A METHOD FOR MONITORING OPERATING EQUIPMENT EFFECTIVENESS WITH THE INTERNET OF THINGS AND BIG DATA

A Thesis

presented to

the Faculty of California Polytechnic State University,

San Luis Obispo

In Partial Fulfillment

of the Requirements for the Degree

Master of Science in Agribusiness

by

Carl D. Hays III

June 2021

COMMITTEE MEMBERSHIP

TITLE:	A Method for Monitoring Operating Equipment Effectiveness with the Internet of Things and Big Data
AUTHOR:	Carl Dufford Hays III
DATE SUBMITTED:	June 2021
COMMITTEE CHAIR:	Tali Free, Ph.D. Professor of Industrial and Manufacturing Engineering
COMMITTEE MEMBER:	Jim Prince, Ph.D. Associate Dean Research and Graduate Programs
COMMITTEE MEMBER:	Sean P. Hurley, Ph.D. Professor Department of Agribusiness

ABSTRACT

A Method for Monitoring Operating Equipment Effectiveness with the Internet of Things and Big Data

Carl D Hays III

The purpose of this paper was to use the Overall Equipment Effectiveness productivity formula in plant manufacturing and convert it to measure productivity for forklifts. Productivity for a forklift was defined as being available and picking up and moving containers at port locations in Seattle and Alaska. This research uses performance measures in plant manufacturing and applies them to mobile equipment in order to establish the most effective means of analyzing reliability and productivity. Using the Internet of Things to collect data on fifteen forklift trucks in three different locations, this data was then analyzed over a six-month period to rank the forklifts' productivity from 1 – 15 using the Operating Equipment Effectiveness formula (OPEE). This ranking was compared to the industry standard for utilization to demonstrate how this approach would yield a better performance analysis and provide a more accurate tool for operations managers to manage their fleets of equipment than current methods. This analysis was shared with a fleet operations manager, and his feedback indicated there would be considerable value to analyzing his operations using this process. The results of this research identified key areas for improvement in equipment reliability and the need for additional operator training on the proper use of machines and provided insights into equipment operations in remote locations to managers who had not visited or evaluated those locations on-site.

Keywords: IoT, Big Data, OEE, Productivity, Fleet Operations, Fleet Management, Industry 4.0

ACKNOWLEDGMENTS

First and foremost, I would like to thank Dr. Tali Freed for reviving this opportunity to finish my master's degree by taking on this project. I wish to thank application engineers Nick Kennelly and James Howland of Motion & Flow Control Products for their help in data acquisition, Steven Hardin for creating this IoT project at Alaska Marine Lines and for the permission to use the data collected on their fleet of Svetrucks, William Hill and Adam Livesay for the use of Elevat-IoT platform to collect and analyze the data, and my wife Kelly Hays, sons Duffy and Hauk Hays and bonus daughter Sierra Norris for putting up with me during the last two years of working on this project.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: INTRODUCTION

1.1 Statement of Problem

In mobile equipment, utilization is typically calculated using the standard inputs of Engine Hours and Idle Hours (when available). Engine hours is a universal standard, because it is used on every manufactured engine. Engine hours are communicated through an open-source standard, J1939, so that companies other than the engine manufacturer will have access to the current value. Engine hours are typically displayed either mechanically through a dial, or digitally through a display on the machine. Regular service and maintenance intervals are associated with engine hours. Reliability analysis on useful life is quantified using engine hours.

Engines typically operate in two states, an idle state, and under load state. Idle state status indicates that an engine is turned on and ready for load. Load state indicates that an engine is performing work. In an automobile, the idle state is most commonly associated with being “at rest,” for example when a car is at a red stop light. Load, on the other hand, would be when a car is traveling at a speed greater than zero miles per hour. With these two variables established, a utilization ratio may be calculated indicating the percentage of time an engine is at rest versus performing work.

These percentages are evaluated against a standard of performance often referred to as a key performance indicator, allowing managers to evaluate equipment performance. Key performance indicators are established using a variety of methodologies but are meant to provide a “bright line” for when equipment is performing above or below standard. While utilization is not a new concept within mobile equipment, establishing a generally accepted indicator to measure performance associated with utilization could be very valuable to organizations.

Many companies are already providing utilization calculations based on engine hours and idle time. However, there are a number of industries and machines that do not rely on idle time to determine when a machine is performing work. By adding a few hardware items and connecting to the machines CAN system, we were able to establish custom data points to generate the utilization calculation we are looking for.

Large machinery in ports and agriculture applications waste energy and fuel. Industrial Internet of Things, smart technology, and big data are methods that use sensors and data collection to identify inefficiencies from their sources. Elevat is an IoT platform that identifies such inefficiencies using a standard array of sensors that provide an engine and additional sensors that provide performance data. IoT applications have focused primarily on engineering and service applications collecting data that can assist with troubleshooting issues or provide a notification when there is an issue. While engineering and service has benefitted from the widespread adoption of IoT and telematics, business owners were seeking data that focused on different aspects of the application such as productivity.

To determine whether a machine was productive required data when it was working or idle. Until the enhancement of sensors that could create a trigger for the work event and programmable software to manage and measure these sensors. There is considerable economic value to companies that have access to and the ability to measure machine performance. Without this data, most companies would rely on financials to determine how the company was performing without any specific variable to focus on. This lack of data prevented companies from identifying practices that lead to better or worse results. In order to identify best practices, we create large data sets with IoT, generally referred to as “big data”, to identify and track equipment work and use practices such as engine hours, on and off, work and idle time, as well as fuel usage.

1.2 List of Terms

Big Data- storage containers on the internet hosting large amounts of data typically used for historical purposes and analysis.

Edge Technology – hardware used to connect machines in their operational environments (the edge) to the internet of things via wifi or cellular networks.

Engine Hours – the amount of accumulated time on an engine when the key is turned on and off over its useful life.

Data Start Date - this is the date the truck was first transmitting data under an approved for production software release in the time period specified.

Data Stop Date - this is the date the truck stopped reporting data to elevat in the time period specified.

Digital Migration - companies and organizations adopting software and cloud technology to connect things and incorporating digital technology into their operations such as the internet of things. See Industry 4.0.

Idle Fuel used – the total amount of fuel consumed while under 900 revolutions per minute.

Idle Time - total accumulated time while the engine RPM less than 900 revolutions per minute.

IoT- Internet of Things – using cloud applications to connect hardware, machines and devices (things) to the internet typically accessed through applications or websites.

Industry 4.0 – the application of technology to digitally transform how industrial companies operate. These technologies include the industrial IoT, automation and robotics, simulation, additive, manufacturing, and analytics.” (PTC, 2021)

KPI - Key performance indicators are widely accepted as criteria for measuring progress and results.

KPI Lagging- is a result measurement to determine the effect of what was done over a specific period of time.

KPI Leading - is a progress measurement and when taken over time provides a trend as to whether the likelihood of meeting the lagging KPI will be achieved in addition to the gap between the two.

Pick Time – total accumulated time while truck is moving a container.

Non-pick distance – the total distance traveled while empty

Non-Pick Time – total accumulated time while truck is moving while empty.

OEE – Overall Equipment Effectiveness a formula used in plant manufacturing to determine how close to perfect operation is achieved over a period of time using the formula Time * Speed * Quality and expressed as a percentage.

OPEE – Operating Equipment Effectiveness a formula based on OEE to determine equipment productivity using the formula Availability * Work Time * Productive Time and expressed as a percentage.

Pick Distance – this is based on the distanced traveled while carrying a container

PM – Productive Maintenance – “time-based maintenance featuring periodic servicing and overhaul.” (Nakajima, 1984)

SAE – J1939 – “The SAE J1939 standards in this collection define high-speed CAN (ISO 11898-1) communication network that supports real-time, close loop control units throughout the vehicle.” (SAE, 2021)

Svetruck 1.0 - the first version of software which defines and connects the following data

Svetruck 2.0 - the most current version of software which defines and connects the following data sources to elevat.

TPM- Total Productive Maintenance – “is productive maintenance carried out by all employees through small group activities.” (Nakajima, 1984)

Utilization – a percentage calculation from 0 – 100 taking the amount of non-idle time and dividing it by total engine hours.

Work Fuel used – the total amount of fuel consumed over 900 RPM

Work Time – the total accumulated time while engine RPM is greater than 900 RPM.

1.3 Purpose of Study

Overall Equipment Effectiveness (OEE) has been applied in plant manufacturing to measure and manage performance since the 1960's and has been deeply researched and validated in many industries and use case applications. The OEE model calculates the percentage of time that a piece of manufacturing equipment is truly productive. The primary concern of this thesis is both whether and how the OEE model can be applied outside of plant manufacturing – especially for mobile equipment, or machines with wheels and tracks.

