AMERICAN UNIVERSITY OF BEIRUT

AN APPLICATION OF NEURAL NETWORKS IN PREDICTIVE CONSTRUCTION EQUIPMENT MAINTENANCE

by
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ABSTRACT

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Construction project equipment are subject to several types of breakdowns throughout the project duration. As a result, contractors and equipment operators are keen to establish and adopt effective equipment maintenance strategies. Adopting a maintenance strategy that minimizes the downtime of construction equipment and allows for the progression of works in a timely manner is essential to satisfy the increasingly stringent constraints set by project owners. The availability of several types of equipment data is crucial to understand the breakdown patterns of construction equipment. However, in many cases, projects operating with tight profit margins, and particularly projects in developing countries, access to such data is not always readily available. The aim of this research study is to establish a predictive maintenance framework based on machine learning (ML) that leverages historical breakdown data with the absence of information relating to the condition of the equipment and any output extracted from monitoring devices and sensors. The proposed model for accomplishing this task is the multilayer perceptron (MLP) neural network, which is applied to a real-life multi-million-dollar infrastructure project in the Middle East region. The collected data includes an equipment maintenance log database.

The results obtained are promising, with significant improvements shown in accuracy in terms of mean absolute error (MAE) compared to the baseline models: Linear Regression and Non-linear Regression. An improvement of 185% compared to the Linear Regression model, and an improvement of 26% compared to the Non-linear Regression model in the case of equipment of type excavator was witnessed. Moreover, an improvement of 173% compared to the Linear Regression model, and an improvement of 23% compared to the Non-linear Regression model in the case of equipment of type articulated haulers was witnessed. This framework could be of significant value to the industry practitioner, as it could play a role in enhancing the overall productivity of construction equipment by minimizing their breakdown rate and criticality, in turn reducing the associated equipment operating costs and expediting the rate at which works are performed.

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CHAPTER I

INTRODUCTION

On any construction project, resources are allocated as means of achieving the set project goals. Construction project resources typically consist of materials, labor, and equipment. According to Karaa and Nasr (1986), equipment and labor resources, in particular, must be efficiently employed to control the costs incurred on any project. The profit the construction contractor makes on a project is highly dependent on the utilization level of resources, particularly mechanical equipment (Edwards, Holt, & Harris, 1998). The pieces of equipment deployed on any construction job can either be owned by the contractor or, alternatively, rented from an equipment fleet owner or supplier (Siddharth, Vyas, & Pitroda, 2015). Renting equipment would provide the contractor with the benefit of obtaining the latest available equipment technologies (R. S. Lopes, C. A. Cavalcante, & M. H. Alencar, 2015). Nevertheless, in both cases, maintaining any piece of equipment would be in the interest of both the contractor and, if applicable, the equipment supplier. Contractors are interested and keen on adequately and regularly performing maintenance on their pieces of equipment that are deployed on the job being undertaken. This is done in an effort to prevent and mitigate any potential breakdowns that may occur in the piece of equipment in operation, in turn allowing the timely progression of the construction works, activities, and tasks in due time. Equipment owners and suppliers that rent out their owned pieces of equipment are likewise interested in keeping their equipment assets in optimal health to maintain their value as much as possible, preserving them for future rentals and possibly usage in some cases.

The evolving nature and the additional complexities that are gradually incorporated within construction projects have rendered construction equipment more indispensable towards a timely completion of field activities. That being said, contractors strive to ensure that their equipment fleet is at all times operational and maintained to guarantee a smooth and efficient construction process. Nonetheless, contractors are frequently faced with unexpected breakdowns in their fleet (Manikandan, Adhiyaman, & Pazhani, 2018). These sudden failures represent one of the major risk sources that are inherent in the operation of construction equipment (Rogovenko & Zaitseva, 2017). The results of a survey conducted in the United States showed that 46% of major equipment repairs are a result of unexpected failures (H. Fan, 2012). Unexpected failures are drastically detrimental to the progress of the works that are being performed by the equipment, and likewise to the project as a whole when the activity comprising the works happens to lie on the critical path. Therefore, it is essential to put forward effective maintenance strategies that mitigate the effects and minimize the chance of equipment breakdowns.

Several methods can be adopted as part of the on-site equipment maintenance strategy. Corrective maintenance is considered the most primitive form of maintenance that is performed to pinpoint and remedy an unexpected failure that has already occurred in an attempt to resume the normal operation of the failed system (Horner, El-Haram, & Munns, 1997; Stenström, Norrbin, Parida, & Kumar, 2016; Wang, Deng, Wu, Wang, & Xiong, 2014). The major downfall of this maintenance strategy is that it poses an elevated risk of witnessing unexpected breakdowns at critical points in the project, resulting in delays. Time is one of the key parameters that measure project success (Ong, Wang, & Zainon, 2018), and all project participants are invested in meeting the expected project completion date (Petruseva, Zileska-Pancovska, & Car-Pušić, 2019). From a contractor's point of view, exceeding the contractually binding project completion date due to a default committed on their part would render them liable for liquidated damages–a sum of money deducted from the contractor as compensation to the owner for the incurred delays (Assaad & Abdul-Malak, 2020).

Another common maintenance strategy for construction equipment is preventive maintenance. This strategy comprises defining a predetermined interval whereby the maintenance works are planned to take place in an attempt to minimize the chances of unexpected failures (Horner et al., 1997). The main advantages of preventive maintenance can be narrowed down to reduced unexpected breakdowns, decreased maintenance costs, and more durable repairs (Huang, 2021; Ibbs & Terveer Kenneth, 1984). However, Mann, Saxena, and Knapp (1995) argue that this maintenance strategy can in many cases demonstrate low accuracy in terms of establishing a time interval, which typically leads to over-maintenance, in turn diminishing the chance to recognize the full utilization potential of the equipment. Superfluous maintenance implies additional repair costs and unnecessary equipment downtime.

With the advancement and development of robust data analytics and machine learning (ML) tools and technologies, a newer and more effective form of maintenance has emerged: i.e., predictive maintenance (Zhang, Yang, & Wang, 2019). This maintenance approach aims to efficiently schedule maintenance tasks based on distinct categories of historical data and equipment conditions (Cavalieri, 2020; Li, Verhagen, & Curran, 2020). As previously mentioned, it is essential to adopt a reliable construction equipment maintenance strategy that minimizes unexpected failures and streamlines the maintenance cycles. The gap in the literature on data-driven predictive maintenance strategies for construction equipment introduces the need for a generic framework that targets this issue. To that end, this research work presents a generic framework based on advanced ML techniques to assist contractors in preventing or preparing for unexpected breakdowns and avoiding unnecessary maintenance. This framework aims to leverage historical equipment failure data in the absence of equipment condition and sensor data.

CHAPTER II

LITERATURE REVIEW

A. Construction Equipment Maintenance

The literature is rich with studies on construction equipment failure and maintenance (Ahamed Mohideen & Ramachandran, 2014; Clutts, 2010; Gunawardena, 1990; Jiang & He, 2020; Lopes et al., 2015; Mongomongo & Mjema, 2016; Parvari & Roodbarani, 2018; Petroutsatou & Ladopoulos, 2022; Tsado & Tsado, 2014) Mongomongo and Mjema (2016) discussed the factors (e.g., machine manufacturer, machine age, operating hours, etc.) that influence the effectiveness of construction equipment maintenance. Lopes et al. (2015) proposed a delay-time inspection model with dimensioning maintenance. Gunawardena (1990) proposed a methodology for the optimization of maintenance and the replacement of construction equipment Ahamed Mohideen and Ramachandran (2014) developed a strategic reactive maintenance approach for construction equipment using past records of construction equipment breakdowns. Clutts (2010); Tsado and Tsado (2014) studied the importance of adequate equipment maintenance to enhance the overall profitability of construction projects. Petroutsatou and Ladopoulos (2022) proposed an integrated prescriptive productivity-based maintenance system that can be applied on construction equipment. D. Edwards, G. Holt, and F. Harris (1998) analyzed the maintenance management procedures that are most commonly adopted construction equipment and construction plant. Jiang and He (2020) highlighted the importance of sensor technologies in improving construction equipment maintenance decisions. Parvari and Roodbarani (2018) studied the impact that reliability-centered maintenance has on costs that are associated with construction equipment maintenance. However, studies focusing on data driven predictive maintenance techniques to manage construction equipment are rare. The following section discusses these efforts.

B. Equipment Maintenance Using Predictive Maintenance Principles

Dong, Mingyue, and Guoying (2017) studied the application of the internet of things (IoT) on establishing a predictive maintenance system for certain pieces of coal equipment. The adequate application and operation of this system relies heavily on the availability of information gathered from numerous available sensing devices (e.g., vibration, temperature, air pressure, noise, etc.) that are already installed and running on the piece of equipment under study. Similarly, Kaparthi and Bumblauskas (2020) utilized IoT data to design a predictive maintenance model using decision tree-based machine learning (ML) techniques. This predictive maintenance model that can be used in any industrial application allows for more efficient and streamlined maintenance decision-making systems and procedures.

Markudova et al. (2021) presented an application of several machine learning techniques such as linear regression, support vector regressor, random forest regressor, etc. on Controller Area Network (CAN) bus technology to predict the next-day level of utilization for construction vehicles and the number of days to schedule the next preventive maintenance.

Marinelli, Lambropoulos, and Petroutsatou (2014) suggested a model based on artificial neural networks (ANN) to predict the working and operating condition and health of earthmoving trucks. The results of the analysis that was conducted indicated that the most statistically significant parameters that can be used to predict the condition level of a certain piece of equipment and plan for maintenance accordingly narrowed down to the number of kilometers traveled of the piece of equipment and its level of maintenance throughout its years of operation.

Q. Fan and Fan (2015); (Oloke, Edwards, & Thorpe, 2003) utilized an autoregressive integrated moving average (ARIMA) time-series model to predict the number of failures of a piece of construction equipment during certain time intervals and the time between failures.

Yip, Fan, and Chiang (2014); Zong (2017) established various machine learning models for predicting the costs that are associated with the maintenance of construction equipment.

Finally, Shehadeh, Alshboul, Al Mamlook, and Hamedat (2021) evaluated several machine learning models for predicting the residual value of heavy construction equipment.

Table 1 summarizes the relevant literature found in regard to predictive maintenance strategies of construction equipment and heavy machinery. It shows the source, the corresponding strategies adopted, and finally the data that is required to make use of the proposed strategies.

A review of relevant literature suggests the presence of a gap with establishing a predictive maintenance strategy for construction equipment. Most predictive models found require the presence of sensor and equipment condition data, which are not always available at hand. Moreover, an effective ARIMA time-series model that can accurately perform predictions requires the availability of more than 100 observations (Box & Tiao, 1975). This high number of required observations, in the context of the number of breakdowns witnessed in a piece of equipment within certain established timesteps, may also prove to be relatively difficult to obtain for a piece of equipment. These gaps in the literature highlight the need for an equipment maintenance strategy that reduces the requirements for sensing and equipment condition data. The main objectives for this research work and the aim behind it are presented in the following section.

