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An Empirical Study Proposal for Testing Operating Equipment Effectiveness with Reliability Indicators

By Carl D. Hays III

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I. Introduction

Machines with wheels and tracks operate in the field as (opposed to factories) and perform various types of jobs. The street sweeper's job for example, is to clear streets of debris using a spinning broom (see Figure 2). The street sweeper is considered productive when it is in operating in two modes. In the first mode, it is available to sweep streets, and sweeping streets. In the second mode it is available to sweep and traveling to a job site. OpEE® is an established productivity indicator that measures the performance of machines like this street sweeper when it is in the two example modes. These modes are measured by three variables, availability, work time, and non-idle time.

Availability indicates when and how often a machine can perform work over a period of time. Work time is a measure of what percent of time a machine was performing its job function. In the street sweeper example, this would be the percent of time the sweeper was clearing debris off streets. Non-idle time reflects the percentage of time the street sweeper was traveling to a job site to perform work. The street sweeper is considered unproductive when it is not available (due to service or being underutilized) and referred to as downtime or unscheduled downtime and often related to an issue with reliability (Chicheney et. al, 2022).

Chicheney et. al (2022) goes so far as to say, "insufficient reliability of machines…result not only in significant downtime of equipment but also increase their operational cost" (p. 866). To minimize downtime, machines, such as the street sweeper, require regular maintenance to perform the job that they were designed to do. Reliability, as Hays (2022) suggested, is a measure of how well we maintain our machines. The maintenance function is designed to optimize reliability and the associated cost of maintenance (CoM). The CoM refers to the operational cost of maintaining equipment. This expense includes replacing parts and fluids. This cost may be increased or decreased depending on how well machines are serviced and maintained including the frequency of maintenance.

While the maintenance function is critical to overall productivity, it is not typically managed with status and performance indicators to optimize it. A status indicator informs us when to service the machine. A performance indicator informs us how well we are managing the service and productivity of the machine. This lack of performance and status indicators, make it difficult to optimize decisions on increasing productivity and reliability. The research on the topic is likewise scant or focused on specific use cases without a theory and methodology that may be universalized. Furthermore, a measure for both productivity, and reliability is needed to compare how these machines perform over the course of their useful life. The research study in this paper suggests a method and design to test Hays' (2022) theory of using OpEE®, a measure of overall productivity, with quality status indicator(s), a measure of reliability, on a population of machines.

This paper is intended to provide a research design and methodology to test Hays' (2022) theory and is structured as follows: a literature review will be presented to provide a background for the research proposals, define the research problem and address relevant studies related to this maintenance and productivity issue. Furthermore, this review will present a research gap this study intends to bridge. The next

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section will present the study proposal, the hypotheses and their rationale. From the hypothesis a proposed methodology and research design will be presented. Next will be a discussion of the expected results, implications from the results, and recommendations for future research. The empirical study will end with a conclusion tying the elements of this paper together in a coherent narrative.

II. Literature Review

a) Background

Overall Equipment Effectiveness (OEE) has been one of the more important performance indicators in factories since its invention. OEE provided a useful measure of productivity and quality for plant managers to judge overall performance. Wegner (2022) presented a ranked list of the top 15 smart factory Key Performance Indicators that firms are focused on increasing and OEE was number one on this list. Because of the success of OEE as performance indicator in factories, several derivatives were developed to solve various problems in different industries. A possible way to view machine performance would be to consider them as mobile factories performing the job functions, they were designed for. In this light, OEE was a performance indicator that could be modified to fit machine applications in several industries.

OEE "was modified to solve gaps in various issues, such as sustainability, human factor, transport, manufacturing system, mining, cost, port and resources" (Lisbeth, 2020, p.1). One such derivative was Operating Equipment Effectiveness (OpEE®) developed and tested by Hays (2021) to measure overall productivity for lift trucks. OpEE® was not a perfect translation from OEE because the Quality indicator was removed, however OpEE® provided a better measure for productivity than the industry standard, which was utilization. To transfer OEE to machines, Hays (2021) had to sacrifice the quality indicator form OEE which measured the total number of good widgets produced per batch of 100. This was also referred to as a quality defect rate.

To address this gap with the OpEE® score Hays (2022) added a quality indicator focused on reliability. To implement Hays' (2021) conversion of OEE to the OpEE® score a Proof of Concept (PoC) was developed by Faehn (2022). Faehn, an application engineer at Applied Fluid Power, who provided the sensors, status logic, and used the Internet of Things (IoT) platform elevat-iot.com to develop the OpEE® status indicator. In addition to the OpEE® score, Faehn (2022) developed another quality indicator referred to as brush life indicator (BLI), (see Figure 3). The original theory presented by Hays (2022) suggested the quality indicator be a hydraulic fluid contamination sensor (HCI) made by Tan Delta, (see Figure 4). The Tan Delta sensor monitors the condition of hydraulic fluid and was the primary quality status indicator proposed by Hays (2022).

Faehn did not use the Tan Delta sensor, but rather applied the OpEE® score with a different quality indicator on a machine designed to sweep debris off streets, (see Figure 1). This proof of concept (PoC) made some key changes to the OpEE® formula, which provided both leading and lagging indicators, (see Figure 3). As a leading indicator, the OpEE® score would provide performance productivity up to the last operating event, allowing managers to determine how well each machine had performed over time because the score was cumulative. Faehn (2022) modified the score to allow for a rolling 24-hour update. This modification provided day-to-day data, or a lagging indicator, to determine how the machine was trending over time.