Recent advances within the last 10 years in both software and sensors have made possible new methods for collecting data from mobile equipment. This thesis identifies a three-step method that leverages the OEE model and uses capabilities of the Internet of Things (IoT) and big data collection in mobile equipment. Companies are becoming increasingly interested in such a framework, because it helps them understand how their mobile equipment is being utilized. From this information, they can optimize the performance of their equipment and make better economic decisions about the use and operations of the equipment. This research project was focused on defining equipment effectiveness in such settings, and then acquiring and analyzing IoT data to determine the overall productivity of mobile equipment. The specific type of equipment tracked was Svetrucks that carry shipping containers shown in Figure 1.

Figure 1: Svetruck Picking a Shipping Container

Source:http://www.lynden.com/aml/tools/gallery/SVE_truckw53-10k.jpg

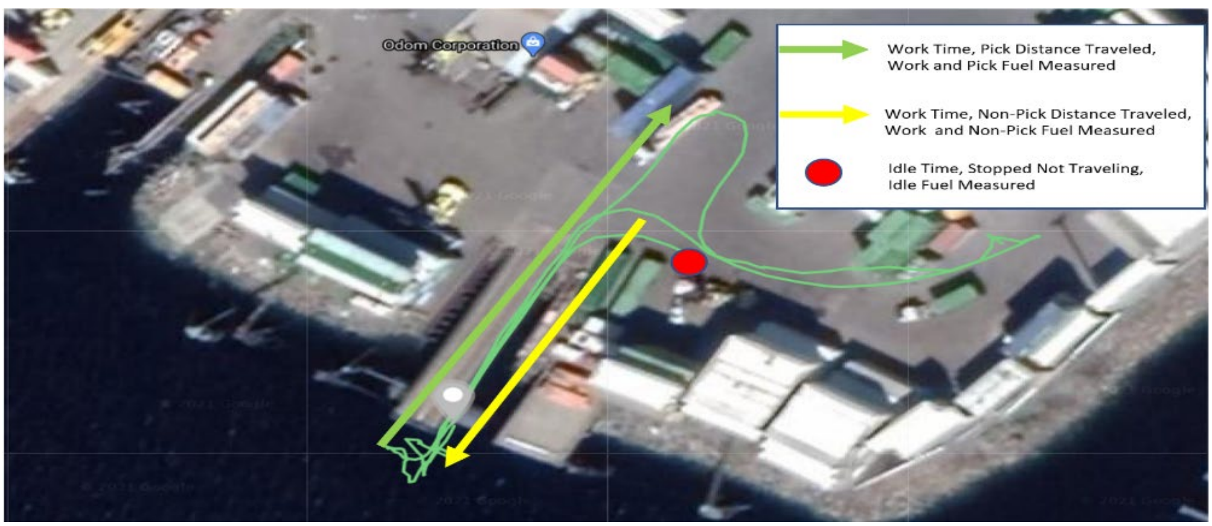

Figure 2: Map Layout and Visual Representation of Data

Source: www.portal.elevat-iot.com

Figure 2 represents the data collected from these trucks. The green arrow indicates when the truck has "picked" a container and moved it from the docked barge and stacked it at port. The yellow arrow indicates when the truck is returning to the barge to pick another container. The red dot indicates when the truck is parked and idling. From this data collection effort, it was determined that several key considerations must be taken into account to design an effective OEE framework for mobile equipment. First, a model must be designed around the nature of the equipment so that we can differentiate what we mean by “productive time” and “non-productive time.” Second, we used a trigger sensor with a digital clock to establish productive time. Third, the data is collected and available in a analyzable format and in this case we used Elevat-IoT Big Data platform. From there the data was cleaned and organized and then evaluated in a statistical model to establish Operating Equipment Effectiveness (OPEE) = Work Time x Productive Time x Availability. We used Elevat-IoT, a big data mobile equipment cloud platform, to accomplish this objective.

By applying our three-step method and generating an OPEE score, companies with mobile equipment can better evaluate overall utilization and establish performance benchmarks to improve fleet performance over time. This model could yield performance insights and provide managers with the ability to improve operations, reduce operating expenses, and improve productivity. In modern applications, these data points use SAE standard J1939 signals for work time based on engine idling or not idling (SAE, 2021) but they do not yield meaningful performance data for these trucks. We added customized data points for “pick-time” and “non pick-time” that are more reflective of the equipment purpose and defined the Operating Equipment Effectiveness formula to produce the best indicator of overall performance.

Chapter 2: LITERATURE REVIEW

The focus of this literature review is to cover the history of OEE and at the same time relate it to IoT mobile equipment applications. This equipment was essentially treated as mobile factories. Rather than reinvent the wheel and establish a completely different practice for measuring performance, it made more sense to adopt and modify a methodology that had been established, proven, and documented thoroughly. Because the majority of the research papers covering OEE were on use cases in plant manufacturing applications, the heavy lift was in translating this work to the world of IoT in order to establish the foundation, methodology, data collection, and interpretation for this paper. Primarily, the literature review covers a few key concepts and elements underpinning this thesis approach: IoT, Big Data, and OEE, to both explain and explore the existing research relevant to this topic. IoT is still an emerging field and has complex requirements to be successful from the machine application, data transmission and collection, to analyzing the data in insightful ways.

In sports like baseball, performance statistics are an ordinary and deeply integrated aspect of the game. When evaluating individual players' offensive performance, the batting average has existed for more than 100 years. The batting average does not necessarily answer performance related questions such as why one player performs better than another or even how to increase performance; it does provide a key performance indicator for managers to initiate the inquiry and work to develop players to increase this statistic, thereby benefiting the team as a whole.

As baseball, and the application of statistical analysis matured, new insights into what actions provided the best indicator of overall performance determined that on base percentage, rather than batting average, was the best metric for predicting success. On base percentage is also a ratio determined by the number of plate appearances versus the number of times a player was able to get on base. In order to score more runs, a player must first get on base whether they do that by getting a base hit (which shows up in a higher batting average) or by being walked with four total balls (non-strikes) being thrown. In the latter case, a walk would actually lower the batting average. A manager paying attention to only the batting average would potentially miss out on players who were really skilled at getting on base and pay a premium for players with the highest batting average rather than selecting players based on a stronger indicator of what helps score more points and win more games e.g., on base percentage.

What exists in the mobile equipment world is the equivalent of a machine's batting average. What does not exist is something akin to an on-base percentage - or the best measure of overall productivity. On base percentage equates closely to overall productivity because the goal of the offense is to score runs. Scoring runs requires players to advance to base. With respect to mobile equipment, each machine is designed to perform a function. The more that the machine does the required function, the more productive it is. This metric would better allow fleet managers to determine which assets, operators, and equipment were performing at the highest and lowest level. It would have both tangible and intangible benefits. The tangible benefits would be evidence of which machines were potentially more reliable, and which operators were the most skilled. It would provide a basis to make operational changes and to explore and adopt best practices. Additionally, equipment that is highly efficient will also be better for the environment for because it does not waste fuel on idle time. By identifying top performers better training programs can be adopted for operators setting them up for success at their positions and even providing opportunities for performance rewards and benefits. Last but not least, it impacts the company's bottom line making it more profitable, competitive, and better able to sustain operations over time. In some industries which operate on razor thin margins it could mean the difference between solvency or insolvency.

With the maturity of high-speed and low-cost cellular data plans, a new era of connecting to mobile machines and extracting data in remote locations has become possible. The baseball batting average is based on player data, and without it the batting average cannot be achieved. The same is true with mobile equipment in that we need equipment data in order to understand its performance with this thesis was both whether and how this performance approach could be applied to equipment applications outside of plant manufacturing, such as mobile equipment or machines using wheels and tracks.

2.1 Background

In the manufacturing industry, there is a long history of measuring performance and loss based on overall equipment utilization. This methodology has been well researched and widely used. The major variables used in Overall Equipment Effectiveness have been established in the past 20+ years focus on engine idle vs. non idle time. For example, in the freight industry, tracking engine hours and engine idle time has a strong correlation with performing work, because the trucks are taking cargo from one point to another. If the engine is on and in a non-idle state, it indicates the truck is traveling and moving cargo from point A to B, which is its function.

Figure 3: Jarraff Mini

Source: https://www.jarraff.com/products/mini-jarraff-tree-trimmer/

Additionally, tracking engine idle time to identify potentially wasted fuel consumption is another typical IoT fleet application. In industries where work is being performed by other mechanisms than moving cargo, the ability to capture performance data has been much more difficult. For example, forestry equipment such as the Jarraff Mini in Figure 3 performs work when the saw blade is cutting branches near power lines.

In Figure 4, the Barko log stacker performs work when it is picking and stacking

Figure 4: Barko Log Stacker

Source: https://www.barko.com/products/rtc-loader-495b

logs. These two functions, cutting trees and stacking logs, have very little to do with whether their engine is idling or not. In order to determine asset utilization for this equipment requires another method to measure data and performance.