Table 1: Predictive Maintenance Strategies of Construction Equipment Found in the Literature

Source	Strategy	Required Data
(Dong et al., 2017)	Expert evaluation of extracted equipment condition parameters	Information gathered from onboard sensing devices (IoT)
(Kaparthi & Bumblauskas, 2020)	Decision tree-based ML models	
(Markudova et al., 2021)	Several ML models	CAN bus technology monitoring data
(Marinelli et al., 2014)	ANN	Kilometers traveled and maintenance level data
(Q. Fan & Fan, 2015)	ARIMA time-series	Historical time between failure data and parameters
(Yip et al., 2014; Zong, 2017)	Several ML models	Historical maintenance costs and parameters

CHAPTER III

RESEARCH OBJECTIVES

The primary objective of this research study is to provide contractors working in the construction industry with a robust predictive maintenance framework that serves as a decision-making tool that is aimed towards minimizing the risk, magnitude, and potential ramifications that are witnessed as a result of unexpected construction equipment breakdowns. Any piece of equipment, ranging from the smallest hand-held tool to the heaviest piece of machinery, is susceptible to having breakdowns at any point throughout its operation; it is an inherent trait in any piece of equipment that cannot be avoided. When pieces of equipment that are critical to the progress of a certain activity that is either in progress or about to start fail suddenly and unexpectedly without showing any prior symptoms, signs, or notice, the progress of the activity being or planned to be worked on by the piece of equipment is severely affected; both from an activity time perspective and activity cost perspective. A comparative example for this issue is the case where only one piece of equipment is available for a certain critical activity that requires only one piece of equipment, and another where more than one piece of equipment is available for the same activity. In the former case, the magnitude associated with having an unexpected breakdown is significantly elevated compared to the latter case, as no alternate piece of equipment would be readily available to replace the one that has broken down. However, in the latter case, a breakdown in one piece of equipment would have a lower impact compared to the former case, as the other available pieces of equipment may be used to permanently or temporarily replace the piece of equipment that has broken down. A substantial number of construction activities and tasks are dependent on construction equipment. These activities and tasks can either not be accomplished at all or can in fact be accomplished but at a much slower productivity rate compared to using the recommended piece of equipment.

This framework operates by providing the construction contractor with a prediction in the form of a timestamp as to when the next theoretical breakdown is expected to occur. This available information could be used in the field to coordinate internally and at the equipment supplier level in the case of rented equipment. It also allows the contractor to preemptively schedule maintenance and prepare by mobilizing the necessary resources, spare equipment parts, and specialized maintenance teams. Additionally, proactive decisions can be made by the contractor at the equipment supplier procurement level, where they may come up with the decision to opt to procure another alternative piece of equipment as a temporary replacement to the one that will be undergoing the scheduled maintenance.

Many contractors do not enjoy the luxury of having advanced sensors and monitoring devices installed on their construction equipment fleet. This is particularly true for contractors operating in developing countries or generally contractors working with tight budgets and profit margins. Furthermore, sufficient sensor data and information pertaining to the breakdown history of the fleet are also not always readily available. The proposed framework aims to leverage historical breakdown data with the absence of information relating to the condition of the equipment and any output extracted from monitoring devices and sensors. This framework also aims to remain reliable in the case where little historical failure data is available for the equipment under study, i.e., a small number of data points to work with.

CHAPTER IV

METHODOLOGY

C. Generic Framework

The main milestone that should be achieved as part of the proposed generic framework consists of extracting a clean and organized set of all the relevant hour meter values that correspond to the natural breakdown occurrences of each equipment over a certain period of time. By providing the algorithm at hand with the available hour meter values, the model can be generated, and predictions can be made as to the expected number of operating hours until the next breakdown occurs.

Typically, the contractor employed on a construction project is responsible for handling and operating a large fleet of heavy equipment and machinery. Each piece of equipment must be studied and analyzed independently, as the failure of one piece of equipment is impertinent to the operational status of another. Therefore, it is essential that the instances of failure of each piece of equipment are separated and sorted independently; ideally through a unique equipment code allocated to each piece of equipment.

It is also vital that the hour meter values accurately represent the reality of the situation on-site. For example, if an hour meter belonging to a piece of equipment is reset at a certain point in time throughout the relevant data collection period, the necessary adjustments must be made to the hour meter values. This process is necessary to maintain the continuity of the hour meter values, as an hour meter that is reset after a breakdown does not represent the actual time that the piece of equipment has been in operation. Different data sets may elicit different data cleaning processes. However, the main aspect of the generic framework remains obtaining a list of continuous breakdown hour meter values for every piece of equipment that is under study. When the cleaned data for the pieces of construction equipment under study are available in this continuous breakdown hour meter format, the model can be run for each piece of equipment, and results can be obtained as to the time at which the next theoretical breakdown is expected to occur.

If no historical breakdown data and parameters are available to use at all, a reactive maintenance strategy would be the most effective to use. As the work progresses while implementing a reactive maintenance strategy, breakdown data would be collected, which could later be used to evolve the maintenance strategy. If both historical breakdown data and sensor and equipment monitoring data are available on hand, then a fully integrated maintenance model should be adopted. If only historical breakdown data and parameters are available for a certain piece of equipment, then either a preventive maintenance strategy or the proposed predictive maintenance strategy can be adopted.

Error! Reference source not found. illustrates a flowchart with the series of steps needed to apply the proposed framework on any other case study. The process begins by making the decision to prepare and put into effect some sort of maintenance strategy for a certain piece of equipment. After deciding on the piece of equipment to be studied, either a global equipment maintenance log for the piece of equipment can be obtained and used, or several project-specific maintenance logs can be aggregated into one and then used. After obtaining the available databases, the existing types and quality of data should be studied and organized to identify which maintenance approach is best to be adopted for the case on hand. If no historical breakdown data and parameters are available, then a reactive maintenance strategy is to be adopted. If historical breakdown data and parameters are available along with sensor and equipment monitoring data, then fully integrated maintenance models and strategies should be adopted. If only historical breakdown data and parameters are available, then either a preventive or the proposed predictive maintenance strategy should be adopted.

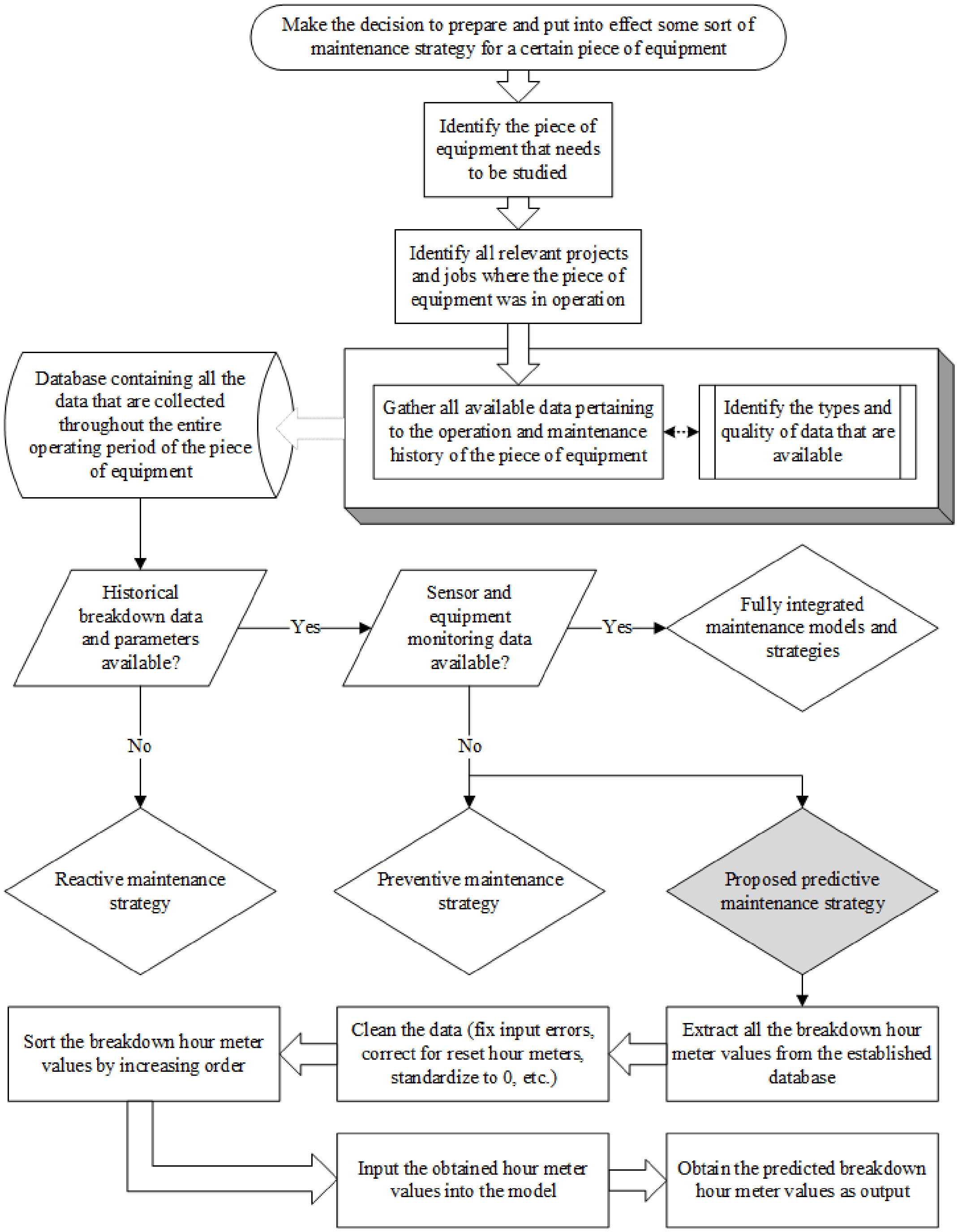

Figure 1: Generic Framework

D. Data Preparation

Data Collection

The database used in this analysis was collected from the general contractor of a multi-million-dollar infrastructure project in the Middle East region at an elevation of approximately 800 meters above sea level. It includes a corrective maintenance log spanning roughly two years for all the equipment that is being used on-site. The types of equipment that are available within the data set are presented in Table 2.

Table 2: Types of Equipment in Dataset

Equipment Category	**Brands**
Bulldozers	Caterpillar
Excavators	Caterpillar, New Holland, Volvo
Articulated Haulers	Volvo
Hydraulic Surface Drillers	Sandvik, Tamrock

The weather conditions at the project site are variable, spanning the four different seasons. The equipment maintenance log encompasses a total of 1,933 failure records for 67 different pieces of equipment, each falling within one of the following equipment categories: bulldozers, excavators, articulated haulers, and hydraulic surface drillers. The brands of these pieces of equipment are presented in Table 2. For some of the pieces of equipment that are found in the equipment maintenance log, their corresponding equipment age is available.

Most breakdown records fall under the equipment categories of excavators and articulated haulers. Therefore, the analysis will be preliminarily focused on these two categories, as there is an exceedingly small number of data points that correspond to the bulldozer and hydraulic surface driller equipment categories that contribute to the overall database.

The project manager assigned to the project from the contractor's side is keen on understanding the breakdown pattern and behavior of the available construction equipment. With the currently adopted reactive maintenance strategy and preventive maintenance strategy, the contractor is suffering from unexpected breakdowns in their equipment fleet, which are negatively affecting the progression of works in accordance with the baseline time schedule in the magnitude of several months, plenty of which attributed to the unexpected equipment breakdowns, and leading to additional costs. A large volume of construction works is dependent on the availability of the equipment required for the job, and numerous delays can be attributed to the unavailability of such equipment. As a result, the project manager is hoping to utilize the corrective maintenance log that has been established from this project to devise a more robust construction equipment maintenance strategy. By doing so, the downtime of the different pieces of equipment in the contractor's fleet can be minimized, which in turn maximizes the productivity of the equipment resources available for the contractor.

A snapshot of the records for one of the pieces of equipment found in the corrective maintenance log is shown in Table 3.