In addition to modifying the OpEE® formula, Faehn added a quality indicator, which provided the remaining useful life of the broom, referred to as the 'core,' used to sweep the streets. The quality score, ranging from 0-100%, provides a status indicator, much like the fluid condition indicator, for when each core needs to be serviced, (see Figure 5). The sweeper must maintain a specific amount of pressure on the core to move material. This pressure causes the core container to move closer to the pavement as the whisker length changes.

When the machine reaches the caution status, this indicates to the service manager that the core needs to be scheduled for replacement. Having this service indicator would allow managers to schedule core changes during downtime rather than when the machine is sweeping streets. Timely core maintenance would eliminate the use of cores that were past their maintenance due date and when they are least effective at sweeping streets due to poor whisker length, and or could cause damage to the street sweeper. For both hydraulic fluid and cores, changing them too early costs more money because a higher quantity of both must be replaced. Changing them too late, may reduce the overall replacement expense, but it can lead to carrier damage in the case of the core, and component wear and tear in the case of hydraulic fluid. The key to enhancing productivity and reducing the cost of maintenance, is optimizing the maintenance function.

b) Research Problem

Standard methods for monitoring the reliability of machines are inadequate for predicting and preventing failure. Failure leads to reactive maintenance strategies requiring costly unplanned downtime to replace and repair parts and fluids. Downtime effects the overall productivity of machines because the machine is not available to perform work. How does the research suggest that we address this problem?

Because OpEE® is a relatively new concept, the focus of this review will be on how OEE because addresses the downtime problem as it is a well-established metric. Hays (2021) provided the research and analysis transferring OEE to OpEE® establishing that insights from research on OEE will translate to OpEE®.

In an empirical study of material handling systems using OEE as a measure of efficiency, Yazdi et. al (2018) found that to improve the performance of a system it is important to identify the problems that limit overall efficiency. To evaluate the systems' performance, Yazdi et. al (2018) suggested that focusing on the "sources of productivity," resources can be applied to improve performance (p. 1). The Yazdi (2018) study recommended testing the manufacturing system utilizing sensors and algorithms to identify areas of improvement and evaluate performance over a time series. The sensors would provide the specific data to evaluate performance, and the time series provided a period to evaluate the effects of the research proposal. The benefits of improving OEE are increasing productivity, reducing cost, providing awareness, and extending the useful life of equipment (Yazdi et. al, 2018). These benefits were similarly expected from applying the Hays (2022) theory to mobile factories.

Garza-Reyes' review provided a survey of OEE studies, summarizing OEE as a measurement of performance used in industries to monitor productivity and drive improvements to process and performance (2015). Garza-Reyes identified limitations to OEE, noticing that it does not do an adequate job of "sub-optimization" for each machine or provide an approach to defining performance targets and does not incorporate strategies for a more balanced review of these systems (p. 507). This limitation could be that the quality variable in OEE is focused on the defect rate of the parts being produced but not necessarily on components that could lead to the failure of equipment. This issue, identified by Garza-Reyes, with OEE creates a gap between *what* OEE is used for, a measure of overall productivity, and *how* to improve the system using the OEE score. Hays (2022) theory seeks to close this gap with mobile factories by focusing on the quality indicator as a measure of equipment reliability and not just an indicator of performance quality. This is accomplished through using sensors to monitor key and individual components or the "sources of productivity" as identified by Yazdi (2018) in addition to incorporating reliability sensors that are applicable to each individual machine as suggested by Garza-Reyes (2015).

c) *Machine Maintenance*

The function of maintenance is to optimize the reliability of machines and equipment to meet the needs of the business and companies that own and operate them (Smith & Mobley, 2022). Smith and Mobley (2022) discuss two maintenance approaches to servicing machines and equipment - reactive and proactive maintenance both of which require some form of predictive process to determine machine status. "The common premise of predictive maintenance is that regular monitoring of the actual crafts condition, operating efficiency, and other indicators of operating condition of machine trains and process systems provides the data required to ensure the maximum interval between repairs and minimize the number and cost of unscheduled outages created by machine train failures" (Smith & Mobley, 2022, p. 47).

The reactive maintenance approach responds to the situation where a part requires service. The measure of success is based on the response time to meeting this request. Proactive maintenance on the other hand, responds to predictive data gathered by procedures (Smith & Mobley, 2022). Predictive procedures are most commonly visual inspections where a person checks on the status of equipment following maintenance procedures outlined in the operator's manual. When an issue is identified, maintenance reacts to a request for service.

The goal of both predictive and reactive maintenance is to minimize downtime; however, this begs the question as to what the best path is to provide regular monitoring of the "actual crafts condition" (Smith & Mobley, 2022, p. 47).

d) *Performance Indicators*

The concept of performance indicators has been applied to innumerable use cases from sports to finance, from business to factories, from machines to people, and even to animals. The basis for using a performance indicator is to understand and quantify how systems operate. There are two types of performance indicators- leading and lagging indicators. Leading indicators indicate trends and *lead* to results. Lagging indicators are a measure of performance. "We use leading indicators to manage a part of the business, while lagging indicators measure how well we have managed" (Smith & Mobley, 2022, p. 89).

With this knowledge, new and interesting options are available to determine *what* to do with this information, which often leads to the innovation of *how* to do it. Hays (2021) determined that a new performance indicator was needed to measure the productivity of machines with wheels and tracks. Hays (2021) determined that Overall Equipment Effectiveness had been successfully used and established in manufacturing. In order to transfer OEE to machines technological advances were required.