In the last 70 years, organizations have been working towards measuring productivity, reliability, and working to improve the accuracy and utility of these measurements in both manufacturing and equipment usage. While this approach started in plant manufacturing, the concepts, measurements and practices are transferable to other industries and applications. With the advances made in sensor and IoT technology, we are able to measure equipment performance and properly apply the main variables in

Overall Equipment Effectiveness to create a new performance measurement with OPEE. There is a strong consensus in academic papers focused on OEE measuring performance and identifying 6 big losses in productivity, which are:

- Availability Loss – equipment failure and setup adjustments
- Performance Loss – idling and minor stops, reduced speed
- Quality Loss – process defects and reduced yield (Vorne, 2019)

The ultimate goal in both mobile and plant manufacturing is to have the most reliable machines and equipment working efficiently and effectively for the organization utilizing them. In order to get to this ideal state, it is critical to understand the evolution tying together reliability, efficiency, and effective work time. The first phase of this evolution involved preventative maintenance (PM).

2.2 Preventative and Predictive Maintenance

Preventative Maintenance was established in the 1950's with the objective to develop maintenance functions for equipment to prevent failure and preserve the life of the machine. George Smith first introduced this practice to Japan in 1958, and by 1969, Nippoldensco Company was the first company to be awarded the Distinguished Plant Prize for its achievements in TPM (Nakajima, 1988). The concept of preventative maintenance is plain and simple: by taking care of machines, failure can be prevented. Preventative maintenance strategies are still in place today and include operator's manuals with specific maintenance plans and protocols from changing fluids and filters to identifying wear-and-tear components that require replacement over time. While it was clear that having a maintenance strategy improves plant and equipment performance, what was unclear is what kind of an impact following a maintenance plan will have on the equipment and how to measure this performance. After having established itself as a world leader in maintenance practices, Japan brought their techniques back to the United States as Total Productive Maintenance.

The basic premise of TPM is to develop a maintenance culture that is trained at the lowest level to clean, repair, and maintain the equipment and the facility with the goal of creating an “immaculately” clean manufacturing environment by focusing on the 6 categories - organization, tidiness, purity, cleanliness, discipline and trying hard (Nakajima, 1989). The key to adopting a TPM strategy was having a reliable measurement for performance from which to evaluate how to improve it. OEE has demonstrated its value in monitoring and identifying factors affecting performance with real results that provide benchmarks and increase efficiency through valuable insights (Schermann, 2014).

OEE consists of metrics measuring Plant Scheduled Time, Plant Run Time, and Count of Quality Parts versus defects. This measurement begins with the ideal manufacturing state, where the plant would be scheduled 365 days of the year to run and would actually run all of those days, 24 hours each day, and during that time every part made would be to specification without defect. In the absence of a metric like this, the source for evaluating plant performance relied heavily on total production of good parts in addition to General Accounting indicators like revenue and cost. Prior to the implementation of OEE, it would have been difficult for a manufacturing company to provide evidence of how they were doing outside of total production and financial indicators. By factoring in the 6 categories of losses, plant managers were able to identify the sources and factors reducing the overall score and a lagging Key Performance Indicator.

In order to establish a leading and lagging KPI, it is paramount to have a system or process in place, with inputs and outputs for both, that can be tracked and recorded. This data may then be aggregated on a time basis to produce both lagging and leading KPI. With the data stream in place, the last part of the puzzle is to establish a benchmark, objective, or standard to evaluate the KPI against. Without the benchmark, it would be really difficult to determine where production was at any point of time. The elegance of OEE is in its ability to establish the objective standards in addition to what needs to be measured to get there. Because this metric was developed for plant operations where there were typically assembly lines operating on shifts and producing goods, we need to transition this to mobile factories which was referred to as "run time.". Mobile equipment does not typically have a scheduled "run time" which defines availability or whether the plant was able to make parts during the scheduled period of time.

OEE is based on Availability (0 – 100%), Performance (0-100%), and Quality (0-100%) and its formula is: OEE = A*P*Q. In simple terms, Availability is whether the machine is operating or not, Performance is how fast the machine is running, and Quality is how many products are final and meeting all specs" (Latest Quality, 2018). Simplified, this formula is: Time * Speed * Quality. To convert this to the mobile equipment formula OPEE, we had to determine how best to calculate Time. In this formula, Time was calculated from a count of the total Operating Days in a calendar year e.g. between 0 and 365. For Speed the variable "Work Time" was used or when the engine is not idling, and for Quality the variable "pick time," or when the machine is actually productive during the work time. In general, OEE ratings provides a very useful benchmark to determine how to improve productivity. Other research has identified that the average OEE was around 51.5 percent with significant environmental and ecological impacts due to loss in both availability and operational efficiency (Zammori, 2011).

Establishing benchmark data that provides KPI over time is critical to improving equipment operations. Setting up OEE measurements for success requires good data. Getting good data is a process of calibration and checking whether the measurements can be verified by other analog sensors on the machine. Oftentimes, many versions of software applications are deployed with small corrections to achieve the desired results. It is critically important that the data being used to analyze equipment performance is accurate (Murray,2016). In addition to continuous improvement with software versions, other research identified data collection as an issue (Lugmayr, 2017). The majority of the research covered by Pembert, concluded that OEE was relevant to assessing productivity in operations and a useful tool for industry 4.0 and the digital migration (Peimbert, 2012). OEE has proven to be an effective approach to understanding and improving performance (Prasher, 2020). Likewise, from the research conducted by Muchiri on Overall Equipment Effectiveness, the conclusion was OEE is a valuable tool for identifying losses in productivity and optimizing productivity (Muchiri, 2008).

2.3 Internet of Things and Big Data

IoT is an established concept and has been used through devices installed on equipment for more than 20 years. The challenges to widespread adoption in the mobile equipment industry has been data collection and effective transmission, in addition to specific kinds of technologies in each application to make the IoT implementation successful (Pomorski, 1997) which is still an issue in IoT applications today. Advances at the edge with devices and sensors have played a critical role in defining the data that needs to be collected on mobile applications, where engine idle time will not tell the full story about how productive a machine truly is. The entire system of things, how they connect and communicate with each other and their relationship to an IoT database, requires very specific solutions on each application to recognize the value of the data and information acquired (Hwang, 2016) such as connecting to and monitoring the Svetrucks used in this thesis. These applications can be complex and involved with many opportunities for improvement (Šajdlerová, 2020). To be successful, IoT applications require the integration of a range of information and communication technologies in the form of specific hardware, software, and scalability (Ylipaa, 2016). The use of Elevat-IoT application and machine software programmed by an application engineer has been a critical component to success of this IoT deployment on the Svetrucks.

Software such as IQAN software used in this thesis application allows application engineers to program the machines to produce the kind of data Muchiri referred to which was used to analyze performance. With the data acquisition and transmission handled by the hardware and software on each machine, the next step is incorporating Big Data, through the Elevat-IoT cloud platform, provided the data storage and exporting tools which also organizes and time-stamps the data. This data set can be analyzed and valuable insights or “smart data" can be obtained, which in turn leads to both productivity and financial gains (Almeanazel, 2010). In addition to productivity gains, research demonstrated a higher likelihood of innovation leading to new products and services (Ng Corrales, 2020).

The IoT platform Elevat-IoT provides access to the mobile equipment through edge devices, which transmit data through the cellular network to a Microsoft Azure database, which has services layered on top of it to generate the Excel reports used in this thesis. The “elevat” database architecture incorporates big data rather than discrete data. It is organized in a way to allow for larger dataset analysis. Big Data, in short, provides access to a larger number of forklifts over extended time periods rather than analyzing just one machine, in one location. Having access to this larger dataset was critical to the success of this project. These insights allow companies to resolve questions like “What is different between the machines?” “Why are there differences in performance?” and “How can we improve overall productivity”? The entire IoT project from data collection to analytics required edge technology on the device side, successful transmission collection, and the ability to export large data sets in a format that can be cleaned and organized to establish operating productivity. Furthermore, with sufficient quantity of machines, Key Performance Indicators and benchmarks may be established to determine how populations of machines are performing compared to each other in addition to calculating the average performance of each machine over a 6-month period.

Chapter 3: METHODOLOGY

The methodology produced in this approach required a seven step process:

1) Acquire the data from the Svetrucks- This involved using sensors and hardware installed on each truck.
2) Transmit data from the trucks to the Elevat-Iot Platform. This required the use of the AT&T cellular network.
3) Translate the variables used to analyze the Overall Equipment Effectiveness in manufacturing plants such as *run time* versus *work time* in mobile equipment into an Operating Equipment Efficiency formula.
4) Collect the data using Elevat-IoT to provide the input values required for applying the Operating Equipment Efficiency formula.
5) Export the data to Excel for analysis.
6) Transform the data to the 3 OPEE variables and a rollup into an overall score.
7) Rank each truck based on its score as a key performance indicator.