Table 3: Snapshot of the Records for One of the Pieces of Equipment

Problem Description	Corrective Action	Affected System	Failure Type	Hour meter	Start Date	Start Time	End Date	End Time
Hydraulic Oil Leakage	Change Hyd. Hose	Hydraulic System	Natural Failure	12904	07-11-17	3:15:00 AM	07-11-17	4:00:00 AM
Broken Piston	Change Piston	Hydraulic System	Natural Failure	12959	30-11-17	8:00:00 AM	30-11-17	10:45:00 AM
Broken Piston	Remove Piston from Boom	Implement	Natural Failure	12970	04-12-17	9:15:00 AM	08-12-17	7:30:00 AM
Hydraulic Oil Leakage	Change Hose	Hydraulic System	Natural Failure	12982	13-12-17	9:00:00 AM	13-12-17	11:00:00 AM
Hammer Not Functioning	Replace Switch	Electrical System	Natural Failure	13053	20-12-17	7:30:00 AM	20-12-17	9:00:00 AM
Electric Problem	Change Electric Part	Electrical System	Natural Failure	13662	06-03-18	11:45:00 AM	06-03-18	12:45:00 PM
Broken Piston	Repair Piston	Implement	Natural Failure	13696	09-03-18	7:00:00 AM	14-03-18	10:00:00 PM
Broken Jackhammer	Change Jackhammer	Implement	Natural Failure	13917	07-04-18	10:00:00 AM	07-04-18	3:00:00 PM
Broken Jackhammer	Calibration	Implement	Natural Failure	13951	10-04-18	7:00:00 AM	10-04-18	8:00:00 AM
Broken Axe	Change Axe for Chain	Implement	Natural Failure	13999	16-04-18	12:30:00 PM	16-04-18	2:30:00 PM
Hydraulic Oil Leakage	Calibration for Pump	Hydraulic System	Natural Failure	14062	20-04-18	8:00:00 AM	20-04-18	11:30:00 AM
Hydraulic Oil Leakage	Repair Hyd. Pump	Pneumatic System	Natural Failure	14138	26-04-18	7:00:00 AM	04-05-18	9:00:00 AM
Broken Boom Pipe	Welding Works	Implement	Natural Failure	14206	11-05-18	12:00:00 PM	11-05-18	7:00:00 PM
Broken Chain	Welding Works	Implement	Natural Failure	14298	19-05-18	1:00:00 PM	19-05-18	2:00:00 PM
Broken Bucket	Welding Works	Implement	Natural Failure	14328	23-05-18	7:00:00 AM	23-05-18	11:00:00 AM
Broken Chain	Welding Works	Implement	Natural Failure	14383	31-05-18	11:00:00 AM	31-05-18	12:30:00 PM
Gas Leakage from Boom	Filling Gas	Wearable Material	Natural Failure	14468	08-06-18	10:30:00 AM	08-06-18	11:00:00 AM
Broken Chain	Install New Chain	Implement	Natural Failure	14488	14-06-18	9:00:00 AM	14-06-18	10:30:00 AM
Hydraulic Oil Leakage	Change Hydraulic Hose	Hydraulic System	Natural Failure	14537	19-06-18	5:00:00 PM	19-06-18	6:00:00 PM
Hydraulic Oil Leakage	Change Seal for Hose	Hydraulic System	Natural Failure	14555	20-06-18	2:00:00 PM	20-06-18	3:00:00 PM
Hydraulic Oil Leakage	Change Hydraulic Hose	Hydraulic System	Natural Failure	14573	21-06-18	11:00:00 AM	21-06-18	1:00:00 PM

The available data for each corrective maintenance entry consists of the (1) equipment code, category, brand, and type, (2) problem description, (3) corrective action taken, (4) affected system, (5) failure type, (6) breakdown hour meter, and (7) breakdown start and end dates and times. The problem description describes the cause that led to the equipment breakdown. The corrective action performed explains the action that was taken to remedy the failure. The affected system is the system that failed and caused the breakdown. The failure type describes the nature of the witnessed failure, which can be divided into natural failures, operation failures, and accidents. The breakdown hour meter variable is the value that is observed on the hour meter at the time of breakdown. The hour meter is a device that is installed on the equipment that gauges the time the equipment has been running, i.e., having the engine turned on.

Based on the data found in the database under study, there are 14 systems within the different equipment categories that the breakdown may fall under. The aforementioned systems are the following:

- **BS (Braking System):** The braking system is responsible for applying the equipment brakes and halting the motion of the piece of equipment.
- **CS (Chassis):** The chassis is the structure/skeleton of the piece of equipment.
- **DF (Differential System):** The differential system constitutes of gears that enables the rotation of the wheels connected to the same axle at different speeds.
- **ES (Electric System):** The electric system consists of all electrical components within the piece of equipment.
- **HS (Hydraulic System):** The hydraulic system consists of all the components within the piece of equipment that are responsible for the proper operation of the hydraulic system.
- **IM (Implements System):** The implements system includes the attachments that are installed on the piece of equipment (e.g., jackhammer, bucket, etc.).
- **MT (Motor System):** The motor system is responsible for the proper operation of the engine of the piece of equipment.

- **PS (Pneumatic System):** The pneumatic system utilizes air compression to supply power to several components of the piece of equipment.
- **SI (Safety Items):** Safety items include brake lights, glass, operator chair, and other miscellaneous components that could pose a hazard to the operator and nearby workers, without affecting the actual piece of equipment in and of itself.
- **SS (Steering System):** The steering system is responsible for the proper steering and maneuvering of the piece of equipment by the operator.
- **SU (Suspension System):** The suspension system is responsible for connecting the axles and wheels of a piece of equipment to its chassis.
- **TR (Transmission System):** The transmission system is responsible for transferring the power that is generated by the motor of the piece of equipment to its wheels.
- **TY (Tires):** The tires are the wheels
- **WM (Wearable Materials):** The wearable materials are the items that are installed on the piece of equipment that are, as part of normal operation, subject to wear and tear, and require regular replacement.

Preliminary Data Analysis

A preliminary data analysis was performed in an effort to obtain a better understanding of the nuances accompanying the available data. This analysis plays a significant role in further exploring the data, in addition to producing important observations that are inherent within the data. To that end, the following preliminary data analysis in this section is conducted.

Figure 2 represents the frequency of failures within each affected system. It shows how many times a breakdown in the different pieces of equipment has occurred as a result of a failure in the particular observed system. The frequency distribution bar graph clearly shows that the top three most frequent failure types are those involving the hydraulic system, followed by equipment implements, and finally the motor system. The average breakdown frequency of all systems is calculated to be 138. In percentage form, as shown in Figure 3, failures associated with the hydraulic system account for 41% of total failures, while those associated with the equipment implements and motor system account for approximately 27% and 14% of total failures, respectively.

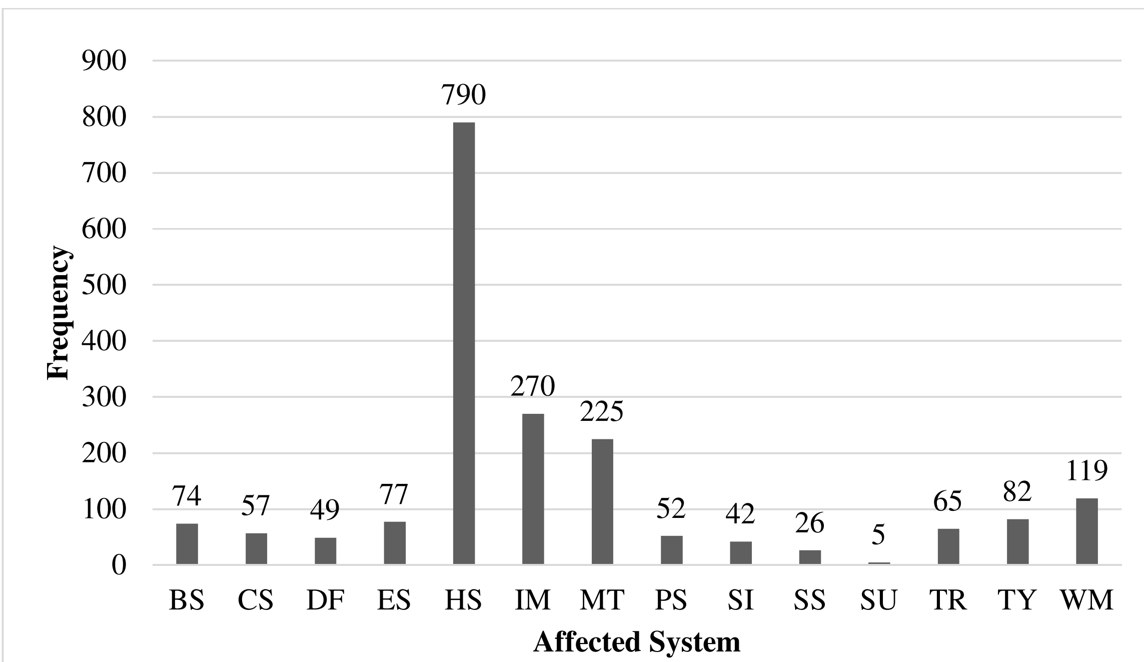

Figure 2: Failure Frequency According to Affected System

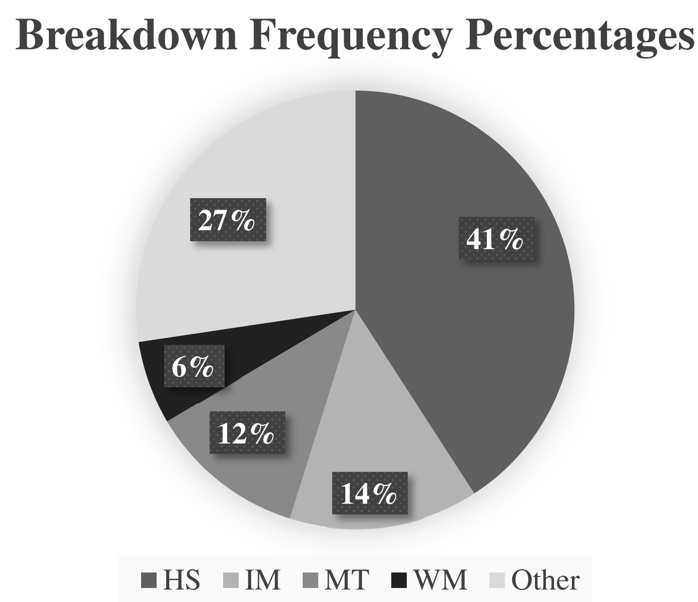

Figure 3: Breakdown Frequency Percentages

Figure 4 represents the average breakdown duration within each affected system. The obtained graph clearly indicates that the three failures that are associated with the highest breakdown durations are those involving the steering system, followed by the motor system, and with a slightly lesser duration than the latter, the transmission system. The average breakdown duration of all systems is calculated to be 94 hrs.