While Hays (2021) had determined *what* would be a useful invention, the *how* involved new technology including but not limited to: an IoT application, which connected a population of machines to a time series database; a hardware and software application that collected the necessary data and transformed it using mathematical equations into the variables Hays (2021) used to derive the OpEE® score; the right sensors to interpret and collect the data from the machines that would be used in the formula. With these ingredients, it was possible for Hays (2021) to develop and transfer the OEE score to machines operating anywhere in the world.

After developing the OpEE® score, new sensor cost effective sensor technologies were incorporated to provide a more complete theory for the OpEE® score (Hays, 2022). This theory provided both a productivity indicator in the OpEE® score, and a reliability indicator measuring hydraulic oil contaminations levels which directly correlate to equipment reliability (Hays, 2022). The sensor used for this theory was made by Tan Delta and designed to detect contamination levels in hydraulic oil. The Tan Delta sensor was unique in that it was incorporated into the hydraulic oil system on the machine referred to as an *inline* sensor. Typically, hydraulic oil contamination is determined by connecting a machine to the hydraulic system, or an oil sample is sent to a lab, to determine particulate levels of contaminants within the scope of analysis. Adding this inline sensor to the machine allowed for a real-time, dashboard view of both productivity and reliability. This research proposal relies on the engineers developing new technology to manage and measure using sensors.

e) Digital Sensors

Sensors detect and transmit information that they are designed to monitor and measure. Digital sensors can do this through data, and when connected to an IoT platform. Iansiti and Lakhani (2014) wrote that digital sensors are increasingly replacing analog tasks typically performed by people. Michalski (2018) indicates that sensors have reached a level of industrial maturity that their primary focus must be on the "expectations" of end customers (p.2) or, in the context of this paper, to maximize productivity and reliability of machines. Sensors perform very important roles in monitoring performance because they provide access to the data used to produce OEE and OpEE® scores. For mobile factories, this data is gathered by sensors. These sensors are critical to capturing the data that can be transformed into meaningful data for use by managers.

Pararach et. al (2021) claims that IoT allows manufacturers' access to critical data produced by sensors. This data provides real-time values used to understand the working efficiencies measured by the OEE score. The empirical study performed by Pararach et al. provides a framework for how to develop a sensor-based IoT-connected solution to extract data from printing machines and connect them to the cloud. These time series data are then used to develop the OEE score. The OEE score is a performance benchmark "used at regular meetings to monitor and improve set up time (where) root cause analysis can be used to find out the actual cause of breakdown (p. 8). Both studies (Michalski, 2008; Pararach, 2021) discuss using IoT with key sensors to extract data and develop OEE scores that can be monitored and managed to improve performance. This empirical study proposes a very similar approach using IoT, sensors, and status indicators on mobile factories to monitor and manage the OpEE® score to improve productivity, reliability, and overall equipment performance.

f) Summary

There has been a lack of research on applying performance indicators to machines with wheels and tracks. Because of this, Hays (2021; 2022) transferred OEE to OpEE® in an empirical study and then proposed a new theory to add a quality status indicator to OpEE® to provide a better measure of both productivity and reliability. Current research on OEE suggests that the quality indicator lacks information as to *why* the value increases or decreases which is likely due to a source that affects production. This gap in the research literature may be covered by this empirical study seeking to test Hays' (2022) theory and what other status indicators could be used. For this study, the first status indicator will be the Hydraulic Fluid Indicator (HCI), the second is the Brush Life Indicator (BLI), and the third will be Visual Inspections (VI) of equipment using a tape measure.

III. Study Proposal

This study intends to determine how status indicators could be used with the OpEE® score to increase productivity and its associated costs related to the maintenance function. The purpose of this quantitative study will be to determine what relationships are found within the time series data from the front broom sweepers using the Operating Equipment Effectiveness (OpEE®) score and status indicators measuring the brush life of the sweeper core, and the fluid condition of the hydraulic oil. The results may show that the population of machines using the OpEE® score and following the status indicator predictive maintenance recommendations will have a significant impact on machine availability and work time. Machine data will also be analyzed to determine whether the status indicators provide for a more consistent replacement with the treatment population versus the control population without the status indicators.

A concept map of the hypotheses to be tested versus the control is provided (see Figure 6). In an ideal world, a part is repaired or replaced at the right time, in the right place, and at the best cost. Adding a quality status indicator to the OpEE® score would optimize the time to replace the component. When a part fails without advanced notice, this could occur in the middle of performing its work function, which would require the machine to be taken out of service and delivered to a service location for repair. This service event impacts both the availability and work time of each machine. When a machine is taken out of service, it is not available to work for the time it is being repaired.

When a machine is not available to work, there is a reduction in both its availability score and its work time score. Availability is the percentage of time in a calendar year the machine is capable of performing work. The work time score is the percentage of time that a machine is performing its actual function such as sweeping streets. This is also referred to as productive time. These two variables can be difficult to optimize without advanced notice on when a part is going to need repair. Predictive data leading to proactive maintenance would provide the advanced notice required to optimize maintenance, which in turn affects availability and work time.

Adding a status indicator that provides advance notice of when a core part needs to be serviced would allow for better scheduling of the machine for service, or proactive rather than reactive. The machine could then be scheduled for maintenance on planned downtime rather than to take out of service when performing work. This proactive maintenance would optimize both the availability and work time variables in the OpEE® score. The anticipated results are that the following hypotheses will be supported by data collected and analyzed.