The basic methodology for this thesis was to define the data needed, acquire it on the Svetrucks using hardware and software installed on each truck, transmit via an AT&T cellular network to the Elevat- IoT cloud platform where it could be organized and exported for analysis.

3.1 Elevat-IoT Platform Architecture

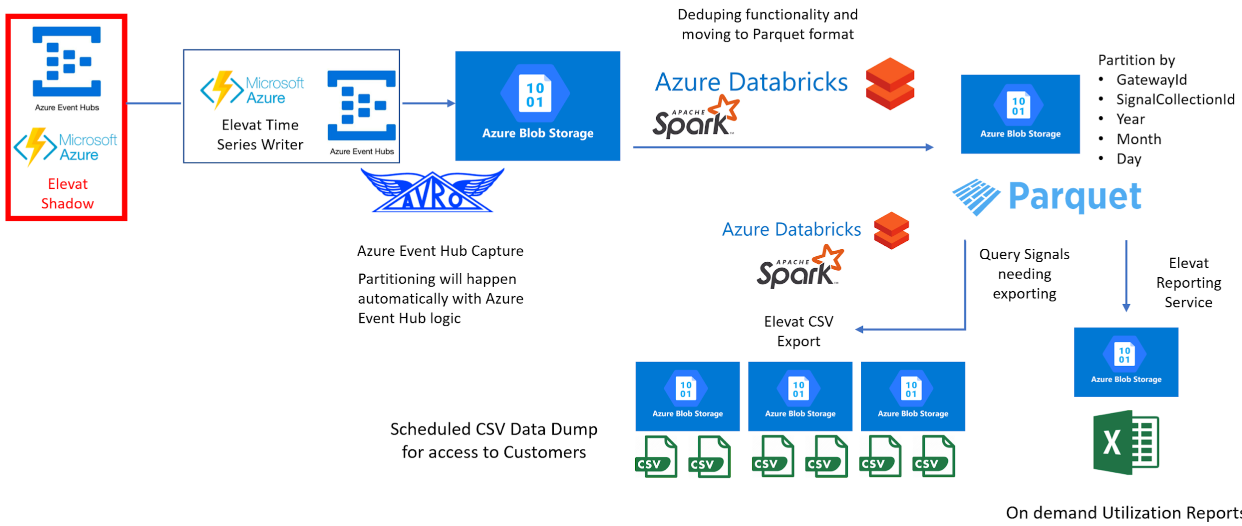

Figure 5: Elevat Cold Storage (Big Data)

After the data is collected on the truck, it starts its path on Elevat-IoT as show in Figure 5 in the red box, the elevat shadow. It is then organized by a unique asset identifier (gateway id) that associates the machine and maps to the signals being collected in a day, month, year format. The elevat architecture provides a path for the data to be exported to a csv report that was used in organizing and analyzing the data.

3.2 Solution Design

Using the Elevat-IoT platform, I was able to use On Demand Utilization reports to extract data on 14 machines in 5 locations over a 6-month period of time from September 14th 2020 to March 5th 2021 and export them into an Excel file for analysis. Each truck is assigned a number in a range of 38 to 51. The locations within this data set are at three different ports.:

Figure 6: Asset Locations.

Source: portal.elevat-iot.com

In Figure 6, the asset port locations are shown for each of the Svetrucks used in this data set. Each port has a different layout, which can affect the data collected.

Figure 7: Port Layout Seattle

Source: portal.elevat-iot.com

Figure 7 is a digital representation of a truck moving from port to a barge to unload containers as an example of a port layout. This was captured on Elevat-IoT using GPS path tracking of the truck.

3.3 Notations and Formulas

i = Equipment index (i=33,34,35,36,37,38,39,41,45,46,47,49,50,51)

Di = Experiment Period in days for Equipment i = Number of days equipment i was available for work.

Hi = Hours for equipment i during the experiment period = Number of hours equipment i was available for work.

Wi = Total work time, where engine RPM is greater than 900, of equipment i during period D

Pi = Total picking time of equipment i carrying load, greater than 600 psi, during period D

Ti = Total travel time of equipment i without load, less than 600 psi, during period D

Ri = Total rest time (idle-engine), where engine RPM is less than 900, of equipment i during period D

Ei = Engine hours during period D

Ei = Pi + Ti +Ri = Wi + Ri

3.4 Asset Overview

Table 1: Asset Matrix Data Date Start and Stop with Software Version

STATE	CITY	TRUCK	DATA START DATE	DATA STOP DATE	TOTAL DAYS	SOFTWARE VERSION
Alaska	Petersberg	33	9/14/2020	3/5/2021	172	SVETRUCK 2.0
Washington	Seattle	34	9/14/2020	3/5/2021	172	SVETRUCK 2.0
Washington	Seattle	35	9/14/2020	3/5/2021	172	SVETRUCK 2.0
Alaska	Whittier	36	9/16/2020	2/26/2021	163	SVETRUCK 1.0
Alaska	Anchorage	37	1/11/2021	2/19/2021	39	SVETRUCK 2.0
Alaska	Juneau	38	9/14/2020	3/5/2021	172	SVETRUCK 2.0
Alaska	Petersberg	39	9/14/2020	3/5/2021	172	SVETRUCK 1.0
Washington	Seattle	41	9/24/2020	3/4/2021	161	SVETRUCK 1.0
Alaska	Juneau	45	12/21/2020	3/5/2021	74	SVETRUCK 2.0
Alaska	Anchorage	46	10/6/2020	3/5/2021	150	SVETRUCK 2.0
Alaska	Anchorage	47	9/18/2020	3/5/2021	168	SVETRUCK 1.0
Alaska	Anchorage	49	9/14/2020	3/5/2021	172	SVETRUCK 2.0
Alaska	Whittier	50	9/14/2020	2/22/2021	161	SVETRUCK 2.0
Alaska	Whittier	51	9/14/2020	3/5/2021	172	SVETRUCK 1.0

Table 1 identifies where each truck is located, the date that elevat started tracking the truck data, and the software version each truck was using. The software version determines what information was collected from the truck and how it was processed. This provides a basic framework for the data analysis of each truck.

Based on these data definitions, an asset could be considered in a work time state as long as it is operating above an RPM threshold of 900 RPM. In order to determine how much time was used moving and not moving containers, we evaluate pick time versus non-pick time. This is an important distinction, because the asset moves from port to the cargo ship and back through the course of its work day unloading containers transported by the cargo ship. Some of this time will involve work that is also non-pick time, because the asset must travel from the cargo ship to drop off a container and then back to the cargo ship to get another load.

3.5 Data Overview by Asset

Table 2: Individual Truck Data Correlations

STATE	CITY	TRUCK	Time (Hours) vs Total	(Hours) vs Total Distance	Distance (Miles) vs Total Fuel	Total Distance (Miles) vs Total Pick Time (Hours)
Alaska	Petersberg	33	0.97	0.91	0.92	0.93
Washington	Seattle	34	0.97	0.90	0.91	0.93
Washington	Seattle	35	0.91	0.86	0.85	0.87
Alaska	Whittier	36	0.96	0.93	0.97	0.97
Alaska	Anchorage	37	0.91	0.92	0.97	0.97
Alaska	Juneau	38	0.91	0.94	0.94	0.95
Alaska	Petersberg	39	0.96	0.96	0.97	0.97
Washington	Seattle	41	0.96	0.94	0.97	0.97
Alaska	Juneau	45	0.95	0.95	0.95	0.96
Alaska	Anchorage	46	0.95	0.88	0.9	0.92
Alaska	Anchorage	47	0.9	0.72	0.87	0.89
Alaska	Anchorage	49	0.95	0.88	0.9	0.92
Alaska	Whittier	50	0.96	0.90	0.92	0.94
Alaska	Whittier	51	0.93	0.89	0.95	0.96
			R value correlations over time period between two data sets			

The Table 2 asset matrix identifies the R^2 values for each asset to establish the data integrity by asset. Each truck is assigned an identifying number. The strength of the data correlation with other data depended on the logic used to define and extract the data. This correlation was determined through R^2 values and was critically important to demonstrating whether the logic used in the software, on each truck, has been tested to determine if it is producing a valid and reliable source of data. For example, the operating hours clock is based on a key on or key off trigger, whereas work time and non-work time are based on whether the engine is over or below its idle point. If these two data sets do not strongly correlate with each other, then a standard utilization calculation would be of little value. Furthermore, the total pick time is based on a hydraulic pressure reading of greater than 600 lbs, which has no relationship to whether the engine is idling or not. For this thesis to provide valid conclusions, the data validity must be tested through basic correlations with each data set analyzed, for example total engine hours, work time hours and idle time hours.

3.6 Basic Correlations Data Integrity

The following figures provide a regression analysis of the data as a whole. The purpose of this analysis is to determine whether the data is reliable or unreliable.

