Equipment Management Towards Sustainable Mining

Enzo Angeles Pasco

Department of Mining and Materials Engineering

McGill University, Montreal, Quebec

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Abstract

A typical mining company has three important assets: the human labor-force, the orebody, and the equipment. Trucks, excavators, drilling machines, crushers, grinders, classifiers, and concentrators comprise the equipment. Mining operations that want to take advantage of economies of scale have huge equipment fleet, and the worth of the equipment may easily exceed a hundred million dollars. The reliability and availability of this equipment play critical roles in increasing the efficiency and productivity of a mining operation. The losses associated with low performance or unavailability can be significant. The contribution of this thesis can be divided into two sections. The first part proposes an effective maintenance management approach to be used in the mining industry such that equipment availability and reliability are improved. The second section investigates the reduction effect on greenhouse gas emissions due to maintenance activities since most of these enormous equipment fleets used in mining are still diesel-powered.

Using failure data of a mining truck fleet in an open-pit Canadian mining operation, a case study is conducted to determine the optimal inspection intervals based on the desired reliability level to detect potential catastrophic failures. Next, a preventive maintenance scheduling plan based on systems' rejuvenation after each repair is explored for mining equipment. Finally, the relationship between equipment reliability and CO_2 emissions is quantified and a regression model to predict emission is developed. The research outcomes show that the proposed approach has the potential to increase the efficiency and productivity of the mining equipment and can be used to contribute to equipment management towards more sustainable mining operations.

Résumé

Une société minière typique possède trois atouts importants : la main-d'œuvre, le gisement, l'infrastructure et l'équipement. Les camions, les excavateurs, les machines de forage, les concasseurs, les broyeurs, les classificateurs et les concentrateurs constituent l'équipement. Les exploitations minières qui veulent profiter d'économies d'échelle disposent d'un énorme parc d'équipement, dont la valeur peut facilement dépasser les cent millions de dollars. La fiabilité et la disponibilité de ces équipements jouent un rôle essentiel dans l'augmentation de l'efficacité et de la productivité d'une exploitation minière. Les pertes associées à un faible rendement ou à une indisponibilité peuvent être importantes. La contribution de cette thèse peut être divisée en deux sections. La première partie propose une approche efficace de gestion de la maintenance à utiliser dans l'industrie minière afin d'améliorer la disponibilité et la fiabilité des équipements. La deuxième section étudie l'effet de réduction des émissions de gaz à effet de serre dues aux activités de maintenance, étant donné que la plupart de ces énormes parcs d'équipement utilisés dans l'industrie minière sont encore alimentés au diesel.

En utilisant les données de défaillance d'un parc de camions miniers dans une exploitation minière à ciel ouvert au Canada, une étude de cas est menée pour déterminer les intervalles d'inspection optimales en fonction du niveau de fiabilité souhaité pour détecter les éventuelles défaillances catastrophiques. Ensuite, un plan d'entretien préventif basé sur le rajeunissement des systèmes après chaque réparation est étudié pour les équipements miniers. Enfin, la relation entre la fiabilité de l'équipement et les émissions de CO_2 est quantifiée et un modèle de régression permettant de prévoir les émissions est élaboré. Les résultats de la recherche montrent que l'approche proposée

a le potentiel d'augmenter l'efficacité et la productivité de l'équipement minier et peut être utilisée pour contribuer à la gestion de l'équipement en vue d'une exploitation minière plus durable.

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Contributions of Authors

The author of this thesis submits two journal articles based on this research. He is the primary author of the manuscripts given below. Dr. Kumral and Dr. Sushama are the supervisors of the master candidate.

- Angeles, E. and Kumral, M. Optimal Inspection and Preventive Maintenance Scheduling of Mining Equipment.
- Angeles, E., Kumral, M. and Sushama, L. Equipment Management for Environmental Sustainability in Mining Industry.