The information that this study intends to provide is the actual fleet availability of the equipment to perform work, the utilization of the equipment during operation, and the remaining life of the core over time. By having this information available to them, a fleet manager will be able to optimize operational decisions. This study does not aim to provide a qualitative analysis of the scaled solution, but rather to configure and deploy the application so that a future study may be conducted to determine its value to fleet managers.

Operational decisions will be enhanced through the availability indicator by informing fleet managers how often the machine is being used during a calendar year. The utilization indicator will inform fleet managers as to the rate of productivity the machine is performing when it is being used. The BLI will provide information on when a machine needs to be scheduled for service when the core bristle length reaches the minimum acceptable length for service. The objective of this study is to scale the PoC and present it on an IoT platform so that a further qualitative study can be done with fleet managers. The research questions that this paper intends to explore is whether firms (or managers) by adding status indicator(s) will increase timely and consistent maintenance over firms using a standard maintenance approach as measured by the OpEE® score. The status indicators proposed to be tested are the brush life indicator (BLI), Hydraulic Condition Indicator (HCI), Dashboard Indicator (tachometer), and Visual Inspection. The following is an analysis of each hypothesis and what results are expected form the study.

IV. Hypotheses

a) Brush Life Indicator versus Visual Inspection

The first proposed hypothesis is to determine what relationship there is between the BLI status indicator and core maintenance. The optimum whisker length for a core change is 10.25”. If the core is too late (when the whiskers are shorter than 10.25”) or too early (when the whiskers are longer than 10.25”) this could impact overall productivity, and the CoM. This study will likely show that adding the BLI indicator to the maintenance function will significantly improve the consistency of the core change at the 10.25” marker, and result in a more timely and proactive maintenance function to replace the core. This real-time status indicator will allow fleet managers to optimize maintenance scheduling to improve operations. Standard practice for core replacement requires visual inspection and typically a physical measurement of the whisker length. This practice can be unreliable, inconsistent, and imprecise when distributed through a population of machines.

The standard maintenance practice could result in replacing the core too early or too late. Replacing the core too early results in more cores being used during a calendar year resulting in higher CoM. Replacing the core too late could result in damage to the machine system operating the core due to its distance from the pavement during operations, which is based on whisker length. The closer the core is to the ground the greater the risk for damage. Monitoring whisker length using the BLI indicator may significantly improve overall cost of core replacement and limit unnecessary damage to the machine while also improving the quality of the work being performed.

Furthermore, when a machine is damaged it is taken out of operation for repair. This repair requires unplanned downtime and results in lost productivity. Lost productivity would be accounted for with the OpEE® score which measures machine availability. When a machine is being serviced it is not available to work. To optimize CoM, the best case would be to change the core at the right time, and in the right place. The right time is when the whisker length reaches 10.25”. The right place is a planned service event at the maintenance shop rather than in the field. If machines are being serviced based on inconsistent visual inspections, or damaged because the whisker length is too short, or the core is replaced to early, this will be more costly to the firm. Additionally, unplanned downtime will result in lost productivity.

Global Journal of Researches in Engineering (A) Volume XXIII Issue I Version I Year 2023

Hypothesis 1: Firms (or managers) using the BLI will result in more consistent and timely core maintenance which will increase overall productivity and reduce CoM versus companies that do not.

b) Hydraulic Fluid Condition Indicator versus Visual Inspection

The anticipated results from this study will likely indicate that there is a significant difference in timeliness for hydraulic fluid changes. Machine using the HCI indicator will provide more consistent and timely maintenance than machines not using the HCI indicator. The standard process for servicing equipment is based on visually inspecting the engine hour tachometer of each machine to determine where it is in its service journey and whether to replace the fluid. Some businesses may do this inspection daily weekly or monthly depending on overall seasonal or contract demand for services.

This approach will likely result in inconsistent maintenance functionality under best case. Under worst case, the approach could result in machines operating with significantly contaminated hydraulic fluid, causing additional and preventable wear and tear to components, requiring lubrication. Monitoring and managing the hydraulic oil service function using a real-time, fluid condition indicator will likely, and significantly, outperform standard maintenance practices.

As with the BLI, timeliness of maintenance matters to the overall CoM. Changing hydraulic fluid too early results in an increase to the CoM because more fluid is being used to lubricate parts in a calendar year than necessary. Changing too late, as mentioned, can result in premature failure of parts due to wear and tear. Premature failure may also result in unplanned downtime requiring service to repair or replace components. This service event will impact productivity because the machine will not be available to work and thus reflected in the OpEE® Score.

Hypothesis 2: Firms (or managers) using the HCI will result in more consistent and timely hydraulic fluid maintenance which will increase overall productivity and reduce CoM versus companies that do not.

c) BLI and HCI versus Visual Inspection

Because the HCI indicator monitors hydraulic fluid condition, and the BLI indicator monitors core status, having both status indicators on the same machine will improve productivity and reduce CoM more than either one is on its own. Managing fluid health in a more timely and consistent maintenance function preserves the life of components in the hydraulic system that requires lubrication and could result in a longer, more productive life.

We would expect to see issues with hydraulic fluid contamination increase wear and tear on parts and components. This wear and tear over time will express as component failure. Component failure leads to both preventable and unplanned downtime for maintenance. This downtime is preventable because the proper maintenance of hydraulic fluid based on contamination will result in more timely replacement. This downtime is more costly because it results in replacing parts earlier than necessary due to increased wear and tear. On the alternative, if the hydraulic fluid is replaced too early, this results in unnecessary increases in the CoM. Replacing hydraulic fluid before it is required may result in better maintained hydraulic system, however it increases the CoM because due to an increased frequency of service. This is also true for the core and brush life indicator.