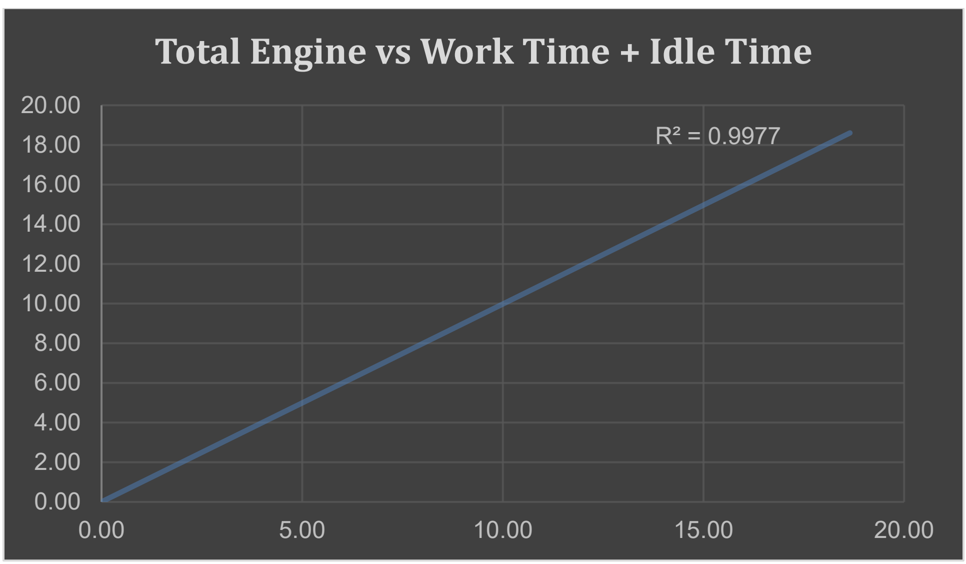

Figure 8: Total Engine Hours vs Work Time + Idle Time R^2= .99

Figure 8 validates that the majority of the work and idle time data collected on each machine was valid data. Based on the data definitions, adding the work time hours plus idle time hours ought to strongly correlate with total engine hours. It is possible that these datasets would not strongly correlate if there was an error in the logic used to define them. As previously mentioned, the software logic is not based on a closed loop where the trigger used for Total Engine hours is the same trigger that is used for work and idle time. Because they are different triggers, key on/off is the trigger for engine hours and engine RPM is the trigger for work time and idle time, it is possible that they would not strongly correlate if there was a bug or error in the logic.

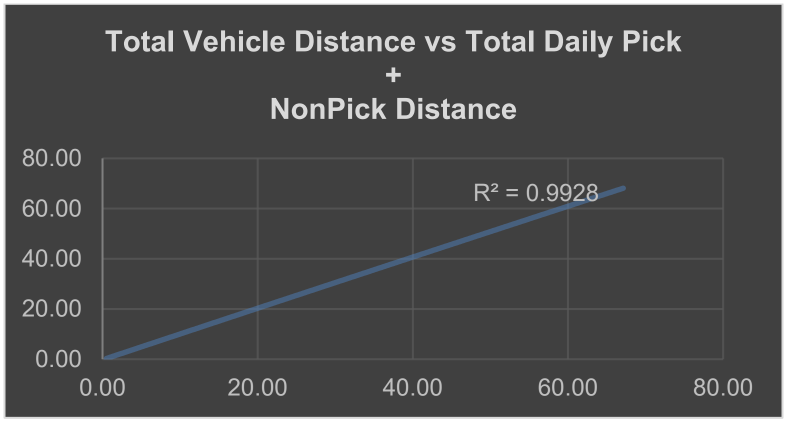

Figure 9: Total Vehicle Distance vs Total Daily Pick and Non-Pick Distance R^2 = .99

Figure 9 validates that the total vehicle distance calculation is strongly correlated with daily pick and non-pick distance. Adding pick and non-pick distance together ought to equal daily total distance. It is possible that they would not strongly correlate if there was a bug in the software or error in the logic defining this data collection.

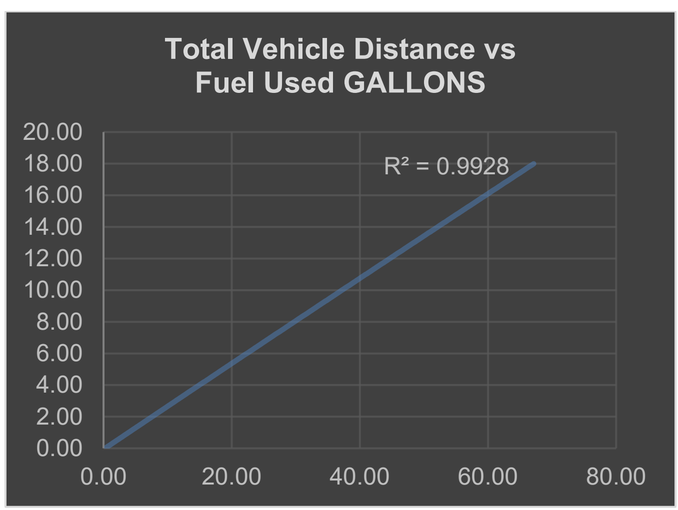

Figure 10: Total Vehicle Distance vs Fuel Used Gallons R^2=.99

Figure 10 validates that the total vehicle distance calculation is strongly correlated with total fuel used.

3.6 Advanced Correlations Data Integrity

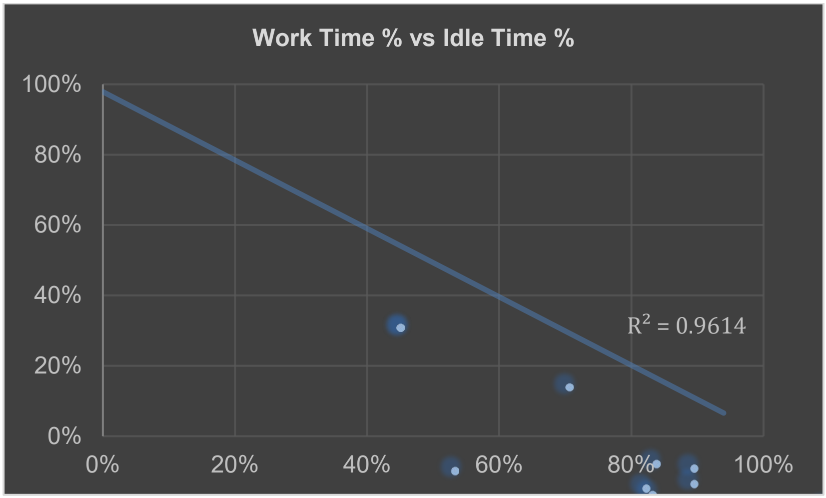

Figure 11: Work Time % versus Idle Time % R^2 = .96

Figure 11 validates that the work time percentage vs idle time percentage calculations. A strong correlation indicates that the data set distribution adds up to 100% between the two values.

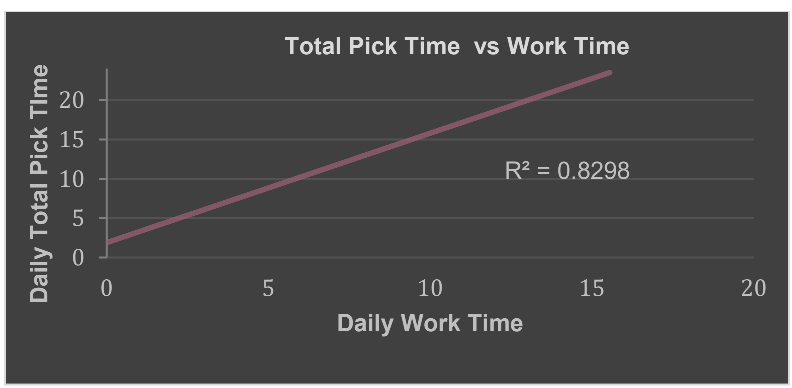

Figure 12: Work Time vs Total Pick Time R^2=.82

Figure 12 indicates how closely correlated the assets' work time was with total pick time. The remaining time would be idle time.