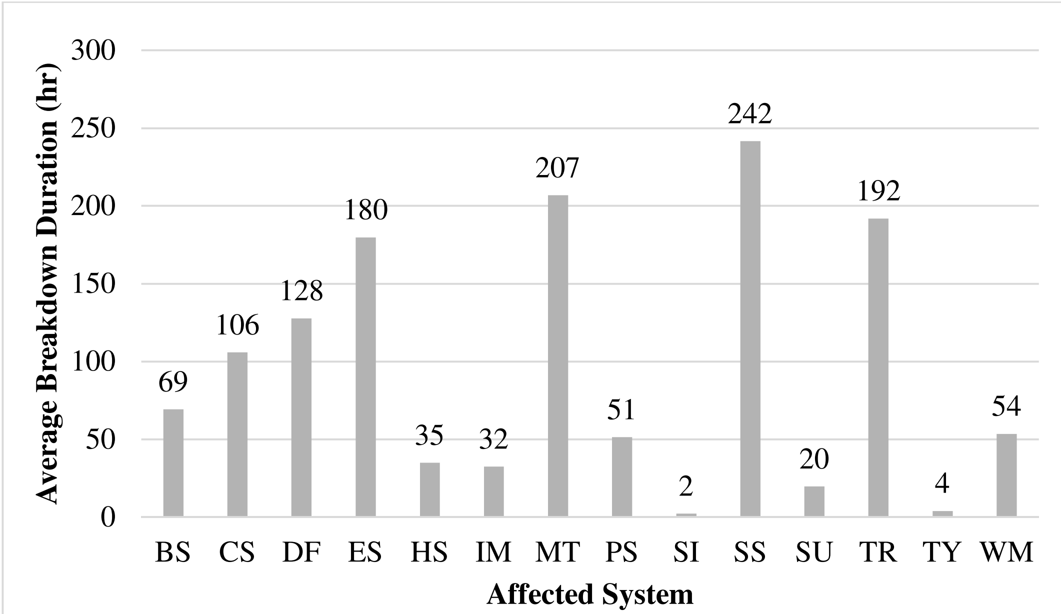

Figure 4: Average Breakdown Durations According to Affected System

After combining both Figure 2 and Figure 4 and adding the previously mentioned average values for both parameters in a single demonstrative represented by **Figure 5**, the following major observations can be made graphically:

- There is a significant gap between the breakdown frequency and average breakdown duration of the hydraulic system. Even though this system contributes to the highest number of breakdowns, its associated breakdown duration is significantly below the average. This observation implies that although the hydraulic system is prone to breakdowns more than any of the other systems that are present, these failures are typically minor in nature and do not cause a long downtime relative to the other systems.
- Unlike all other systems, the motor system, as can be observed in the bar chart shown in Figure 5, is the only one whose breakdown frequency and average breakdown duration values are both above their corresponding average values

for all systems. This observation signifies that the motor system may be considered among the most critical systems. In other words, failures in the motor system are likely to happen more often than other systems, and its associated downtime is considerably high relative to the other systems.

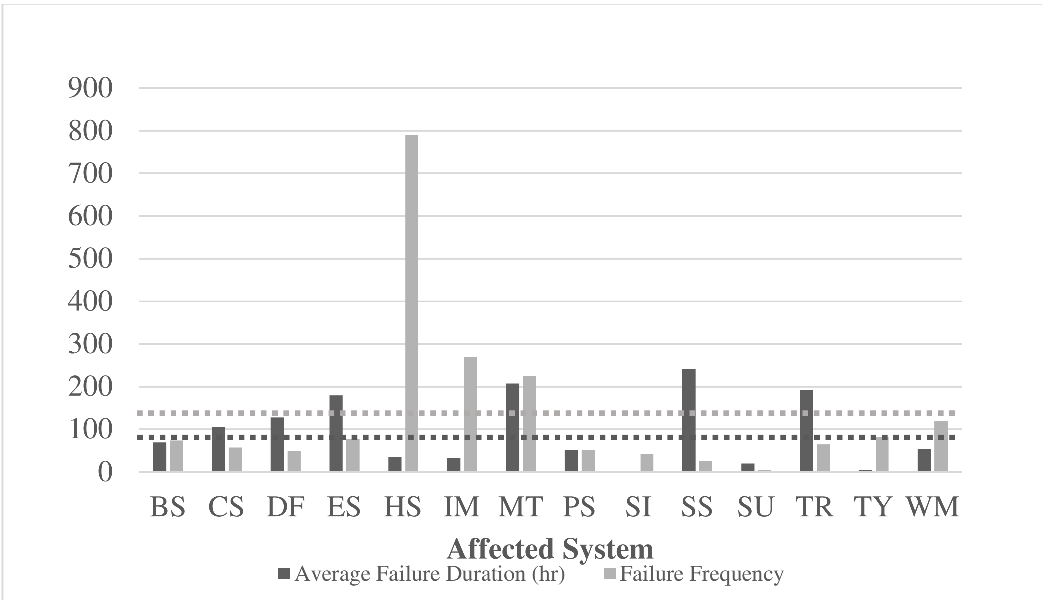

Figure 5: Frequency and Average Breakdown Durations According to Affected System

To numerically establish the level of failure criticality for each of the existing systems, the number of breakdowns and the average breakdown duration values corresponding to each system are extracted from the existing database, and the results are summarized and tabulated in Table 4.

Table 4: Number of Breakdowns and Average Breakdown Durations for Different Systems

System	Number of Breakdowns	Average Breakdown Duration (hr)
BS	74	69
CS	57	106
DF	49	128
ES	77	180
HS	790	35
IM	270	32
MT	225	207
PS	52	51
SI	42	2
SS	26	242
SU	5	20
TR	65	192
TY	82	4
WM	119	54

When the issue of failure criticality is addressed, three types of criteria can be established in as far as measuring the level of failure criticality, and consequently, identifying the equipment systems that are considered the most critical to the operational status of the piece of equipment under study. The identified criteria are the following:

- **Breakdown Frequency:** This criterion represents the total number of breakdowns that are attributed to a certain system during a specific period. It can be directly obtained from the breakdown dataset by counting the number of failure instances that occurred in the system under study. For example, if there are 17 failures that have the affected system as "Hydraulic system", the breakdown frequency in this case is 17.
- **Average Breakdown Duration:** This criterion represents the average breakdown duration corresponding to the breakdowns attributed to a certain system during a specific period. It can be calculated by averaging the breakdown duration values for the failures that occurred in the system under study. The breakdown duration for each failure can be obtained by subtracting the breakdown start data and time from the breakdown end data and time.
- **Weighted Breakdown Duration:** This criterion can be calculated by multiplying the breakdown frequency by the average breakdown duration of each system. This criterion, compared to the breakdown frequency and average breakdown duration, is the most representative, as it combines both the frequency and duration aspects of the breakdowns that have occurred throughout the project.

Since the weighted breakdown duration value takes into account both the failure frequency and average breakdown duration, this criterion is selected for the process of identifying the most critical systems that constitute the construction equipment. A summary of the weighted breakdown duration values representing the different systems can be found in Table 5 below. The average weighted breakdown duration for all systems is calculated to be 10,179 hours.

Table 5: Weighted Breakdown Duration of Different Systems

System	Weighted Breakdown Duration (hr)
BS	5106
CS	6042
DF	6272
ES	13860
HS	27650
IM	8640
MT	46575
PS	2652
SI	84
SS	6292
SU	100
TR	12480
TY	328
WM	6426

An analysis of the above obtained data is performed. A bar chart illustrating the values provided in Table 5 is shown in Figure 6.

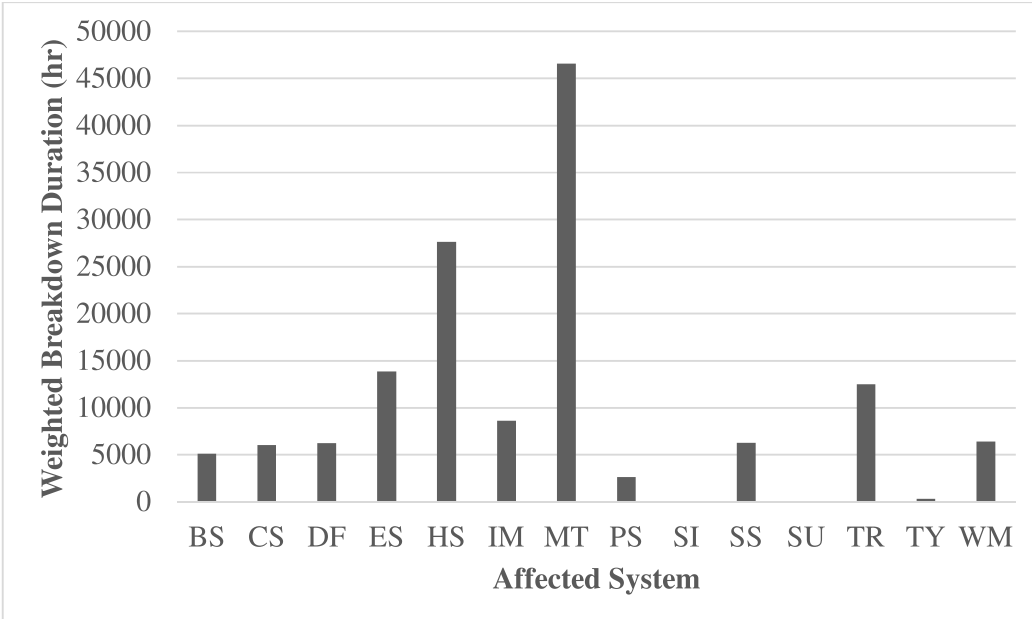

Figure 6: Weighted Breakdown Duration According to Affected System

The main and most important observations that can be inferred from **Figure 6** and the values shown in **Table 5** are the following:

- The motor system is undoubtedly the most critical system among all other systems, with a weighted breakdown duration of 46,575 hours. For reference, the second most critical system is the hydraulic system, having an average weighted breakdown duration of 27,650 hours. Moreover, the average weighted breakdown duration for all systems is 10,179 hours, with a standard deviation of 12,696 hours. Therefore, the weighted breakdown duration of the motor system is roughly four standard deviations above the average for all systems, which further bolsters the aforementioned observation.

- The safety systems, in terms of frequency of failure and associated downtime, is the least critical system, having a meager weighted breakdown duration of 84 hours, preceded by the suspension system and the tires system, which have a weighted breakdown duration of 100 hours and 328 hours, respectively.

Data Cleaning

To make effective use of the data, it must first be cleaned. Cleaning the data is essential in the process of developing any model. To obtain a dataset that can be effectively worked with and analyzed, the following adjustments to the data were made:

- The data were sorted according to the equipment code. Every piece of equipment is represented by a unique equipment code that is used as an equipment identifier. This step allows for a clearer and more organized representation of the breakdown cycle of each equipment.
- All failures of the type "Operation Failure" and "Accident" were removed from the dataset. In this dataset, operation failures are failures that are caused due to a certain misuse in operation on the part of the personnel operating the equipment at the time of failure, while accidents are the instances where the equipment are involved in physical accidents. These types of breakdowns cannot be integrated as a part of the predictive model, as they are highly dependent on the proficiency of the personnel that are operating the piece of equipment. Hence, these failures do not represent the actual health and natural breakdown pattern of the different pieces of equipment. Consequently, the breakdowns that are used are those belonging to the type "Natural Failure",

which are the failures that naturally occur as a result of the normal operation of the equipment.

- The data for each piece of equipment was extracted and placed on a unique worksheet. The result is a worksheet for every piece of equipment consisting of its failure data.
- There exist several instances where the hour meter installed on a piece of equipment was replaced after conducting the corrective maintenance following a breakdown. In these cases, the hour meter values are reset to 0. To account for this and to maintain a continuous and logical hour meter reading, the hour meter value prior to the reset is added to that after the reset, and the following values are adjusted accordingly.
- The hour meter values for the equipment under study were standardized. This was done by subtracting all hour meter readings of specific equipment by the first reading. By doing so, all equipment hour meter readings should start from a value of 0, making them easier to understand.

The methodology followed for cleaning the data is summarized in Figure 7.