Monitoring the whisker length of the core results in more timely replacement of each core resulting in either less costly overall use of the machine by preventing premature core replacement, or less quality work and potential machine damage by preventing late core replacement. Using both together may significantly improve the useful life of the machine so that it will work more hours with the optimization of the hours worked being affected by the BLI.

Hypothesis 3: Firms (or managers) using the BLI and the HCI, will result in more consistent and timely hydraulic fluid maintenance which will increase overall productivity and reduce CoM versus companies that do not.

V. Methodology

The focus of this research will be on using a quantitative experiment to explore and validate the hypotheses. This empirical study proposes to use longitudinal, time series study. These data will be acquired from a cellular-enabled device connected to the machines that can be transmitted to the elevat-iot cloud. The population of machines will be spread out in regions, providing diversity for field testing. When the data has been collected by the cloud platform it will be exported to Microsoft Excel for analysis. The focus of the interpretation and analysis will be to determine how close to the target replacement status machines were serviced, referred to as the delta and expressed as a percentage. In addition to the maintenance delta, OpEE® score, and CoM comparisons will be made between the treatment and control group.

VI. Research Design

a) Quantitative Method

Yazdi et. al (2018) provided an excellent approach to studying the relationship between a performance indicator as a measure for a system over time period. Their study proposed to measure OEE using a time study on manufacturing production line. A time study monitors and measures the instruments to determine how they are individually performing with OEE being the measure for overall quality and productivity (Yazdi et al, 2018). With this understanding of performance, an evaluation of the overall system can be made (Yazdi, et. al, 2018). Measuring a complex system requires a software application to record events and provide a report of the events and activities. These reports can then be analyzed using mathematical or statistical models to determine productive versus wasted time (Yazdi et. al, 2018). Yazdi's study incorporated devices that were used to collect performance data, and then the effect on time was studied to determine overall performance as measured by OEE. Using this methodology, a similar approach is recommended for this study.

This research will evaluate the OpEE® score on a population of machines with the appropriate status indicator(s) measuring and monitoring event data over a time series. Each machine will a hardware and software kit installed on each machine to collect the data and connect to the elevat-iot platform. The elevat-iot platform will record the detailed event data required to analyze performance. Each kit will have an elevat-iot approved IoT Gateway with Cellular SIM card. The elevat-iot gateway will connects to the and transmit data through the AT&T cellular network. Each machine will have a computer controller which contains the software programming and logic required collect the sensor data and calculate the OpEE® score and BLI and HCI indicator logic. The BLI status indicator connects to an arm angle and pressure sensor. HFI indicator connects to a Tan Delta fluid condition sensor. These sensors transmit data to the elevat platform through the IoT gateway.

Once the machines are set up correctly and are connected to the elevat-iot platform the data will be collected over a 6 month period. The elevat platform has two different views that will be used by maintenance personnel. Each organization has dashboard indicators, (see figure 3 and figure 4), that provides an individual machine view in addition to a fleet view indicator, (see figure 7) providing an overview for all of the machines. The combination of these dashboard views provides maintenance personnel with status indicators to schedule maintenance for each machine. At the end of the 6 month collection period a time series data set will be exported for statistical analysis to determine the OpEE® score and the maintenance delta for each service event. This statistical analysis will present the differences between productivity and the CoM as defined in the experiment.

b) Productivity and Cost of Maintenance Measures

For this study, OpEE® will provide the productivity measure and CoM will be the measure for maintenance costs. For this research proposal, the OpEE® score has been modified from its original version in Hays (2021, 2022). Availability will be a standalone percentage rather than multiplied to work time and non-idle time. This will allow for a direct comparison of machines on unscheduled and unscheduled downtime as discussed in the hypothesis sections. The OpEE® score will be based on the last 24 hours rather than an accumulating score over the 6 month period. This design will allow for a comparison of changes to the score every 24 hours rathe than the final score at the end of the period.

The first version of the OpEE® score, was designed as an accumulating score. This did not provide a very good lagging indicator. This version of the OpEE® score will provide a more useful measure for changes to availability, work time, and non-idle time which are the elements to measure productivity. These changes will not sacrifice the integrity of the original score as the performance objectives of measuring productivity over a times series will remain intact with this experiment. The overall score may be calculated from each daily interval, in addition to averages which were not possible with the original version of the OpEE® score.

The CoM will be calculated based on the number of changes for hydraulic fluid and core between treatment and control with respect to the target time to replace. When a machine is serviced too early, this results in an increase of service intervals. There is a cost associated with each service interval, to replace components, therefore increasing the frequency and increasing the CoM. On the alternative, servicing a machine after its due date can result in component damage and downtime.

For the BLI, the target time will be when the core has reached 10.25" where the IoT status indicator will indicate "replace" in the elevat platform. In the case of the HFI, the fluid will be replaced when the status reaches roughly 35% contamination and the IoT indicator status will be "replace." The method for analysis will be comparing the time stamp of when both the core and the hydraulic fluid return to a value of 100%. The time stamp will be expressed as a Universal Time Coordinated (UTC). At a value of 100% on the status indicator will mean the core and the hydraulic fluid have been replaced. This replacement UTC time will be compared to the UTC time and value of when the status indicated to replace them.

