the machine is working? Yes, it does. In this study area, it is found that steel track wear is correlated to the hours per percent of bushing wear as described by the equation: Hours of Machine Operation / 1 % Bushing Wear = 58.79 - 0.4584 Sand. 50.11% of the variation witnessed in the study was due to the sand content of the soil in which the machine was working.
2. Do steel track undercarriage systems hours per percent wear vary depending on the annual precipitation totals in the location on which the machine is working? No. In this study area, it was found that there is no statistical correlation between steel track wear and annual precipitation however further field research should be performed here with a different measurement.
3. Do steel track undercarriage systems hours per percent wear vary depending on the elevation above sea level at the location on which the machine is working? No, at least not in this study area. There is insignificant correlation to elevation above sea level where the machine was working and the wear rate of the track bushing in this study.
4. Do steel track undercarriage systems hours per percent wear vary depending on the model number of the machine being investigated? No. The track wear rate between the models was not statistically different in this study area.

5. Do steel track undercarriage systems hours per percent wear vary depending on the weight of the machine being investigated? No. The weight of the machine did not correlate to significantly increased track wear in this study area.
6. Do steel track undercarriage systems hours per percent wear vary depending on the work type code that is assigned to the customer grouping? No. The type of work performed by the equipment did not significantly impact the bushing wear rate in this study area.
7. Do steel track undercarriage systems hours per percent wear vary depending on the yearly average ambient temperature at the location the machine is working? Not in this study. There was no statistical correlation between the differences in temperature in the study area and the track system wear rate in this study area.

Opportunities for Further Research

Only 50.11% of the track wear rate variation is attributable to the sand content in the soil. Further research should be considered to discover the sources for the remaining 49.89% of variability impacting undercarriage bushing wear rate. There are a few input variables that could be additional significant factors to consider.

Equipment operator experience level or training are similar in nature and could both be good possibilities for further investigation. Do trained operators with experience understand efficient machine operating practices and take great care to follow all daily maintenance practices? Measuring years of operator experience and formal training taken could be a very worthwhile exercise to further investigate and quantify this impact to track bushing wear rate.

Equipment operator negative habitual actions could be another area for further investigation. Actions such as consistently turning the machine in one direction more than another, unnecessary sloping work and excessive operation in reverse drive could all be possibilities to investigate (Caterpillar, 2018). If an operator continually operates equipment in these manners could these actions accelerate wear rate and to what extent? These negative habits could be mitigated if the operator is trained properly to ensure they know the negative impacts of these actions so this may also be tied back to operator training and experience which is already mentioned above.

Track tension maintenance could be an input factor that may offer some significance to the wear rate variability. Improper track tension is spoken in general terms as an attributing factor for track wear (Deere, 2019). Track tension is a daily maintenance check that measures the slack in the track group as it drapes across the carrier roller and idler assembly. Tracks that are too tight can generate triple the pressures where the bushing contacts the sprocket assembly (Customer Track, 2013). This increased track tension can be the result of dirt or other debris packing in the bushing cavity or simply the track adjuster being pumped out too far. Keeping the tracks clean and properly adjusted reduces the impact of this additional input factor but the correlation to hours per percent bushing wear is not understood. Track tension is an easily measured input factor that could be another viable next step in research in this study territory.

Conclusion

This research investigated several input factors for possible impact to steel track bushing wear rate in a population of dozers in the eastern half of North Carolina. The input factors considered were temperature, precipitation, machine model, machine weight, elevation and sand content in the soil. It was found that only sand content had significant impact on the wear rate of the track bushing which is the critical component to monitor in track system maintenance. This impact was quantified in a regression equation that can be used to better predict undercarriage wear in soils with different sand percentages. Bidding jobs in different soil types can now be better estimated to help account for the differences in wear rate and cost per hours of operations. This indeed helps construction companies be more profitable and assisting them better time the undercarriage maintenance intervals.

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APPENDIX: MEASUREMENT SYSTEM ANALYSIS

A measurement system analysis was performed to assess the accuracy of the undercarriage measurement system. Ten different track bushings of various sizes from different machine models were assembled and each assigned a number with a paint marker for tractability. The bushing sizes ranged from the smallest model 3 bushing to the largest model 9 bushing found in this research. These 10 bushings were to be measured by three different track inspectors using the same ultrasonic instrument specifically designed to measure these components. Each operator randomly measures each of the 10 bushings for three different replicates. This results in all 10 of the bushings being measured three times by three different operators producing 90 measurements. Figure 30 shows the ultrasonic tool being used by the operator and the different sized bushings being measured.