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List of Abbreviations

CBM	Condition Based Maintenance
CM	Corrective Maintenance
GBR	Gradient Boosting Ensemble Regressor
GHG	Greenhouse gases
IPdM	Intelligent Predictive Maintenance
LK	Likelihood Function Value
MAE	Mean Absolute Error
ML	Machine Learning
MLR	Multivariate Linear Regression
MTTR	Mean Time to Repair
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
OEM	Original Equipment Manufacturer
PdM	Predictive Maintenance
PM	Preventive Maintenance
RBM	Risk-Based Maintenance
RCM	Reliability Centered Maintenance
RFR	Random Forest Regressor
RMSE	Root Mean Square Error
SGD	Stochastic Gradient Descent Regressor
TBM	Time Based Maintenance
VIF	Variance Inflation Factor

1 Introduction

1.1 Problem Statement

One of the most important assets of mining companies, besides their mineral resources, infrastructure, and the workforce, is their equipment. Current technologies allow modern equipment to increase the efficiency of diverse processes related to mineral extraction and mineral processing. Hence, it is usual for mining companies to rely on a variety of machinery to carry out activities such as drilling, blasting, loading, hauling, and mineral processing.

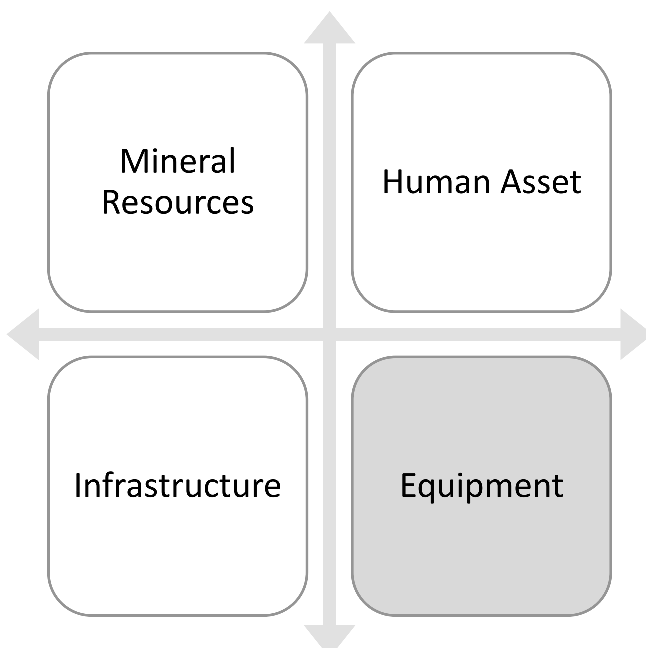

Figure1. 1 A general classification of assets for mining operations

The current trend in the mining industry is to design enormous equipment. As can be observed in Figure 1.2, in open-pit mining, truck capacities have significantly increased since the 1950s to take advantage of economies of scale. Mining dump trucks with payload capacities of near 500 short tons (tons) and bucket wheel excavators of more than 90 meters in height are examples of this gigantic equipment.

Moreover, with more complex and larger mining equipment being produced, maintenance costs such as labor and repair expenses have increased considerably. The more efficient the mining equipment is, the more of an impact it will have if the objective is to reduce costs and maximize productivity. As equipment availability and reliability increase, the overall mine productivity increases. The availability of the equipment plays a vital role in achieving high productivity targets, and it is usually a key performance indicator for the mine management. High levels of availability are related to proper working conditions and proper maintenance. In addition to availability, the equipment should have high reliability as possible to succeed in the intended targets.