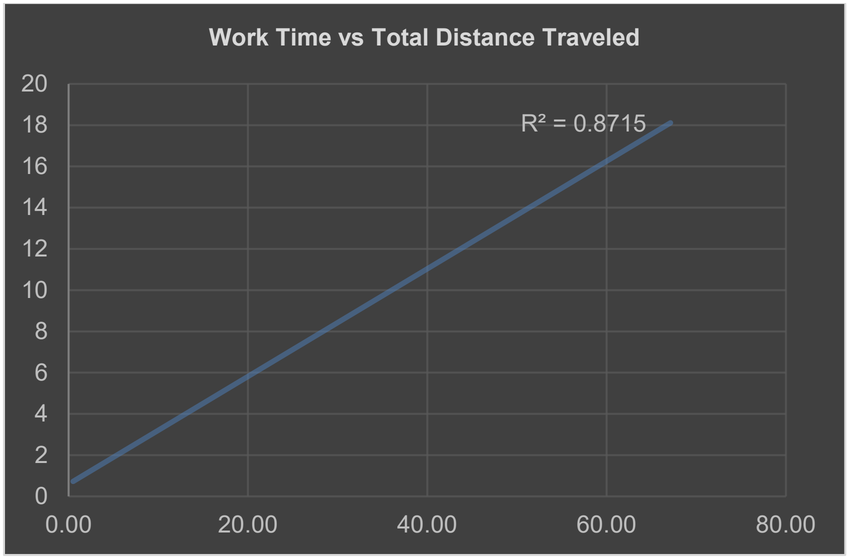

Figure 13: Work Time vs Total Distance R^2= .87

Figure 13 indicates how closely correlated the assets' work time was with total distance travelled. The remaining time would be idle time.

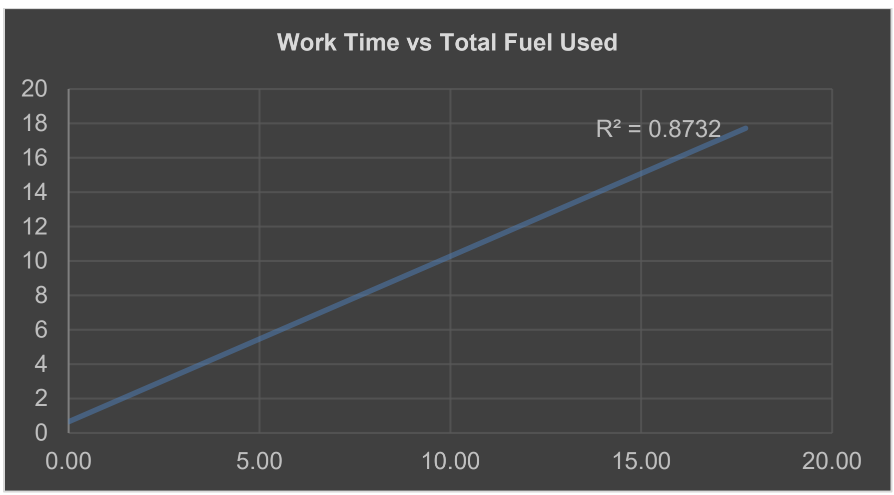

Figure 14: Work Time vs Total Fuel Used R^2= .87

Figure 14 indicates how closely correlated the assets work time was with total fuel used. The remaining fuel used would be during idle time.

Chapter 4: RESULTS AND DISCUSSION

4.1 Results

After reviewing and analyzing individual data as well as aggregates, I found a number of strong correlations. These correlations also yield benchmark formulas to determine whether or not an asset was underperforming the benchmark. By doing a basic correlation test initially, I was able to determine that the data had a high enough degree of reliability to analyze performance, yielding a graph of KPI indicators.

In order to analyze the data, I started with the standard "batting average" calculation, which is the average percentage of work time each truck did. This is shown in Table 3. In most industries, this is how performance is evaluated:

Table 3: Ranking based on Daily Average Work Time %

RANK	LOCATION	TRUCK	Average Daily Work Time %
1	Seattle	39	76%
2	Anchorage	38	72%
3	Seattle	46	70%
4	Petersberg	33	66%
5	Seattle	47	63%
6	Anchorage	50	63%
7	Petersberg	37	62%
8	Anchorage	34	60%
9	Whittier	49	58%
10	Anchorage	51	58%
11	Juneau	45	57%
12	Whittier	35	56%
13	Juneau	36	55%
14	Whittier	41	51%

Based on Table 3, or the industry equivalent of a batting average, we would conclude that the top performing trucks in table 3 are #39, 38, 46, 33 and 47.

Next, I looked at the percent each asset performed based on carrying a load greater than 600 pounds, which typically indicated moving a container from barge to port.

I kept the same ranking to determine where each asset would fall in comparison to the first ranking.

Table 4: Ranking Based on Average Pick Time %

RANK	LOCATION	TRUCK	Average Pick Time %
9	Anchorage	49	59%
4	Petersberg	33	50%
10	Whittier	51	46%
13	Whittier	36	37%
7	Anchorage	37	27%
12	Seattle	35	25%
6	Whittier	50	23%
8	Seattle	34	21%
11	Juneau	45	20%
2	Juneau	38	20%
3	Anchorage	46	16%
5	Anchorage	47	15%
1	Petersberg	39	15%
14	Seattle	41	14%

After doing this, I found movement in ranking between the assets that performed at the top on Work Time percentage in Table 3 and did not necessarily perform at the top of the Pick Time percentage in Table 4. For example, the top 5 trucks in this Table 4 are #49, 33, 51, 36 and 37. Focusing on time that was only spent moving containers creates a different ranking. The issue with using “work time” as a key performance indicator is that a truck can be productive when it is both carrying a container and not carrying a container, because it has to deliver and drop the container and then go back to the barge to get another container. When it is traveling to get a container, it is empty, so this would not show up as pick time. It would also penalize trucks that had longer distances to travel in between picks. By using both pick and work time, this allows for trucks that have shorter and longer distance between picks.

The next comparison I did was based on Work Time and Pick Time. This provided an evaluation of the assets that were both working the highest percentage of time and picking the highest percentage of time. This would indicate the assets that achieved the best of both when a machine was considered “productive,” because it was also doing its performed task of moving containers and cargo while getting credit for moving from point A to B while empty.

Table 5: Average Work Time * Ave Pick Time

RANK	LOCATION	TRUCK	Ave Work Time * Ave Pick Time
9	Anchorage	49	34%
4	Petersberg	33	33%
10	Whittier	51	26%
13	Whittier	36	20%
7	Anchorage	37	16%
2	Juneau	38	15%
6	Whittier	50	14%
12	Seattle	35	14%
8	Seattle	34	13%
1	Petersberg	39	12%
11	Juneau	45	12%
3	Anchorage	46	11%
5	Anchorage	47	10%
14	Seattle	41	7%

When comparing Table 5 with Table 3, Based on this ranking, the top five trucks remained 49, 33, 51, 36, and 37. However, the next spots did change. Truck #35 dropped in the ranks, while truck #38 rose in the ranks as did truck #39, but none of the rankings closely matched the original ranking based on work time.

Finally, the last view of the data takes into account a truck's availability. This looks at the total operating days a truck is available to work. A truck that is available more often to do the work would be more valuable than a truck that is not available to work. This could be due to breakdowns or having more trucks than needed to perform the work. The data presented includes the start and stop dates for the data set, which could be when the truck first showed up on elevat, not necessarily when it started working, and a total for the days the truck operated.

Table 6: Sorting based on Average Daily Work Time * Average Daily Pick Time * Availability with previous Ranking.

RANK	Location	TRUCK	START DATE AVAILABILITY	STOP DATE AVAILABILITY	Total Operating Days	Average Daily Work Time %	Average Daily Pick Time %	Availability Days/365	**Operating Equipment Efficiency**
9	Anchorage	49	9/14/2020	3/5/2021	127	58%	59%	35%	**11.9%**
4	Petersberg	33	9/14/2020	3/5/2021	111	66%	50%	30%	**9.9%**
10	Whittier	51	9/14/2020	3/5/2021	92	58%	46%	25%	**6.7%**
2	Juneau	38	9/14/2020	3/5/2021	124	72%	20%	34%	**4.9%**
12	Seattle	35	9/14/2020	3/5/2021	111	56%	25%	30%	**4.3%**
6	Whittier	50	9/14/2020	2/22/2021	107	63%	23%	29%	**4.2%**
1	Petersberg	39	9/14/2020	3/5/2021	127	76%	15%	35%	**4.1%**
13	Whittier	36	9/16/2020	2/26/2021	74	55%	37%	20%	**4.1%**
8	Seattle	34	9/14/2020	3/5/2021	112	60%	21%	31%	**3.9%**
3	Anchorage	46	10/6/2020	3/5/2021	84	70%	16%	23%	**2.5%**
5	Anchorage	47	9/18/2020	3/5/2021	70	63%	15%	19%	**1.9%**
11	Juneau	45	12/21/2020	3/5/2021	53	57%	20%	15%	**1.7%**
14	Seattle	41	9/24/2020	3/4/2021	33	51%	14%	9%	**0.6%**
7	Anchorage	37	1/11/2021	2/19/2021	9	62%	27%	2%	**0.4%**

Table 6 represents the OPEE formula which is the closest translation to the Overall Equipment Effectiveness formula through adding in an ‘availability’ variable which defines whether the asset is consistently doing the highest level or work and pick time in the given period of time analyzed. The formula used to generate the OPEE score: OPEE= Di/365 *AVERAGE(Wi/Ei) *AVERAGE(Pi/Ei)

Availability * Average Daily Pick Time % * Average Daily Work Time %. Availability was generated from taking the Total Operating days and dividing it by 365. By using the highest sum of operating days and then dividing the other operating days for each asset, in the case of truck 49, 127 days, and dividing it by a 365-calendar year, we are able to see an availability from 0-100%. The Average Daily Work Time % was generated by taking the average Work Time % over all of the operating days. The Average Daily Pick Time % was generated by taking the average of Pick Time % over all of the operating days.