Figure 30. Gage R&R Measurement Process

Table 15 is the output of the Gage R&R analysis. The measurement system shows to be very robust. The total Gage R&R is only 0.76% meaning of which 0.63% is the measurement repeatability measurement variation. Only 0.13% reflects reproducibility or between operator measurement variation. The remaining 99.24% of the variation is due to the part to part variation. The total Gage R&R is well below the 10% threshold for acceptability of a measurement system.

Table 15

Gage R&R Two Way Anova Table with Interactions

Source	DF	SS	MS	F-Value	P-Value
Parts	9	68.661	7.62900	3491.24	0.000
Operators	2	0.0762	0.03811	17.44	0.000
Parts*Operators	18	0.0393	0.00219	0.35	0.993
Repeatability	60	0.3800	0.00633	0.10	
Total	89	69.157			

Gage R&R Results

Source	Variation Components	% Contribution of Variation Components
Total Gage R&R	0.006467	0.76
Repeatability	0.005376	0.63
Reproducibility	0.001091	0.13
Operators	0.001091	0.13
Part-To-Part	0.847069	99,24
Total Variation	0.853537	100.00

The graphical output of Gage R&R study is show in Figure 31. In the top left graph of this six pack is a bar chart of the components of variation. As expected, most of the variation is due to the differences between the parts. The repeatability and reproducibility bars are much smaller and when added together, comprises the Gage R&R total. In the top right graph showing the measure by parts, there is very little variation shown. Part one does have one measurement that was noticeably high along with some other small variations in other parts. The box plot “measure by operator” graph shows very little variation. Overall the MSA is very robust and with a Gage R&R value of less than 1% is most acceptable.

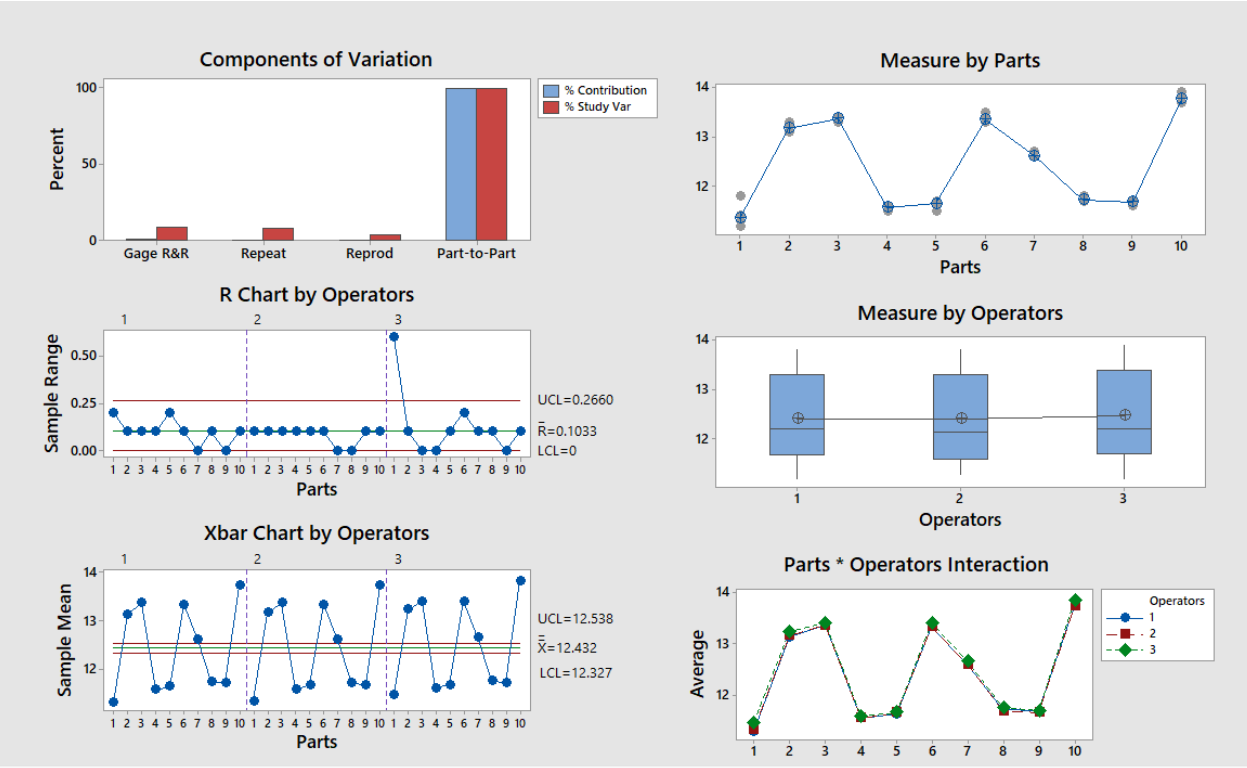

Figure 31. Gage R&R Graphical Results.