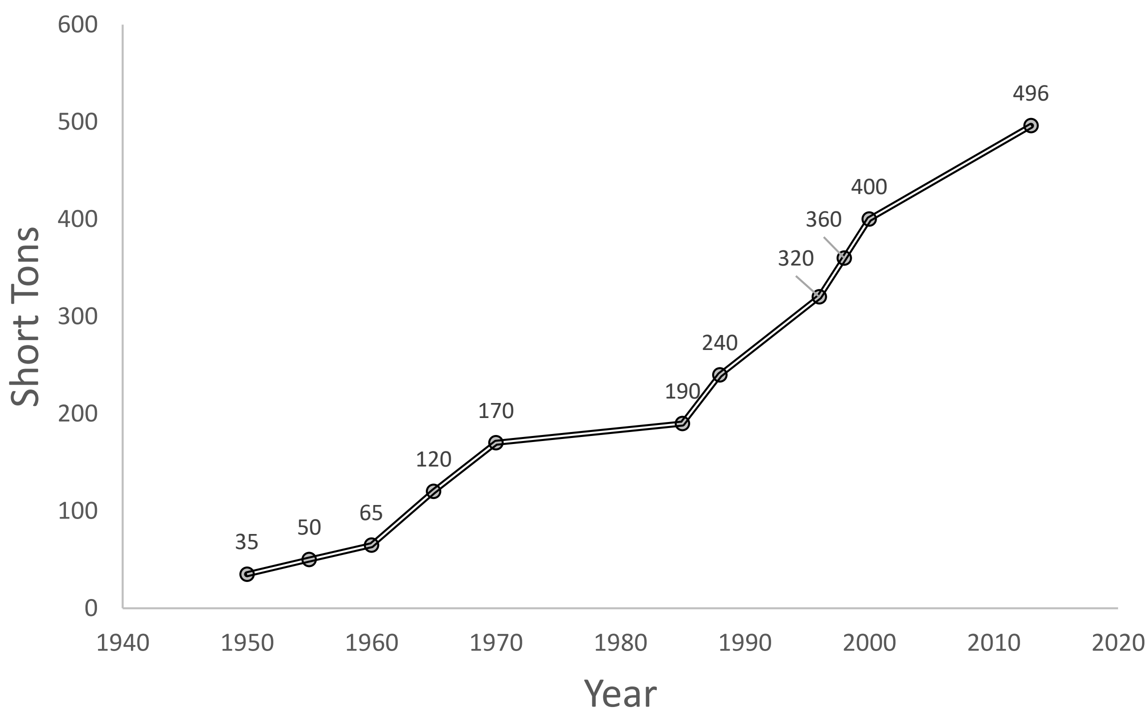

Figure1. 2. Maximum haul trucks capacity over the last 70 years adapted from Bozorgebrahimi, Hall, and Morin (2005)

Being equipment a critical asset for mining companies, an appropriate maintenance policy is necessary to ensure excellent performance. Maintenance has the potential to contribute to the sustainability of mining operations in two ways. First, maintenance has a direct impact on availability to reduce production losses. Second, maintenance has the potential to reduce environmental impacts by increasing the reliability of equipment. Environmental aspects of a mining operation such as the carbon footprint and gas emissions could be addressed by an adequate maintenance policy. Consequently, equipment fleets with high levels of reliability, as well as with minimum greenhouse gas emissions, are a high-priority mission for the mining industry. The problem sentence of this thesis is how can a maintenance strategy be developed in such a way to maximize equipment availability and reliability, and minimize greenhouse gas emissions.

1.2 Research Objectives

- Develop an effective maintenance management approach to be used in the mining industry in order to improve the equipment's availability and reliability.
- Explore optimal inspection intervals based on a reliability-based maintenance methodology in such a way that potential catastrophic failures are detected on time.
- Propose an optimal preventive maintenance scheduling, which contemplates the rejuvenation of the trucks after each repair, by introducing the concept of the virtual age.

- Develop a predictive model based on regression techniques to study the relationship between equipment reliability and greenhouse gas emissions.

1.3 Economic and Environmental Benefits

Economic Benefits

- Improve the performance of mining equipment and its availability by reducing the risk of unexpected failures.
- Reflect the importance of equipment for mining companies and the potential to maximize its efficiency as well as reduce its associated costs.
- Promote the importance of maintenance organization and strategy in mining operations.

Environmental Benefits

- Contribute to the reduction of greenhouse gas emissions related to mining equipment.
- Promote the use of greener technologies in the mining industry.
- Reduce the impact of carbon tax or cap and trade policies in mining companies.

1.4 Originality and Success

The originality of this work rests on how the proposed link between equipment maintenance and greenhouse gas emissions could be beneficial for the sustainability of the mining operations. The uniqueness of this study lies in three main pillars: First, the determination of optimal inspection intervals of mining trucks is based on a reliability-based methodology instead of a typical physical age interval suggested by equipment manufacturers. Second, a preventive maintenance scheduling approach is proposed by utilizing the concept of virtual age and system rejuvenation, which has not been fully addressed in the mining industry for mobile equipment, to the author's best knowledge. Finally, a tailored predictive model for the estimation of CO_2 is suggested based on a specific case study considering operational parameters and highlighting the importance of reliability for the sustainability of the mining industry.

1.5 Thesis Organization

This thesis is divided into the following sections:

Chapter 1 defines the problem statement, the research objectives, and the original contributions.