The daily Pick Time was generated by taking the daily hours the asset was moving containers and dividing it by the daily engine hours as a percentage from 0 -100% Pi/Ei:

Daily Pick Time/Engine Hours

The Work Time percentage was generated by taking the Daily Work Time and dividing it by the daily engine hours as a percentage from 0 – 100% Wi/Ei: Daily Work Time/ Engine Hours

This OPEE percentage is then calculated by multiplying those three values and then sorted descending from largest to smallest, yielding a list of the most productive machine over the given period to the least productive machines. The colors are added for emphasis but do not have any value other than to group the top, middle, and bottom performers.

The color was added based on natural breaks but in the future could be used to establish Key Performance Indicators: top, middle top, middle low, and low. Here we see that the ranking of the top 3 did not change from the last sort based on Average Daily Work Time percentage only - 49, 33, and 51, however, truck #36 and #37 dropped out of the top five to be replaced by truck #38 and #35. This last distinction is very important to note, because a machine could be unavailable for the majority of the period, but when it was available, it achieved very high utilization ratings in work and pick time, which would not tell the complete story of its productivity and performance.

This analysis could provide a model for future evaluations of this fleet of machines and work towards establishing a more consistent performance overall from each asset. While the data do not tell us why each asset performed at the overall percentage identified, it does provide insight into which machines and operators need to be evaluated based on low, middle, and high performance to establish better operational and maintenance guidelines.

4.2 Data Limitations and Exceptions

The dataset used in this thesis had incomplete time frames where some trucks connected to Elevat-IoT in September and generated data until the end of the period in March. Other trucks came online at various times between September and March resulting in a smaller sample for those trucks. On the trucks with smaller datasets, another option for the availability calculation was to take the number of Operating Days and divide it by the total days between the start and stop date. I did this calculation to see the impact on the OPEE score and found that it did not alter the ranking of the trucks sufficiently enough to warrant adopting this formula for availability. In addition, the logic required to implement this calculation for future companies could be overly burdensome and prevent the overall adoption of the OPEE score and therefore was rejected in this data analysis. Some of the data available for this research was not used due to errors in collection or scaling. Fuel data, for example, did not calculate correctly from liters to gallons and was not used.

4.3. Solution Interview with Steve Hardin of Alaska Marine Line

Steve Hardin is General Manager of Shore Side Equipment at Alaska Marine Line, a subsidiary of Lynden. Lynden corporation began in the trucking industry moving cargo and expanded into multiple industries and types of cargo shipping. Lynden is a data-intensive organization and uses that data to understand how to improve their organization and manage their resources more effectively. Steve was chosen to provide feedback because he is the person who wanted to use Elevat-IoT to provide a better means of tracking engine hours to service his equipment. In the process of gathering engine hours, the other data points, pick time, work time, idle time, pick distance, non-pick distance, etc. were added by Lynden corporation. Steve's testimonial is important to establish the value of using this data on managing this fleet of trucks.

In my meeting with Steve, I presented Table 6 to him and asked him questions related to table 6 to understand what the data meant to him. Steve has an operations background as well and provided feedback from that perspective related to the Svetrucks and Lynden as a whole. The following is a summary of our conversation which was recorded on Zoom on April 29th 2021. The entire transcript can be read in the Appendix. Steve appreciated the different elements within this table and was able to explain why the trucks ranked the way that they did. He mentioned that truck 51 in Whittier had been unavailable due to 30 days of maintenance. and this affected its overall score as compared to the other trucks with similar start and stop dates. He said that having an overall score that he could use to determine how each truck was performing against each other would be valuable, because it could provide insight into whether there were too many trucks in a given location or if the truck operators were managing them differently. For example, he had identified operators in both Alaska and Seattle who left their trucks idling during lunch break to either keep them cool when it was hot or warm when it was cold. This practice impacted their idle time and idle fuel use and required a better practice to maintain the cabin temperature than leaving them running. Steve stressed how important data was to both Lynden and Alaska Marine Line and believed that OPEE could be a useful tool in analyzing different types of equipment to better understand the company's operations and would aid in making better economic, environmental, and operational decisions were this in place companywide.

Chapter 5: CONCLUSION

The result of this research and thesis provided an in-depth analysis of the Overall Equipment Utilization journey over the last 50 years, its applicability to mobile factories using IoT and Big Data, with a focus on a use case that could yield valuable information, insights, and economic advantages to fleet and operational managers. The individual performance of each machine on a number of parameters achieved high correlation values, suggesting the data extraction element of this project was successfully achieved, which was demonstrated through both basic and advanced correlations. Through applying the variables to Time * Speed * Quality, a better productivity ranking with a higher degree of accuracy was created to help managers determine which assets and operators were performing at the top of their fleet. This work could provide a basis for adoption of IoT and a justification for the use of Big Data to analyze fleet operations. Furthermore, by applying a known and well documented KPI standard with OEE, the basic legwork of determining how to extract the data, what kind of data to extract, and what analysis would yield value has been explored here with the use of the OPEE formula in this thesis.

With the in-depth interview of Alaska Marine Line's General Manager Steve Hardin from the Seattle port, we were able to validate the real-world utility of this formula and its individual components to provide benchmarks and insights into truck, port, and operator performance as well as the operation as a whole because OPEE applicability to equipment applications other than just forklifts. Steve was able to easily demonstrate equipment and operator insights by viewing availability, work, and productivity data including explaining individual differences between trucks, ports, and operators. Furthermore, he was able to transfer the OPEE value to Lynden's primary cargo moving business and apply its usefulness to selecting the best engines, tires, and overall economics through evaluating performance over time with the OEE value and individual components. Steve's feedback was instrumental in confirming both the purpose and direction of this research and work as a whole.

5.1 Future Direction

The result of this research indicated that a reliable data set, in most cases R^2 value equal to 0.80 or higher was achieved, with the majority at R^2 equal to 0.90 or higher. Because of this strong data correlation, it is both possible and practical to establish benchmarks and trends to assist operation manager with determining how their equipment is performing over time. Ideally, the availability, work time, and pick time would be calculated in real-time with the use of machine learning and/or artificial intelligence which would provide fleet managers with at-a-glance performance metrics to manage their fleet. The goal of IoT and big data is ultimately to extract and load high integrity data. With the use of AI, the transformation and analysis step could be automated eliminating the need to export and analyze large data sets in Excel or other analytics tools. The work required here to extract the data and load it into Excel, then do the work to establish the integrity of the data, and through using Excel formulas to provide a data set to analyze is very time consuming and could be automated with additional software in the future deployments.

BIBLIOGRAPHY

Hwang, Gyusan et al. “Developing performance measurement system for Internet of Things and smart factory environment.” International Journal of Production Research, Vol. 55, Nos. 9-10, 2016, pg 11.

Garg, Amik and S.G. Deshmukh. “Maintenance management: literature review and directions.” Journal of Quality in Maintenance, Vol. 12, No. 3, 2006, pg.3.

Lugmayr, Artur et al. “Cognitive big data: survey and review on big data research and its implications. What is really “new” in big data?”Journal of Knowledge Management, Vol. 21, No. 1, 2017, pp. X-Y.

Latest Quality. 2018 How to Calculate Overall Equipment Effectiveness (OEE). Retrieved April 15th, 2021, from https://www.latestquality.com/overall-equipment-effectiveness/

Mobley, Ricky Smith and R. Keith. *Rules of Thumb for Maintenance and Reliability Engineers*. Butterworth-Heineman, 2008.

Muchiri, P. and L. Pintelon. “Performance measurement using overall equipment effectiveness (OEE): literature review and practical application discussion.” International Journal of Production Research, Vol. 46, No. 13, 2008, p.

Murray, Alan et al. “Evaluating the innovation of the Internet of Things.” Business Process Management Journal, Vol. 22, No. 2, 2016, p.

Nakajima, Seiichi. *Introduction to TPM*. Cambridge Massachusetts: Productivity Press, 1984.

—. *TPM Development Program*. Cambridge : Productivity Press, 1989.

Ng Corrales, Lisbeth del Carmen et al.. “Overall Equipment Effectiveness: Systematic Literature Review and Overview of Different Approaches.” Applied Sciences, Vol. 10, No. 18, 2020.