This comparison will result in a delta Δ score between the replacement UTC and the replaced UTC and expressed as a percentage. For example, if the status indicator for the core is at 63% and the core was replaced at 63%, the delta would be 63% - 63% or zero percent difference. If, on the other hand, the core reads 60%, and the core was changed at 60%, the delta would be 63% - 60% or a 3 percent delta. The greater the delta, the greater the difference between when the core status was "replace" and when the core was actually replaced. In the above example, the core was changed too late. If the core were changed too early, the delta would be expressed as a negative number, for example, 63% - 70%. This would result in a delta of -7%.

Additionally, a count of total replacements can be made by analyzing how many replacement events occurred. A replacement event is when the core or hydraulic fluid drops below 100% and then returns to 100%. This drop and return indicate the core and fluid have been replaced. Counting and comparing these events between the control and treatment group will provide a difference in service events. Each service event will be assigned a cost for labor and materials. The cost of total events in labor and materials will be compared as the CoM for the treatment and control groups.

c) Treatment and Control

The research design will compare the % delta score of the treatment group to the control group, (see Figure 6). The treatment group will be comprised of Superior Broom machines and maintenance personnel. The maintenance personnel will be the mediating variable who are responsible for replacing the core and the hydraulic fluid, (see Table 1). The control group will use standard inspection practices of Ocular (Visual) and an Analog Sensor (Tape Measure). The control group of machines will be monitored with the same software and hardware devices as the treatment group e.g. they will have the BLI, HCI indicators and the OpEE® score logic. Maintenance personnel in the control group, however, will be instructed to follow standard practices for the core and hydraulic fluid maintenance. By having both the treatment and control group measured in the same way, this will allow for comparison of the maintenance practices on the population of machines.

The control group was chosen from a population of machines rather than comparing organizations to other organizations because the maintenance standards for each machine does not change based on the organization. The manufacturer sets the recommended maintenance interval, the recommended form of inspection, and the recommended course of action. What is important in this case is to determine whether any organization may benefit from using status indicators like the BLI or HCI to maintain their machines.

The treatment group will be required to use the BLI or the HCI status to change the core and/or hydraulic fluid. The treatment group will rely on the quality status indicator(s) which will result in timelier, consistent core and hydraulic fluid changes. Additionally, both the treatment and control group will have the OpEE® score to review changes in productivity. The expectation is this the control group will rely on VI to change the core which will result in inconsistent and potentially less timely core changes which will increase downtime. By reducing maintenance downtime overall productivity will be increased. The population of machines is to be determined including the research locations and control/treatment population.

VII. Expected Results

The expected results of this empirical study will inform us about the maintenance practices of the organizations studied. Through incorporating new status indicators that are accessible remotely, we anticipate that this will be used to improve maintenance scheduling, timeliness, and reduce overall downtime. Reducing overall downtime will increase productivity through making machines more available to work. We expect that the maintenance operation will be more proactive in determining when and where to schedule machines for maintenance. We expect the OpEE® score to show a difference between machines using the BLI and HCI indicators in both productivity and CoM. With the evidence that the HCI and BLI indicators provide for more optimized maintenance, increased productivity, and reduced CoM, we expect rapid adoption of this approach within the organizations participating in the study, and an increased willingness to attempt using the technology in organizations that are maintaining machines based on standard practices.

In addition to accelerated adoption, we expect firms to invent new status indicators based on sensors that can monitor the useful life of key components like hydraulic fluid and cores. We anticipate that this approach could be used in forestry where saw blades need to be replaced based on cutting effectiveness. We expect industries using conveyer belts to incorporate status indicators for ball bearings that are used to run the conveyer. We anticipate that new ways of thinking will be invented to determine how to measure the useful life of key components based on a 0-100% scale.

What are possible alternate outcomes? In an ideal world the maintenance function will follow the treatment recommendations and use the status indicators to plan and schedule maintenance. While this is the design intention, it is possible that maintenance does not adequately utilize the new indicators to perform its function. In this case, we would be able to determine if a population of machines in the treatment group behaved more like the control group, e.g. inconsistently in terms of maintenance timeliness. Another possible outcome could be that the status indicator is utilized but the scheduling and maintenance performance are not as efficient as necessary to perform the maintenance function. Because of the possibility of a poor effect, we will be seeking a statistically significant population of machines to account for non-performance in the treatment group.

Global Journal of Researches in Engineering (A) Volume XXIII Issue I Version I Year 2023

VIII. Implications

a) Overall Impact and Significance

The implication of this study would be to suggest that a variety of quality sensors across industries could be used to increase reliability and overall machine productivity at an economical cost (because manufacturers cannot afford to put sensors on everything). Demonstrating the utility of this technology could greatly influence the adoption of cost-effective sensors and IoT to significantly improve fleet performance and profitability. Demonstrating that more than one type of quality indicator can be used with the OpEE® score could have tremendous impact on industries using machines and equipment.

This study could provide the roadmap for identifying a quality indicator such as a sensor and identify the conditions from 0-100% for the status indicator. These indicators will form the basis for component needs to be repaired or replaced allowing maintenance managers to use more consistent, timely, and proactive rather than reactive maintenance. Furthermore, this paper will suggest that the research conducted in this proposal will lay the foundation for applying machine learning to automate proactive maintenance and scheduling based on the scores to enable better scheduling, optimized performance, reducing operational cost and maximizing the return on assets.

b) Potential Impact on Business

Businesses seek to maximize return on investment (ROI). There are significant expenditures on the machines used to perform the work that businesses are either contracted or directly own the machines performing the work. To maintain these machines so that can perform the work they are designed for, businesses employ service and maintenance personnel. Measuring the work time of these machines translates to the overall productivity and ROI. Maintenance personnel are responsible for servicing the machines so they can perform the work they were designed for during their useful life. This begs the question, what is the best method to optimize this business operation?