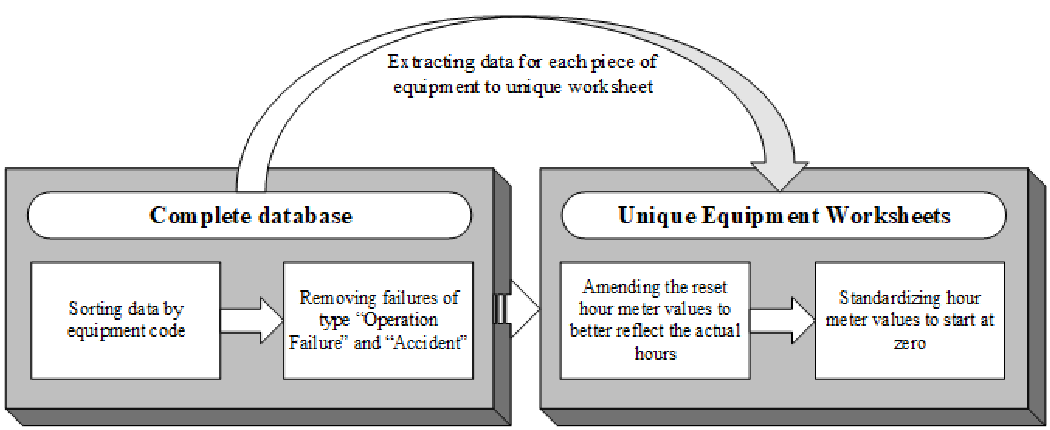

Figure 7: Summary of Data Cleaning Methodology

E. Model Generation

After the data was successfully cleaned, the model generation process was initiated. As previously mentioned, the overall objective of this work is to provide contractors working in the construction industry with a robust predictive maintenance framework that serves as a decision-making tool that is aimed towards minimizing the risk, magnitude, and potential ramifications that are witnessed as a result of unexpected construction equipment breakdowns. This framework operates by providing the construction contractor with a prediction in the form of a timestamp as to when the next theoretical breakdown is expected to occur.

The problem on hand is a univariate regression problem, where the breakdown hour meter is regressed against the indices corresponding to the failure occurrence. A univariate regression approach was adopted instead of a time-series one since the available models for the latter (e.g., ARIMA) typically require a large number of data points for each piece of equipment, which might not always be available. If the timestep of the time-series model was decreased to simultaneously increase the total number of data points for a certain piece of equipment, then there would be numerous instances where there would be no failures throughout a certain timestep, which would negatively affect the results and the applicability of the model. Conversely, if the timestep was increased to prevent this issue from happening, then there would be very few data points for each piece of equipment to work with, which would not be nearly enough to run the model. Additionally, the classification approach was disregarded since the nature of the problem (i.e., predicting a continuous hour meter value) does not elicit a classification type approach.

Independent Variables

A studied alternative consisted of including the failed system in the regression analysis as a categorical variable, making it a multiple regression problem. However, the expected time between breakdowns is not dependent on the previously affected system. All systems are independent, so the failure of one system does not preclude that the following failure is going to be of the same system.

Moreover, another studied alternative that was considered was including the equipment age and/or the operation age in the model. This effort and the reason these parameters were not included is discussed in the upcoming Section 5.1: Equipment Age. Therefore, it was decided that the affected system is not to be included as a variable, leaving the failure index as the only independent variable. The failure index is the incremental number that is assigned to each instance of failure (e.g., for the second failure instance, the corresponding failure index is 2).

Dependent Variables

One alternative was to include the affected system as another dependent variable in the prediction model, making it a multivariate regression problem. However, like all models, which are inherently prone to a certain degree of error, there always remains the chance that the predictions made by the model are inaccurate as to the system that is expected to fail after a certain time interval. In that case, performing maintenance only on the predicted system would be redundant and detrimental to the objective of this framework. When maintenance is performed only on a system that is expected to fail but another does, an excessive amount of time would be spent on two sides: performing the predictive maintenance activity and repairing the equipment after it breaks down.

A sample of the data that was used to generate the models for a single piece of equipment is shown in **Table 6**.

Table 6: Sample Cleaned Data Used for Model Generation

Failure Index	Failure Hour Meter (hr)
1	0
2	121
3	500
4	536
5	557
6	595
7	613
8	641
9	654
10	673
11	714
12	811
13	863
14	902
15	944
16	979
17	1056
18	1130
19	1203
20	1222
21	1237
22	1240
23	1325
24	1428
25	1516
26	1563
27	1619
28	1693

All the data for the different equipment that is used as input for the models has the same format as that shown in Table 6.

F. Model Selection

Three models were taken into consideration throughout this research study: Linear regression, non-linear regression, and the neural network based multilayer perceptron (MLP) regression. The first two models (linear regression and non-linear regression) serve as the primary baselines that are used to assess the relative performance of the MLP model on a comparative basis. The underlying reasons for selecting these two models as the baselines can be summed up by the following points:

- The linear regression model is based on the assumption that the breakdown frequency of the construction equipment follows a linear trend and is independent of its running time. In other words, the time the equipment has been up and running does not affect the breakdown frequency.
- The non-linear regression model is based on the assumption that the breakdown frequency of the construction equipment follows a non-linear trend and does depend on its running time. As the piece of construction equipment is used continuously, the chance of witnessing a breakdown increases correspondingly due to the sustained wear and tear depreciation of the equipment.

As for the MLP regression model that is being proposed, the main reason for selecting it is its ability to make accurate predictions through learning the relationships between data that are linear and those that are non-linear, in addition to its ability to constantly be fed with new information and data regarding the observed breakdown and maintenance patterns. In other words, the MLP regression model combines the advantages that are inherent within linear regression on one side, and non-linear regression on the other.

CHAPTER V

RESULTS

To prepare the model for running, all the steps previously mentioned in the implementation methodology section are followed. After all the needed data are successfully obtained, cleaned, and prepared to be used in the model, the model can now be fully initialized with all the required input. The results were obtained by running the model on seven excavators and seven articulated haulers. Three runs were performed for each available piece of equipment, with each run representing the MLP model, Linear Regression model, and Non-linear Regression model. A detailed presentation of the results obtained is performed for one piece of equipment (E03), and a summary and comparison of all the results that correspond to the other pieces of equipment analyzed follows.

G. Equipment Age

The effects of the equipment age and whether they can be incorporated into the model or not were studied. Every piece of equipment exhibits (1) a time age and (2) and operation age. The time age is the date that the equipment was manufactured in, while the operation age is the time that the piece of equipment has been in operation for. To study whether it is necessary to include these parameters in the model, a Pearson correlation test was conducted on the statistical computing and graphics software R between time age and average time between failure (TBF), and between operation age and average TBF.

The average TBF was calculated by averaging the difference of the consecutive breakdown hour meter values. From this test, Pearson's r, also known as the Pearson product-moment correlation coefficient (PPMCC), is obtained. This value represents whether there is a low, moderate, or high correlation between the different parameters that are evaluated. Table 7 summarizes the significance of different values of Pearson's correlation coefficient (r).

Table 7: Pearson's Correlation Coefficient (Selvanathan, Jayabalan, Saini, Supramaniam, & Hussain, 2020)

Scale of correlation coefficient	Value
$0 < r \leq 0.19$	Very Low Correlation
$0.2 \leq r \leq 0.39$	Low Correlation
$0.4 \leq r \leq 0.59$	Moderate Correlation
$0.6 \leq r \leq 0.79$	High Correlation
$0.8 \leq r \leq 1.0$	Very High Correlation

Time Age

For some of the pieces of equipment that were studied, the manufacturing date (year if make) was available. This data was available for six excavators and seven articulated haulers. The data that was used to conduct the Pearson correlation test is represented in Table 8.

Table 8: Equipment Time Age vs. Average TBF

	Year of Make	Equipment Age (Year)	Average TBF
E03	2009	11	52
E07	2008	12	80
E13	2010	10	51
E16	2009	11	54
E21	2010	10	58
E27	2010	10	74
E28	NA	NA	56
H03	2000	20	62
H05	1997	23	91
H06	1997	23	72
H07	1997	23	92
H08	1998	22	121
H09	1999	21	83
H10	2000	20	64

The results of the Pearson correlation test that were obtained are as follows:

- Excavators: $r = 0.39$
- Articulated Haulers: $r = 0.42$

According to **Table 7**, there is a low correlation between the equipment age and average TBF for the excavators, and a moderate correlation between the equipment age and average TBF for the articulated haulers. However, the obtained Pearson coefficient correlation r values for both types of equipment are positive, which indicates a positive correlation between equipment time age and average TBF.

This observation is counter-intuitive, since if there were to be a correlation between these two parameters, this correlation should be negative (i.e., if the equipment is older, then it is expected to fail more frequently, hence a lower TBF). Therefore, this indicates that other factors such as equipment motor temperature, pressure, quality of parts, equipment operation, and other factors that cannot be monitored in this case may have come into play, affecting the time between failures of each equipment. As a result, the equipment time age has not been used as a parameter in the predictive model.

Operation Age

The operation age for seven excavators and seven articulated haulers was inferred from the breakdown hour meter values that are available in the maintenance log database. The data that was used to conduct the Pearson correlation test is represented in Table 9.

Table 9: Equipment Operation Age vs. Average TBF

Equipment	Operation Age (hr)	Average TBF
E03	12904	52
E07	14885	80
E13	11928	51
E16	3537	54
E21	12139	58
E27	11649	74
E28	9803	56
H03	24839	62
H05	28708	91
H06	24169	72
H07	26125	92
H08	26388	121
H09	22055	83
H10	2589	64

The results of the Pearson correlation test that were obtained are as follows:

- Excavators: r = 0.50
- Articulated Haulers: r = 0.34

According to **Table 7**, there is a moderate correlation between the equipment age and average TBF for the excavators, and a low correlation between the equipment age and average TBF for the articulated haulers. However, similar to the values obtained for the equipment time age correlation test, the obtained Pearson coefficient correlation r values for both types of equipment are positive, which indicates a positive correlation between equipment operation age and average TBF. This observation is counter-intuitive, since if there would be a correlation between these two parameters, this correlation should be negative (i.e., if the equipment is older, then it is expected to fail more frequently due to equipment depreciation and wear and tear, hence a lower TBF). Therefore, this indicates, similar to the observations made from the equipment time age correlation test, that other factors that cannot be monitored in this case may have come into play, affecting the time between failure of each equipment. As a result, the equipment operation age has also not been used as a parameter in the predictive model.

H. MLP Model

As previously mentioned in the methodology, the problem on hand is a univariate regression problem, where the breakdown hour meter is regressed against the indices corresponding to the failure occurrence. The detailed preliminary results of the MLP model are obtained for one excavator (E03). The same approach for obtaining the model results for the different models of this particular piece of equipment is adopted in obtaining the model results for the remaining pieces of equipment. The evaluation metric that is used for this model is the mean absolute error (MAE). In this case, the MAE provides an accurate and discernable indication as to the differences between the predicted and actual breakdown hour meters. The obtained MAE values can be directly interpreted as the time difference by which the predicted breakdown time is off from the actual breakdown time. The root mean squared error (RMSE) can also be used as the performance metric, but it lacks the aforementioned advantages of the MAE performance metric. Table 10 represents these results in terms of the difference between the predicted breakdown hour meter values and the actual breakdown hour meter values.