OEE. "Free Resources and Fresh Perspectives on OEE." Retrieved 28 Jan. 2020 from www.oee.com.

Peimbert-García, Rodrigo E. et al. "An Economic Framework for Total Productive Maintenance (TPM)." Industrial and Systems Engineering Research Conference, 2012, https://www.researchgate.net/publication/289050081 pp. 2760-2769.

Prasher, Vikram Singh and Stephen Onu. "The Internet of Things (IoT) Upheaval: Overcoming Management Challenges." Journal of Project Management, Vol. 8, No. 2, 2020, p.SAE.

J1939 Standards Collection on the Web: Content. Retrieved May 30, 2021, from https://www.sae.org/standardsdev/groundvehicle/j1939a.htm

SAE. "About SAE International." Retrieved June 5th, 2021 from SAE.org

Šajdlerová, Ivana et al. "Potential and Limits of OEE in the Total Productivity Management." Advances in Science and Technology Research Journal, Vol. 14, No. 2, 2020, pp.

Schermann, M. et al. "Big Data An Interdisciplinary Opportunity for Information Systems Research" Business & Information Systems Engineering, Vol 6, 2014, pp. .

Pomorski, Tom. "Managing Overall Equipment Effectiveness [OEE]." 1997.

PTC. "Industry 4.0: Optimize Operations & Shape Future Innovation." Retrieved from www.ptc.com June 5th, 2021.

Vorne Industries. "Six Big Losses." Retrieved June 4th, 2021 from https://www.oee.com/oee-six-big-losses.html.

Wang, Qing and LiLi Zhou. "Research and Application of J1939 Protocol in Engine Parameter Monitoring System." 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference

Ylipää, Torbjörn. “Identification of maintenance improvement potential using OEE assessment.” International Journal of Productivity and Performance Management. Vol. 66, No. 1, 2017, pp. X-Y. Accessed March 9, 2021

Zammori, Francesco Aldo et al. “Stochastic Overall Equipment Effectiveness.” International Journal of Production Research. Taylor & Francis, 2011, pp. X-Y.

APPENDICES

Appendix A. Steve Hardin Interview Transcript

Carl: “This truck (#49) is the same Total Operating Days as this truck (#51), but it does not tell me why this is 92 versus 127 operating days?”

Steve: “Okay well that one in particular that is one of the two new ones that we put in Whittier because they are a specialized unit and they have a new engine in it, a Volvo. Mostly the rest of them are Cummins. The last handful we got was SVE Volvo’s because the tier 4 (diesel engines) and the tier 4 in Whittier (#51) failed us horribly. It was down for almost a month.”

Carl: “And that is exactly what this data is intended to show so if I am not talking to you and I do not know anything about these trucks, the fact that it shows up with less availability (25%) is supposed to be an indicator of reliability or some other issues.”

Carl: “What about this Anchorage truck (#49) versus this Petersburg truck (#39)? They both operated 127 days. What would have created such a difference between their non-idle time (Average Work Time - 76% vs 58%)?

Steve: “The only thing that comes to mind for me is temperature. Anchorage is going to be considerably colder in the winter. And I have found here in Seattle experience that some of these operators even in the summer-time here, one thing we have caught them doing in the past is if the parking brake is set and there is no operator in the seat the truck will shut off after 5 minutes. So, the mechanics have figured out to not apply the parking brake and leave a heavy shackle in the seat so it thinks somebody's in there, and it can run their air conditioner while they are at lunch and vice versa in Anchorage they can do the same and come back to a warm cab in the winter rather than shut them down for whatever their lunch is, 45 minutes. That could be happening still. We put a stop to it down here once we figured it out, but I do not know up there. And I wouldn't frown on it in those conditions because shutting off a machine in below zero conditions and starting it back up probably causes more harm than letting it run idle. But that could be the difference. Location is always going to be a little bit different because it is not only the temperature going on but the cargo that they are doing. For instance, Whittier does a lot of really long runs with their machines and I don't know how that would affect the pick time, but they are running a long ways empty sometimes that might be part of it too."

Carl: "So the work time is the one where it is not idling, and over RPM which suggests it is moving. So the 76%, this Petersburg truck, would that indicate long runs? When you have a pick time of 15% but 76% of its time is over engine idle?

Steve: "Yeah that could very well indicate that. I have not been to Petersburg so I am not familiar with their yard layout but that certainly could be a good reason."

Carl: "So if you are looking at this data set, what value does this bring to you, or what are your thoughts?"

Steve: "Well it brings a lot of value at a bunch of different levels, my first thing is the ones that have the lower total operating days, how much of that was breakdowns and how much of that was not being used? If they were not broken, if they were available but not being utilized, do we move those machines somewhere they could be better utilized, do we have too many machines at that port, that stuff is not really under my realm, I am not in operations, I don't deal with operations so much I am more of the maintenance, but coming from the operations background, that is something I would be looking at."

Carl: "In terms of benchmarking, so that over time let's say looking at their Operating Equipment Efficiency score, does that provide any value to you or are you more interested in the specifics like operating days, work time, things like that?"

Steve: "No I think the efficiency is good, any data you can get over a period of time, and start seeing some trends is always good. The more you can dial into it and try to understand it the more meaningful it is. So the one thing is, if you are looking at the machine at 11.9% (#49) and it stays 11.9% all the time, but you see some other one's moving around but start dialing into the other ones and figure out what is going on with the other ones. Why is this one so consistent? Is there only one operator driving it versus multiple operators in a machine that happens down here (Seattle)? Is it an operator that is abusing a piece of equipment? Why does one have so much time on it than the others with the same amount of stuff?"

Carl: "And then, my thinking too was, instead of just looking at a SVE Truck, that we could identify work time, versus productive time - in a SVE it is easy because productive time pulling a container and moving it - but other pieces of equipment at Lynden may have a different definition of that productivity, but we could do this same formula fleetwide so that someone from a fleet perspective could look in and say okay, here's what my SVE trucks are doing, here's what my barges are doing, here's what this is doing. What are your thoughts in terms of an overall view with your operations knowledge?"

Steve: "I think it would be very beneficial, you know Tractors, for instance Lynden started out as a trucking company and that is still a large part of what they do, you know tractors, knowing your tractors, which one's in what lanes (driving a specific route from point A to point B) are making you the money. They are always constantly studying that, they get varying to specifics on things like tires, what kind of tires work better when you are on the Alcan highway all summer, versus what kind of tires work better on the other highways. Which engine is more effective in that kind of a lane, you know Texas to Canada, what engine works more effective in that lane. Is there a cheaper operating cost, better fuel economy kind of thing, so any of these kind of thing that we can get is very valuable. Just knowing what piece of equipment to put where, not only that but what to buy in the future that is cheaper and better."

Carl: "So this kind of a data set because it is over a period of six months and it is looking at these values, you could, for example, if you had a truck with certain tires and a certain engine, you could compare their performance over time in this kind of equation to see how they rank."

Steve: "Yeah."

Carl: "And that would start to give you some at least insight to start asking those questions like you just did, like what's going on with the operator? What's going on with the reliability - the Whittier tier 4?"

Steve: "Right."

Carl: "Good. My hypothesis was that, I pulled this formula from overall equipment effectiveness used in plant manufacturing but it has never really been transferred to the mobile IoT world."

Steve: "Oh interesting."

Carl: "Overall Equipment Effectiveness is basically Time, Speed, and Quality in manufacturing. So the time is based on plant run time versus actual run time. The speed is based on how many widgets did I make? And the quality is what was my defect rate. That value gives a percent number and how they rate performance in manufacturing. What I tried to do was take that concept and apply it to the mobile world which does not really have that.”

Steve: “Interesting, we kind of do that in a way. We have a meeting on Friday where everybody kind of goes over their numbers and I know the yard will do how many tons did we move, how many forklift hours did we have this week, that kind of thing and charts and graphs to go over and kind of see how we did compared to last year. In the southeast we are doing how many UPS packages did we get each day of this week and versus how many we did last year….so this is right along those lines.”

Carl: “Yeah so that is a key performance indicator that I talk a little about so there are lagging and leading KPI, lagging would be how many tons you did at the end of the quarter, but the leading would be when we look at these machines and see how we are trending, or is there something that is going on with a truck that is going to make us miss that performance, reliability for example, trucks down, you know you are going to miss that number. So this could be a daily, weekly, monthly calculation that you can see over time but that is helpful to know.”

Steve: “Yeah that would be really good.”

Carl: “Anything else I haven't thought of or asked related to this?

Steve: “Not at the moment I think you are probably headed in the right direction like I say we are a very data driven organization and the more I can get my hands on the productivity of my guys, tracking hours and productivity of my guys, how many orders did you close this week, how many touches did you have, that kind of thing so how many labor hours do I have available to me and how many people came to work. Any of this data is very valuable stuff.”