Through adding sensors that monitor the key components required to perform work that indicate when a machine needs to be serviced, businesses will optimize the health, performance, and useful life of these machines and therefore maximize their ROI. On the contrary, not measuring the productivity or reliability of equipment performing work leaves maintenance at a disadvantage, with cumbersome, manual processes like visual inspections, to determine whether a machine requires maintenance. This lack of convenient data results in less timely maintenance and often disrupts the normal workflows while service reacts to a failure. It is in the business' best interest to enable maintenance to proactively service machines to maximize ROI through extending the useful life of the equipment and improving overall work time and reliability.

c) Potential Impact on Teaching and Instruction

This study will have significant implications for academic institutions and instructions. This study proposes that there are multiple sources for status indicators and provides the framework to evaluate those sources and construct a status indicator to significantly improve the maintenance function. With a logical methodology and clear roadmap to implement Hays' (2021; 2022) theories, educators may focus on *how* to design and implement this empirical proposal rather than determining both *what* needs to be done and *how* it could be performed. If the theories presented by Hays are adopted, it could provide new industry standards for academia to implement best practices in machine performance with a key performance indicator, OpEE®, to enable the overall measure of success.

As an industry standard, OpEE® with a status indicator could drive course materials to focus on sensors that could be used to develop additional status indicators. Numerous institutions could join and produce significant research efforts in applying Hays' theory to various applications including, but not limited to, forestry, construction, municipalities, oil and gas, agriculture, and even manufacturing. In this respect, this empirical study is simply a seed that can be planted in numerous institutions, researchers, students, and practitioners to produce significant forests all over the world.

IX. Future Research

This study proposes implementing Hays' (2022) theory, connecting it to an IoT platform to acquire, maintain, and analyze the sensor data. This effort may require a significant amount of labor to determine the results and whether the quality status indicators have a significant impact on the maintenance delta between when the core or hydraulic fluid should be replaced and when it is replaced. The results could be automated using machine learning to supervise and transform this data into descriptive views, removing the data analytics portion of the exercise (e.g. extract, transform, and evaluate).

Furthermore, machine learning could be designed to automate the maintenance scheduling function to improve overall response times. This study proposes to replace the current dashboard status indicator on the machine with a remote status indicator connected to an IoT platform. Both require monitoring and scheduling to be successful because people are still involved within the service chain. The serviced chain is an analogy of linking workflow steps together where step one is the machine requires service all the way to

Global Journal of Researches in Engineering (A) Volume XXIII Issue I Version I Year 2023

the last step where the machine is serviced. Each step is a link in the chain. The less links in the chain the more efficient the service will be. One step is scheduling the maintenance. This step usually requires a person to do multiple actions that could be automated.

For example, this could be changing hydraulic fluid, or replacing the core. When the machine is ready for service e.g. they are near the "replace" status automation would be able to assess when a machine needs service. After assessing service status, the machine learning algorithm could access the maintenance calendar and select an open date, time, and location for service. The algorithm could then submit the appropriate work order to obtain the parts, and the facilities required to perform maintenance. This automation could have significant operational impacts related to scheduling machines and people, parts procurement, and inventory management, optimizing facility use, and reducing overall costs associated with the maintenance function.

X. Conclusion

This empirical study proposal sought to develop the method and justification for testing Hays' (2022) theory that Operating Equipment Effectiveness would be a more effective measure for productivity with a reliability indicator. Because OpEE® is a new theory there is very little research on its use, hence why this paper focused on the large body of work on OEE. Even the research on OEE from which the OpEE® score was transferred suggested OEE did not do an adequate job of monitoring sources that effect the overall score. Other research studies on OEE suggested adding sensors and software to monitor the system to make improvements. To address this, this study proposed the research questions focusing on what other kinds of sensors could be used to develop status indicators.

The implications of this study may impact businesses in maximizing their ROI, and academia by providing a reproduceable theory for new quality status indicator innovations, research, and studies to determine its effectiveness. To achieve the maximum return on this theory and technology, this paper proposed to automate the discovery of critical components that may be used as quality status indicators through the adoption of Artificial Intelligence referred to here as a Machine Learning algorithm. Using AI could enhance the research efforts. In addition to AI usefulness in research, the automation of the maintenance function could enhance service scheduling and mitigate the human impact on overall results because a service manager is still required to monitor the IoT platform and schedule machine maintenance. With this in mind, we conclude the future is bright for the adoption and implementation of OpEE® with a reliability indicator.

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Tables

Table 1: Hays (2022) theory vs. standard maintenance practice

Indicators	Theory HCI and BLI	Standard Maintenance Hydraulic Fluid	Standard Maintenance Brush Core
Sensor	Condition Measure	Engine Hours	Visual Inspection
Sensor Value	65%	1500	10.25”
Status Logic	Change	Change Fluid	Change Core
Status Indicator	IoT Gauge	Tachometer	Measuring Tape
Maintenance Response	Check IoT Gauge Change	Check Machine Tachometer Change Fluid	Check Measuring Tape Change Core

Note: HCI is the hydraulic condition indicator. BLI is the brush life indicator. A tachometer is the equivalent of an odometer however it tracks engine hours versus engine miles. Standard maintenance practice is based on the operator’s manual for the equipment. The value of 1500 engine hours is an example and could be an interval of every 500 hours.