Table 10: MLP Predicted Values vs. Actual Values for Excavator E03

E03 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	12	55	-43
2	39	66	-27
14	1433	1424	-9
16	1543	1564	-21
18	1618	1633	-15
21	1725	1751	-26
24	1831	1880	-49
25	1867	1893	-26
26	1900	1913	-13
27	1917	1914	3
33	2019	2027	-8
38	2103	2083	20
39	2136	2095	41
45	2434	2501	-67
51	2741	2876	-135
53	2843	2915	-72
54	2894	2925	-31
57	3048	3026	22

The MAE obtained for this model is 35 hours. Considering the fact that no equipment data other than the historical breakdown hour meter values are available, the results obtained are promising. The largest error is witnessed for the prediction at index 51, which underestimates the actual breakdown hour meter value by 135 hours (about 5 and a half days). A boxplot representing the error distribution for the breakdown hour meter values can be viewed in Figure 8. This distribution, in practice, represents the difference between the actual time that the breakdown has occurred at and when it was predicted through the MLP model to occur.

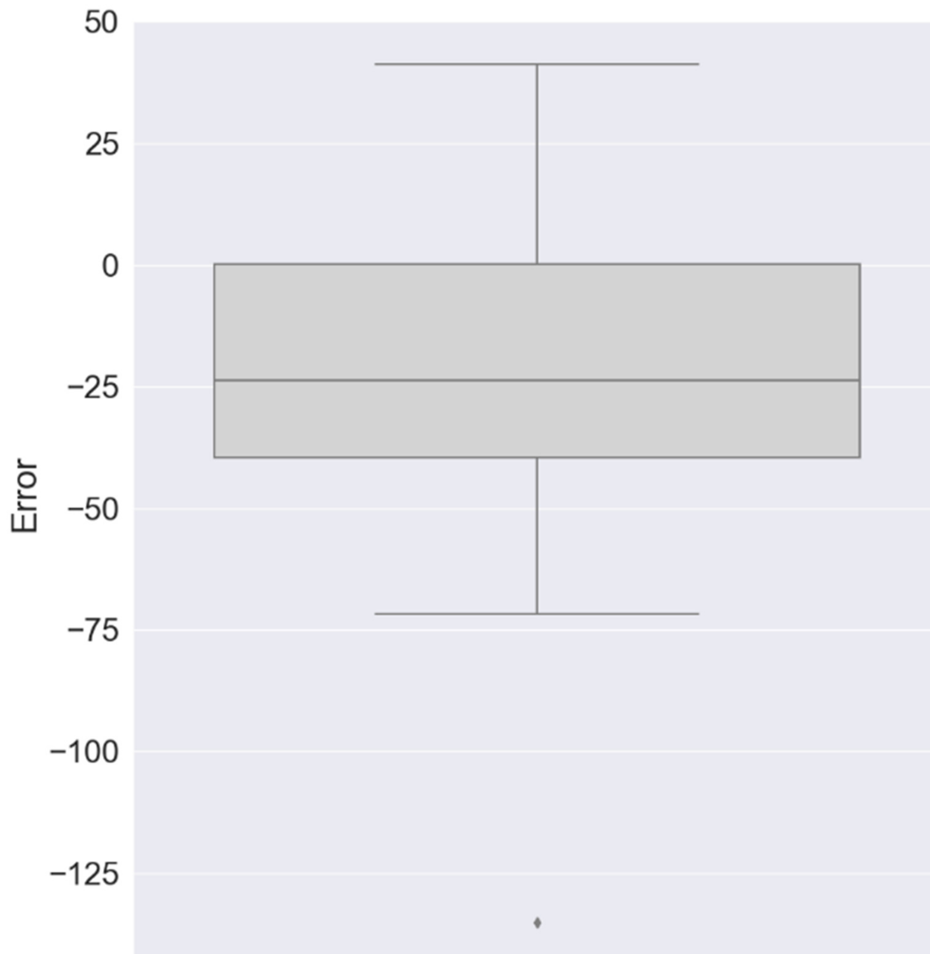

Figure 8: Boxplot Representing Error Distribution for Excavator E03

I. Linear Regression Model

Similarly, for the Linear regression model, the breakdown hour meter is regressed against the indices corresponding to the failure occurrence. The results of the Linear Regression model for excavator E03 are represented in **Table 11**.

Table 11: Linear Regression Predicted Values vs. Actual Values for Excavator E03

E03 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	625	55	570
2	668	66	602
14	1186	1424	-238
16	1272	1564	-292
18	1359	1633	-274
21	1488	1751	-263
24	1618	1880	-262
25	1661	1893	-232
26	1704	1913	-209
27	1747	1914	-167
33	2006	2027	-21
38	2222	2083	139
39	2265	2095	170
45	2524	2501	23
51	2783	2876	-93
53	2869	2915	-46
54	2912	2925	-13
57	3042	3026	16

The MAE obtained for the Linear Regression model above is 202 hours, which is considered remarkably high, especially when compared with that obtained from the MLP model. The largest errors occur at indices 1 and 2, where the predicted breakdown hour meter values are significantly overestimated compared to the actual breakdown hour meter values.

J. Non-linear Regression Model

Finally, for the Non-linear regression mode, the breakdown hour meter is also regressed against the indices corresponding to the failure occurrence. The results of the Non-linear Regression model for excavator E03 are represented in Table 12Table 12.

Table 12: Non-linear Regression Predicted Values vs. Actual Values for Excavator E03

E03 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	43	55	-12
2	194	66	128
14	1442	1424	18
16	1558	1564	-6
18	1654	1633	21
21	1765	1751	14
24	1843	1880	-37
25	1864	1893	-29
26	1883	1913	-30
27	1901	1914	-13
33	1998	2027	-29
38	2118	2083	35
39	2150	2095	55
45	2422	2501	-79
51	2795	2876	-81
53	2913	2915	-2
54	2963	2925	38
57	3053	3026	27

The MAE obtained for the Non-linear Regression model above is 36 hours, which is approximately equal to that obtained from the MLP model. The largest errors occur at indices 1 and 2, where the predicted breakdown hour meter values are significantly overestimated compared to the actual breakdown hour meter values.

K. Model Result Comparison

The same approach for obtaining the model results for the different models of excavator E03 was adopted in obtaining the model results for the remaining pieces of equipment. After all simulations have been run on the available breakdown data for the different pieces of equipment, the results of the three models per equipment were obtained. The obtained results are shown in the Appendix.

Table 13 below represents the MAE values obtained for the different pieces of equipment belonging to the excavator type.

Table 13: MAE Values of Different Models for Excavators

Model	E03	E07	E13	E16	E21	E27	E28
MLP	35	80	62	56	66	106	29
Linear Regression	202	199	106	105	156	145	328
Non-linear Regression	36	89	76	57	88	96	103

Table 14 below represents the MAE values obtained for the different pieces of equipment belonging to the articulated hauler type.

Table 14: MAE Values of Different Models for Articulated Haulers

Model	H03	H05	H06	H07	H08	H09	H10
MLP	73	67	76	59	142	59	37
Linear Regression	75	156	188	157	151	329	160
Non-linear Regression	62	81	84	76	136	104	87

From the MAE values obtained and represented in Table 13, it is clear that the prediction accuracy of the MLP model in the case of excavators surpasses both those of the Linear Regression model and the Non-linear Regression model. The MLP model surpasses the performance of the Linear Regression model in all instances. Moreover, it performs better than the Non-linear regression model for all but one excavator (E27), where the resulting MAE of the MLP model is 106, compared to 96 for the Non-linear Regression model. By averaging the MAE results for the different models across the available excavators, the obtained average MAE results are as follows:

- **MLP model:** 62 hours
- **Linear Regression model:** 177 hours
- **Non-linear Regression model:** 78 hours

From the values obtained, the MLP model displays a prediction performance improvement of 185% compared to the Linear Regression model, and an improvement of 26% compared to the Non-linear Regression model in the case of equipment of type excavator.

Similarly, in the case of articulated haulers, as shown in Table 14, the MLP model also performs better than the Linear Regression Model and the Non-Linear Regression

Model, since the MLP model also resulted in the lowest MAE value compared to the other models. The obtained average MAE results are as follows:

- **MLP model:** 73 hours
- **Linear Regression model:** 174 hours
- **Non-linear Regression model:** 90 hours

From the values obtained, the MLP model displays a prediction performance improvement of 173% compared to the Linear Regression model, and an improvement of 23% compared to the Non-linear Regression model in the case of equipment of type articulated haulers.

Significance Test

To verify whether the MLP model improvement in accuracy compared to Non-Linear Regression is significant, a one-tailed t-test was conducted between the MLP model results and those of the Non-linear regression model for each piece of equipment. A significance level of 5% is adopted, and the hypotheses studied are as follows:

- Null Hypothesis (H_0): The MLP model does not perform significantly better than the Non-linear Regression model.
- Alternate Hypothesis (H_a): The MLP model performs significantly better than the Non-linear Regression model.

The results obtained for the different pieces of equipment are as follows:

1) **Significant Improvement (p-value < 0.05):** E07, E13, E28, H05, H09, H10
2) **Non-significant Improvement (p-value > 0.05):** E03, E16, E21, H05, H06, H07

3) **No improvement (Non-linear Regression lower average MAE):** E27, H03, H08

From the results obtained, the MLP model shows significant improvement compared to the Non-linear Regression in 43% of the cases, non-significant improvement in 38% of the cases, an no improvement in 19% of the cases.

L. Model Usage

The results obtained confirm that the performance of the MLP model in terms of predicting the breakdown time of a piece of equipment is better than the baseline models used. After setting up the model, predictions in the form of the breakdown hour meter corresponding to the next failure could be made. To perform a prediction, the failure index that corresponds to the next theoretical breakdown that succeeds the most recent breakdown that has occurred to the piece of equipment under study is used as input for the model.

After the predicted hour meter value that corresponds to the next breakdown expected to occur is calculated by the model, a maintenance timeframe that takes into consideration the predicted breakdown hour meter, in turn the working duration until the next breakdown, would be established. In other words, the predicted output indicates the time at which the piece of equipment is expected to break down in the future. From this value obtained, the project manager on the project would be able to schedule and perform a maintenance task on the piece of equipment at around the predicted hour mark of equipment operation. This maintenance would occur primarily for the top three most critical systems that were previously established: motor system, hydraulic system, and electrical system.

The expected breakdown value that is provided by the model could be of vital importance in terms of the decisions that are made by the contractor. The main benefit would be implementing a robust proactive approach in the field. This available information could be used in the field to coordinate internally and at the equipment supplier level in the case of rented equipment. For example, if five excavators are needed for a critical activity that will start next week, and only four are being used for the predecessor activity, the equipment that will fail the soonest according to the model would undergo a maintenance before the critical activity starts to prevent witnessing a breakdown throughout the activity. The project manager can also opt to procure a temporary substitute for the piece of equipment while the maintenance works are being performed. The primary aim of the proposed model is to establish a timestamp corresponding to the next theoretical breakdown that is expected to occur. By running the model on the different pieces of equipment that will be assigned to the critical activity, the piece of equipment that is expected to witness a breakdown the soonest according to the model would be sent for maintenance before the activity starts to reduce the risk of it failing mid-activity. An example for this prediction is given from excavator E03 from the project dataset. After the model is run on this excavator, an hour meter value of 3151 hr is obtained. The last witnessed breakdown had a breakdown hour meter value of 3059 hr. Therefore, this piece of equipment is expected to break down at 92 hours of operation after the last witnessed breakdown. These steps would be applied to the different pieces of equipment as previously mentioned, and the equipment that is expected to fail the soonest within the next critical activity would have a maintenance scheduled and performed.

In addition, a proactive approach can also be implemented in terms of procuring a maintenance team on-site that is equipped with the necessary maintenance tools at the time at which the breakdown is expected to occur. In case the equipment breaks down, the presence of a maintenance team would mitigate the severe repercussions that would have emanated if said team was not prepared and on the field.

After the maintenance is successfully performed, the hour meter value that is observed at the time of maintenance is used as additional input into the model to perform another prediction down the road.

CHAPTER VI

CONCLUSION

In conclusion, there is no doubt that heavy construction equipment is an essential resource in every construction project. As the complexity of construction projects all over the world is increasing, the reliance on heavy equipment to get project activities and tasks done is increasing. However, any piece of equipment, from the smallest tool to the biggest piece of machinery, is inherently prone to breakdowns and failures. Therefore, it is vital for contractors to ensure that their available pieces of equipment, whether owned or rented, are consistently and reliably maintained in an effort to prevent or mitigate these unexpected breakdowns. Equipment maintenance strategies such as reactive maintenance and preventive maintenance are most commonly adopted among contractors and equipment fleet owners. Unfortunately, these strategies are associated with several setbacks, including but not limited to (1) an increase in the risks of unexpected breakdowns, (2) a lack of preparation for an unexpected breakdown, and (3) in some circumstances, over-maintenance. All these setbacks are associated with an increase in total project costs and possible delays in the project completion date that is agreed upon by the different project entities. Therefore, it is clear that a robust construction equipment maintenance strategy should be adopted to decrease maintenance costs and delays, consequently maintaining the baseline project cost and duration, especially in the absence of sensor and equipment condition data.

To that end, this paper proposed a predictive construction equipment maintenance framework based on MLP neural networks that aims to achieve these objectives. The devised model was tested on several excavators and articulated haulers, and then compared to the results of two baseline models: Linear Regression and Non-linear Regression. An improvement of 185% compared to the Linear Regression model, and an improvement of 26% compared to the Non-linear Regression model in the case of equipment of type excavator was witnessed. Moreover, an improvement of 173% compared to the Linear Regression model, and an improvement of 23% compared to the Non-linear Regression model in the case of equipment of type articulated haulers was witnessed. From the results obtained, it is clear that that the MLP model outperforms the base models and is more robust in predicting the time between the most recent failure or maintenance that was witnessed in a piece of equipment and the next theoretical breakdown. This framework could be of significant value to the industry practitioner, as it could play a role in enhancing the overall productivity of construction equipment by minimizing their breakdown rate and criticality, in turn reducing the associated equipment operating costs and expediting the rate at which works are performed.

As for the limitations that are present within this study, the most prominent issue that maybe be addressed in future works is to ensure that the operation status and the various conditions that the pieces of equipment were operating in are available. This should be done in order to re-check the equipment age issue that was deemed to be counter-intuitive in this study, which led to not including the equipment age parameters in the model. By doing so, this may allow the incorporation of the equipment time age and operation age of the different pieces of equipment that are intended to be studied into the model. This may result in obtaining more accurate results that take into consideration the age of the pieces of equipment analyzed. Moreover, an additional idea that can be explored in future works is applying this strategy on different types of equipment that are not included within this study such as trucks, compactors, and other types of equipment.

APPENDIX

Table 15: MLP predicted values vs. actual values for excavator E07

E07 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	320	121	199
2	481	500	-19
14	959	944	15
16	1068	1056	12
18	1176	1203	-27
20	1285	1237	48
21	1340	1240	100
22	1394	1325	69
27	1695	1693	2
30	1976	1903	73
38	2724	2953	-229
41	3005	3096	-91
44	3285	3339	-54
48	3660	3572	88
49	3753	3629	124
51	3940	4076	-136

Table 16: Linear regression predicted values vs. actual values for excavator E07

E07 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	93	121	-28
2	164	500	-336
14	1014	944	70
16	1156	1056	100
18	1297	1203	94
20	1439	1237	202
21	1510	1240	270
22	1580	1325	255
27	1935	1693	242
30	2147	1903	244
38	2714	2953	-239
41	2926	3096	-170
44	3139	3339	-200
48	3422	3572	-150
49	3493	3629	-136
51	3635	4076	-441

Table 17: Non-linear regression predicted values vs. actual values for excavator E07

E07 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	340	121	219
2	383	500	-117
14	933	944	-11
16	1036	1056	-20
18	1144	1203	-59
20	1260	1237	23
21	1320	1240	80
22	1383	1325	58
27	1736	1693	43
30	1981	1903	78
38	2747	2953	-206
41	3052	3096	-44
44	3333	3339	-6
48	3600	3572	28
49	3633	3629	4
51	3638	4076	-438

Table 18: MLP predicted values vs. actual values for excavator E13

E13 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	71	26	45
2	146	106	40
3	222	124	98
6	690	775	-85
13	991	947	44
14	1034	1009	25
16	1119	1072	47
17	1162	1129	33
21	1334	1195	139
22	1377	1302	75
24	1463	1476	-13
25	1506	1524	-18
26	1549	1608	-59
27	1592	1656	-64
30	1720	1778	-58
32	1806	1811	-5
37	2021	2078	-57
39	2107	2193	-86
52	2665	2617	48
64	3180	3109	71
67	3309	3390	-81
72	3523	3686	-163

Table 19: Linear regression predicted values vs. actual values for excavator E13

E13 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	411	26	385
2	455	106	349
3	500	124	376
6	632	775	-143
13	942	947	-5
14	986	1009	-23
16	1074	1072	2
17	1119	1129	-10
21	1296	1195	101
22	1340	1302	38
24	1428	1476	-48
25	1472	1524	-52
26	1517	1608	-91
27	1561	1656	-95
30	1694	1778	-84
32	1782	1811	-29
37	2003	2078	-75
39	2092	2193	-101
52	2667	2617	50
64	3197	3109	88
67	3330	3390	-60
72	3551	3686	-135

Table 20: Non-linear regression predicted values vs. actual values for excavator E13

E13 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	310	26	**284**
2	363	106	**257**
3	415	124	**291**
6	573	775	**-202**
13	938	947	**-9**
14	989	1009	**-20**
16	1091	1072	**19**
17	1142	1129	**13**
21	1342	1195	**147**
22	1392	1302	**90**
24	1489	1476	**13**
25	1537	1524	**13**
26	1585	1608	**-23**
27	1632	1656	**-24**
30	1770	1778	**-8**
32	1860	1811	**49**
37	2074	2078	**-4**
39	2155	2193	**-38**
52	2635	2617	**18**
64	3133	3109	**24**
67	3313	3390	**-77**
72	3725	3686	**39**

Table 21: MLP predicted values vs. actual values for excavator E16

E16 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	66	42	24
2	163	112	51
14	1150	1238	-88
16	1231	1241	-10
18	1311	1262	49
21	1432	1385	47
24	1552	1502	50
25	1593	1547	46
26	1633	1611	22
27	1673	1650	23
33	1915	1817	98
38	2116	2158	-42
39	2156	2190	-34
45	2398	2357	41
51	2639	2560	79
53	2720	2701	19
54	2760	2838	-78
57	2881	3092	-211

Table 22: Linear regression predicted values vs. actual values for excavator E16

E16 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	142	42	100
2	266	112	154
14	1183	1238	-55
16	1269	1241	28
18	1344	1262	82
21	1447	1385	62
24	1543	1502	41
25	1575	1547	28
26	1608	1611	-3
27	1641	1650	-9
33	1855	1817	38
38	2056	2158	-102
39	2098	2190	-92
45	2356	2357	-1
51	2626	2560	66
53	2730	2701	29
54	2788	2838	-50
57	3000	3092	-92

Table 23: Non-linear regression predicted values vs. actual values for excavator E16

E16 Non-linear Regression Model			
Index	Predicted Breakdown Hour Meter	Actual Breakdown Hour Meter	Error
1	142	42	100
2	266	112	154
14	1183	1238	-55
16	1269	1241	28
18	1344	1262	82
21	1447	1385	62
24	1543	1502	41
25	1575	1547	28
26	1608	1611	-3
27	1641	1650	-9
33	1855	1817	38
38	2056	2158	-102
39	2098	2190	-92
45	2356	2357	-1
51	2626	2560	66
53	2730	2701	29
54	2788	2838	-50
57	3000	3092	-92

Table 24: MLP predicted values vs. actual values for excavator E21

E21 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	260	114	146
2	517	235	282
3	773	682	91
6	1116	1212	-96
13	1556	1423	133
14	1619	1511	108
16	1744	1710	34
21	1961	1976	-15
22	1991	1993	-2
25	2082	2093	-11
26	2112	2101	11
27	2142	2111	31
30	2232	2163	69
32	2292	2192	100
39	2503	2512	-9
42	2593	2612	-19
48	2903	2973	-70
55	3295	3242	53
57	3408	3510	-102
61	3632	3589	43
66	3913	3883	30
67	3969	3969	0
71	4193	4322	-129
75	4418	4419	-1

Table 25: Linear regression predicted values vs. actual values for excavator E21

E21 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	849	114	735
2	895	235	660
3	941	682	259
6	1081	1212	-131
13	1406	1423	-17
14	1452	1511	-59
16	1545	1710	-165
21	1777	1976	-199
22	1823	1993	-170
25	1963	2093	-130
26	2009	2101	-92
27	2055	2111	-56
30	2195	2163	32
32	2287	2192	95
39	2612	2512	100
42	2752	2612	140
48	3030	2973	57
55	3355	3242	113
57	3448	3510	-62
61	3633	3589	44
66	3866	3883	-17
67	3912	3969	-57
71	4098	4322	-224
75	4283	4419	-136

Table 26: Non-linear regression predicted values vs. actual values for excavator E21

E21 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	478	114	364
2	599	235	364
3	713	682	31
6	1022	1212	-190
13	1565	1423	142
14	1626	1511	115
16	1737	1710	27
21	1963	1976	-13
22	2001	1993	8
25	2105	2093	12
26	2137	2101	36
27	2167	2111	56
30	2255	2163	92
32	2312	2192	120
39	2522	2512	10
42	2627	2612	15
48	2877	2973	-96
55	3250	3242	8
57	3371	3510	-139
61	3626	3589	37
66	3950	3883	67
67	4011	3969	42
71	4234	4322	-88
75	4386	4419	-33

Table 27: MLP predicted values vs. actual values for excavator E27

E27 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	60	59	1
2	125	180	-55
16	1572	1536	36
21	1921	1798	123
22	1990	1846	144
24	2130	1935	195
25	2200	2429	-229
27	2339	2602	-263
30	2548	2725	-177
33	2757	2810	-53
35	2897	2957	-60
36	2967	2980	-13
41	3315	3256	59
44	3525	3666	-141
50	3943	3981	-38
54	4222	4136	86
56	4361	4192	169
57	4431	4355	76
60	4640	4547	93

Table 28: Linear regression predicted values vs. actual values for excavator E27

E27 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	387	59	328
2	460	180	280
16	1483	1536	-53
21	1848	1798	50
22	1921	1846	75
24	2067	1935	132
25	2140	2429	-289
27	2286	2602	-316
30	2505	2725	-220
33	2725	2810	-85
35	2871	2957	-86
36	2944	2980	-36
41	3309	3256	53
44	3528	3666	-138
50	3967	3981	-14
54	4259	4136	123
56	4405	4192	213
57	4478	4355	123
60	4697	4547	150

Table 29: Non-linear regression predicted values vs. actual values for excavator E27