Figures

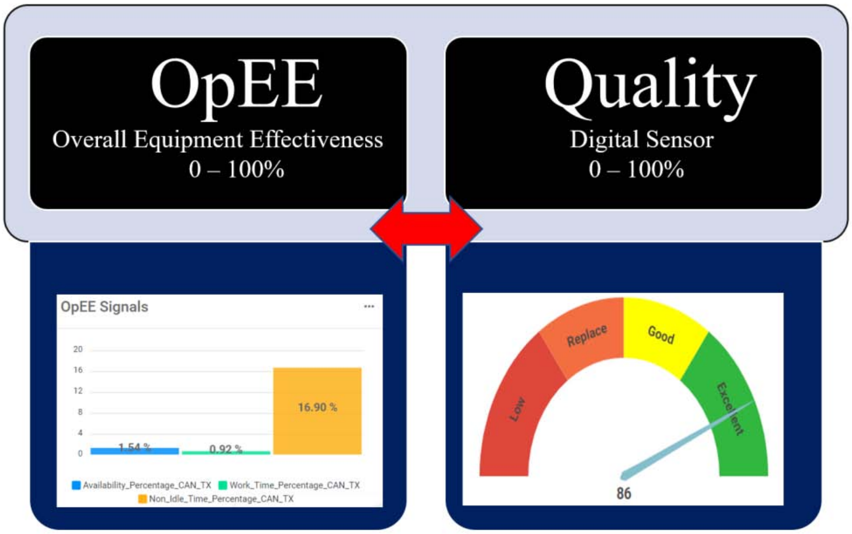

Figure 1: Hays (2022) theory OpEE® and a quality indicator

Figure 2: Front Broom Sweeper

Note: This broom sweeper's primary function is to sweep streets, performing this work when the broom is spinning. The blue broom is called the core. Core life is determined by the remaining length of the blue whiskers in the broom.

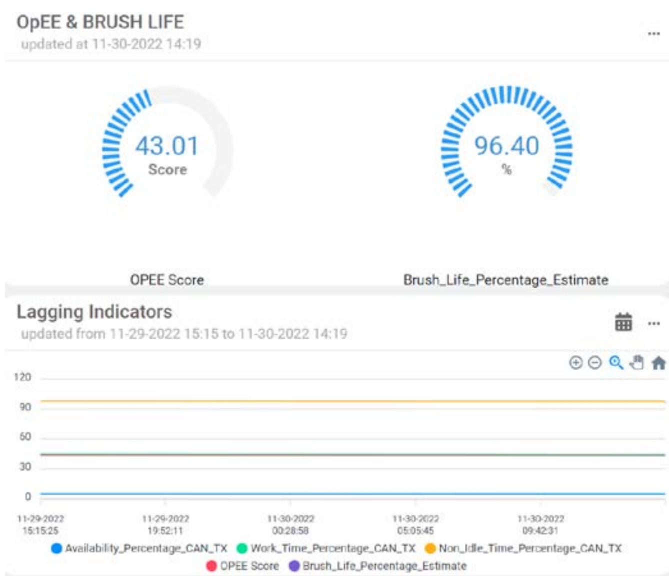

Figure 3: Application dashboard with the BLI, leading and lagging indicators

Note: This is a dashboard view on elevat-iot. The Brush_Life_Percentage_Estimate is referred to as the Brush Life Indicator (BLI) in this paper.

Figure 4: Tan Delta Hydraulic Condition Sensor

Note: This sensor is IoT-enabled, which allows for time series data and a status indicator gauge to inform maintenance when hydraulic fluid is out of specification due to condition deterioration.

Figure 5: New Core Whisker Length

Note: The new core whisker length is 16.25” radius. When the whisker length reduces to a 10.25” whisker length the core should be replaced.

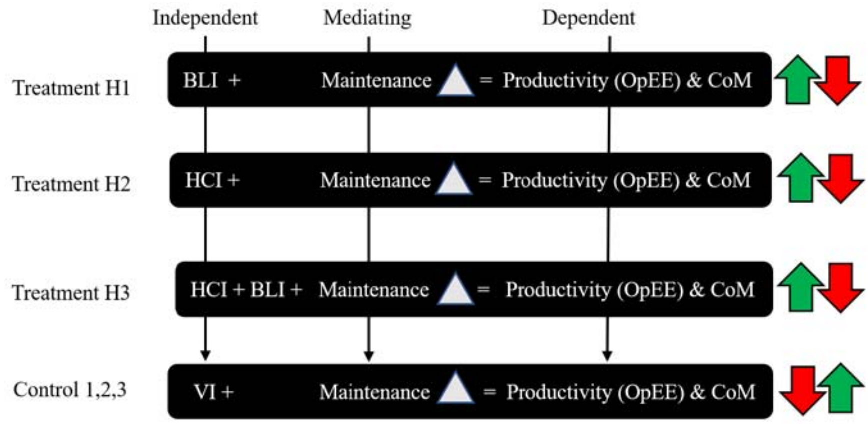

Figure 6: Research Concept Map

Note: BLI is the brush life indicator. HCI is the hydraulic condition indicator. Maintenance Δ is the time difference between when the part or fluid should be changed and when it was actually changed. Productivity is measured by the Operating Equipment Effectiveness score. CoM refers to the cost of maintenance, e.g. when a core or fluid is changed too early, on time, or too late.

Asset	OpEE	Availability	Work_Time	Non_Idle_Time	Indicator
920663	43.01	4.71%	44.10%	97.53%	96.40%
920664	18.96	5.15%	25.10%	75.53%	60.40%

Figure 7: OpEE® and Status Indicator Fleet View

Note: This spreadsheet view provides a comparison of equipment performance and remaining brush life.