E27 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	165	59	106
2	265	180	85
16	1542	1536	6
21	1947	1798	149
22	2026	1846	180
24	2180	1935	245
25	2256	2429	-173
27	2405	2602	-197
30	2624	2725	-101
33	2838	2810	28
35	2978	2957	21
36	3047	2980	67
41	3386	3256	130
44	3583	3666	-83
50	3965	3981	-16
54	4202	4136	66
56	4313	4192	121
57	4366	4355	11
60	4513	4547	-34

Table 30: MLP predicted values vs. actual values for excavator E28

E28 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	14	37	-23
2	38	44	-6
14	1068	1095	-27
16	1245	1184	61
18	1666	1751	-85
21	2070	2074	-4
24	2266	2247	19
25	2302	2287	15
26	2332	2325	7
27	2361	2338	23
33	2520	2516	4
38	2639	2601	38
39	2663	2675	-12
45	2805	2845	-40
48	2876	2906	-30
52	2971	2934	37
55	3064	2979	85
57	3147	3132	15
58	3189	3178	11

Table 31: Linear regression predicted values vs. actual values for excavator E28

E28 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	397	37	360
2	453	44	409
14	1122	1095	27
16	1234	1184	50
18	1345	1751	-406
21	1513	2074	-561
24	1680	2247	-567
25	1736	2287	-551
26	1792	2325	-533
27	1848	2338	-490
33	2182	2516	-334
38	2461	2601	-140
39	2517	2675	-158
45	2852	2845	7
48	3019	2906	113
52	3242	2934	308
55	3410	2979	431
57	3521	3132	389
58	3577	3178	399

Table 32: Non-linear regression predicted values vs. actual values for excavator E28

E28 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-126	37	-163
2	-19	44	-63
14	1204	1095	109
16	1389	1184	205
18	1565	1751	-186
21	1813	2074	-261
24	2037	2247	-210
25	2106	2287	-181
26	2172	2325	-153
27	2236	2338	-102
33	2548	2516	32
38	2719	2601	118
39	2743	2675	68
45	2841	2845	-4
48	2872	2906	-34
52	2929	2934	-5
55	3013	2979	34
57	3107	3132	-25
58	3170	3178	-8

Table 33: MLP predicted values vs. actual values for articulated hauler H03

H03 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	344	391	-47
7	948	756	192
16	1468	1480	-12
18	1551	1511	40
20	1634	1591	43
25	1841	1691	150
26	1883	1766	117
27	1924	1925	-1
30	2048	2095	-47
32	2131	2200	-69
34	2214	2326	-112
36	2297	2340	-43

Table 34: MLP predicted values vs. actual values for articulated hauler H05

H05 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	29	4	25
3	81	154	-73
16	1078	1018	60
18	1228	1181	47
20	1433	1434	-1
26	2124	2124	0
29	2469	2443	26
30	2585	2480	105
33	2930	2652	278
34	3045	3120	-75
35	3160	3145	15
38	3501	3599	-98
41	3804	3732	72

Table 35: MLP predicted values vs. actual values for articulated hauler H06

H06 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	70	48	22
2	81	68	13
14	698	668	30
16	787	792	-5
18	875	815	60
21	1045	1086	-41
22	1108	1231	-123
24	1234	1359	-125
25	1297	1421	-124
26	1360	1494	-134
27	1423	1539	-116
32	1738	1809	-71
33	1801	1810	-9
38	2365	2446	-81
44	3089	2808	281
50	3639	3679	-40
55	4004	3951	53
56	4077	4122	-45

Table 36: MLP predicted values vs. actual values for articulated hauler H07

H07 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	51	6	45
3	134	205	-71
14	1014	1208	-194
16	1218	1249	-31
18	1422	1392	30
20	1626	1587	39
21	1728	1671	57
30	3112	3043	69
34	3419	3419	0
36	3572	3721	-149
37	3648	3725	-77
38	3725	3741	-16
41	3928	3909	19
42	3991	4030	-39

Table 37: MLP predicted values vs. actual values for articulated hauler H08

H08 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	70	105	-35
7	1000	1219	-219
16	2083	1881	202
20	2565	2323	242
24	3046	2953	93
25	3167	3035	132
26	3287	3402	-115
27	3408	3696	-288
29	3648	3881	-233
33	4130	4127	3
35	4371	4402	-31
38	4732	4612	120

Table 38: MLP predicted values vs. actual values for articulated hauler H09

H09 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	18	33	-15
3	133	74	59
14	397	400	-3
16	466	456	10
18	534	594	-60
20	603	655	-52
21	638	685	-47
30	1014	941	73
34	1738	1859	-121
36	2124	2201	-77
37	2317	2435	-118
38	2510	2518	-8
41	3088	3120	-32
42	3281	3121	160

Table 39: MLP predicted values vs. actual values for articulated hauler H10

H10 MLP Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	70	60	10
2	122	103	19
15	989	980	9
16	1039	1091	-52
18	1140	1133	7
21	1241	1269	-28
22	1266	1279	-13
25	1342	1310	32
26	1367	1369	-2
32	1722	1664	58
35	2034	1941	93
36	2138	2054	84
37	2241	2180	61
41	2657	2639	18
42	2761	2674	87
48	3384	3481	-97
51	3609	3636	-27
55	3744	3708	36
58	3846	3833	13
61	3947	3936	11

Table 40: Linear regression predicted values vs. actual values for articulated hauler H03

H03 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	587	391	196
7	895	756	139
16	1357	1480	-123
18	1460	1511	-51
20	1563	1591	-28
25	1820	1691	129
26	1871	1766	105
27	1923	1925	-2
30	2077	2095	-18
32	2180	2200	-20
34	2282	2326	-44
36	2385	2340	45

Table 41: Linear regression predicted values vs. actual values for articulated hauler H05

H05 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-214	4	-218
3	-21	154	-175
16	1228	1018	210
18	1420	1181	239
20	1612	1434	178
26	2189	2124	65
29	2477	2443	34
30	2573	2480	93
33	2861	2652	209
34	2957	3120	-163
35	3053	3145	-92
38	3342	3599	-257
41	3630	3732	-102

Table 42: Linear regression predicted values vs. actual values for articulated hauler H06

H06 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-231	48	-279
2	-156	68	-224
14	747	668	79
16	897	792	105
18	1048	815	233
21	1273	1086	187
22	1348	1231	117
24	1499	1359	140
25	1574	1421	153
26	1649	1494	155
27	1725	1539	186
32	2101	1809	292
33	2176	1810	366
38	2552	2446	106
44	3003	2808	195
50	3455	3679	-224
55	3831	3951	-120
56	3906	4122	-216

Table 43: Linear regression predicted values vs. actual values for articulated hauler H07

H07 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-221	6	-227
3	-11	205	-216
14	1149	1208	-59
16	1360	1249	111
18	1571	1392	179
20	1782	1587	195
21	1887	1671	216
30	2836	3043	-207
34	3257	3419	-162
36	3468	3721	-253
37	3574	3725	-151
38	3679	3741	-62
41	3995	3909	86
42	4101	4030	71

Table 44: Linear regression predicted values vs. actual values for articulated hauler H08

H08 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	169	105	64
7	919	1219	-300
16	2043	1881	162
20	2543	2323	220
24	3043	2953	90
25	3168	3035	133
26	3293	3402	-109
27	3418	3696	-278
29	3668	3881	-213
33	4168	4127	41
35	4418	4402	16
38	4793	4612	181

Table 45: Linear regression predicted values vs. actual values for articulated hauler H09

H09 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-466	33	-499
3	-320	74	-394
14	487	400	87
16	634	456	178
18	781	594	187
20	927	655	272
21	1001	685	316
30	1661	941	720
34	1954	1859	95
36	2101	2201	-100
37	2174	2435	-261
38	2248	2518	-270
41	2468	3120	-652
42	2541	3121	-580

Table 46: Linear regression predicted values vs. actual values for articulated hauler H10

H10 Linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	-30	60	-90
2	37	103	-66
15	914	980	-66
16	982	1091	-109
18	1116	1133	-17
21	1319	1269	50
22	1386	1279	107
25	1588	1310	278
26	1656	1369	287
32	2061	1664	397
35	2263	1941	322
36	2330	2054	276
37	2398	2180	218
41	2668	2639	29
42	2735	2674	61
48	3140	3481	-341
51	3342	3636	-294
55	3612	3708	-96
58	3814	3833	-19
61	4016	3936	80

Table 47: Non-linear regression predicted values vs. actual values for articulated hauler H03

H03 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	238	391	-153
7	986	756	230
16	1476	1480	-4
18	1532	1511	21
20	1584	1591	-7
25	1756	1691	65
26	1804	1766	38
27	1856	1925	-69
30	2041	2095	-54
32	2178	2200	-22
34	2307	2326	-19
36	2397	2340	57

Table 48: Non-linear regression predicted values vs. actual values for articulated hauler H05

H05 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	32	4	28
3	151	154	-3
16	1116	1018	98
18	1294	1181	113
20	1479	1434	45
26	2080	2124	-44
29	2407	2443	-36
30	2520	2480	40
33	2870	2652	218
34	2990	3120	-130
35	3113	3145	-32
38	3492	3599	-107
41	3888	3732	156

Table 49: Non-linear regression predicted values vs. actual values for articulated hauler H06

H06 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	105	48	57
2	148	68	80
14	672	668	4
16	767	792	-25
18	867	815	52
21	1030	1086	-56
22	1088	1231	-143
24	1211	1359	-148
25	1276	1421	-145
26	1344	1494	-150
27	1414	1539	-125
32	1810	1809	1
33	1898	1810	88
38	2383	2446	-63
44	3040	2808	232
50	3682	3679	3
55	4050	3951	99
56	4086	4122	-36

Table 50: Non-linear regression predicted values vs. actual values for articulated hauler H07

H07 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	21	6	15
3	110	205	-95
14	981	1208	-227
16	1202	1249	-47
18	1439	1392	47
20	1689	1587	102
21	1818	1671	147
30	3005	3043	-38
34	3471	3419	52
36	3668	3721	-53
37	3755	3725	30
38	3833	3741	92
41	4009	3909	100
42	4046	4030	16

Table 51: Non-linear regression predicted values vs. actual values for articulated hauler H08

H08 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	21	6	15
3	110	205	-95
14	981	1208	-227
16	1202	1249	-47
18	1439	1392	47
20	1689	1587	102
21	1818	1671	147
30	3005	3043	-38
34	3471	3419	52
36	3668	3721	-53
37	3755	3725	30
38	3833	3741	92
41	4009	3909	100
42	4046	4030	16

Table 52: Non-linear regression predicted values vs. actual values for articulated hauler H09

H09 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	54	33	21
3	118	74	44
14	391	400	-9
16	430	456	-26
18	473	594	-121
20	523	655	-132
21	554	685	-131
30	1145	941	204
34	1698	1859	-161
36	2053	2201	-148
37	2247	2435	-188
38	2450	2518	-68
41	3082	3120	-38
42	3286	3121	165

Table 53: Non-linear regression predicted values vs. actual values for articulated hauler H10

H10 Non-linear Regression Model			
Index	**Predicted Breakdown Hour Meter**	**Actual Breakdown Hour Meter**	**Error**
1	95	60	35
2	176	103	73
15	896	980	-84
16	939	1091	-152
18	1025	1133	-108
21	1160	1269	-109
22	1207	1279	-72
25	1362	1310	52
26	1418	1369	49
32	1817	1664	153
35	2057	1941	116
36	2143	2054	89
37	2232	2180	52
41	2608	2639	-31
42	2706	2674	32
48	3291	3481	-190
51	3554	3636	-82
55	3829	3708	121
58	3948	3833	115
61	3965	3936	29

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