Chapter 2 reviews the existing methodology related to mining equipment, reliability concepts, maintenance classification, and the link between maintenance and sustainability.

Chapter 3 describes the methodology considered to propose optimal inspection intervals and preventive maintenance scheduling based on the virtual age of mining trucks.

Chapter 4 introduces a predictive model that demonstrates the importance of equipment reliability to reduce greenhouse gas emissions.

Chapter 5 concludes the thesis by discussing the main ideas of each chapter and how the proposed methodology can be improved for future work.

2 Literature Review

2.1 Mining Equipment

The mining equipment can be classified as to whether the deposit is being mined as an underground or open-pit mine. In underground mines, the equipment can vary according to the mining method. For instance, depending on the mineral being extracted, depth of the mineral deposit, and geomechanical considerations, underground deposits can be mined by diverse methods such as cut and fill, shrinkage, sublevel long hole, room and pillar, block caving, or using a combination. A more specific classification can be proposed according to the type of activity being carried out. Activities such as drilling, blasting, hauling, loading, and mineral processing are related to specific kinds of equipment, which vary in size and specifications.

Underground mining equipment has important design restrictions due to low-seam height operations and reduced size for maneuverability. They include a diversity of drills, loaders, and trucks, depending on the type of environment in which they are expected to perform. From hard rock to soft rock, and with specific safety and operational features, mining companies have the option to choose among diverse equipment manufacturers. In the case of drilling equipment, hydraulic jumbo drills are the most popular due to their design drive for a lower profile. Jumbos can be categorized by their application in jumbo drills (i.e., development jumbos) and shaft jumbos. While the first category refers to the traditional jumbo used for horizontal labors in ramping and tunneling, the second category implies vertical labors or shafts. Both are produced in different sizes, performance, and a different number of boom models to meet productivity targets, with an average boom coverage from 5.1 m to 7.10 m (height) and 5.77 m to 8.90 m (wide).

Figure 2. 1. Sandvik DT1132i jumbo retrieved from (Mining-Magazine, 2019)

Loaders in underground mining are equipment designed to have access to low seam operations and remove material. On average, they can carry loads from 6.6 tons up to 16.5 tons. However, for hard rock applications, there are underground loaders that can haul up to 22 tons. Hauling equipment depends on the mining method. For instance, in the case of underground trucks, they have a rated load capacity from 33 tons up to 70 tons on average. Other types of machinery that can be found in underground applications are shearers, plow systems, continuous miners, roof bolters, and conveyor systems.

Open-pit mining equipment differs from underground equipment due to its considerably larger size. Since there are no size or maneuverability restrictions, equipment manufacturers tend to design larger models to maximize productivity. There are a large variety of surface mining drills in the market for all purposes. Some drills are relatively small, more transportable, and more versatile than others. They can handle not only production blast holes, but also ramp and access development, limited pre-split drilling, and drill holes for secondary blasting. Others are less versatile but able to drill hole diameters from 6 to 12.25 in with a bit load from 71,993 to 92,922 lb. Depending on the type of material, rotary or down-the-hole modes could be selected for single or multi-pass depths. In the case of blasting, ANFO explosive delivery trucks are the most common equipment, but this equipment is considerably smaller than the ones used in other activities.

Regarding loading equipment, hydraulic and electric shovels, draglines, and large wheel loaders are the most representative. Hydraulic shovels can have frontless or face shovel configuration, are usually smaller than electrical shovels and typically preferred when the discrimination between ore and grade could represent a problem for bigger equipment. These shovels can be found with bucket payload starting in 10 yd^3 up to in 68 yd^3. Electric mining shovels have a digging arm operated by winches and steel ropes. They represent a low-cost method of striping compared to other traditional loading equipment due to their capability to remove large amounts of overburden and ore. Nowadays, equipment manufacturers offer electric shovel models with dipper capacities up to 92 yd^3. Another loading machinery for open pit mines is a dragline, which is normally bigger in comparison to shovels. It is typically used in the coal industry where bulk excavation is conducted, and no positive digging is required. The popular models offer bucket capacity from 60 to 160 yd^3.

Similarly, gigantic bucket wheel excavators such as the Bagger 288, also used in the coal industry, is the biggest mining equipment. This excavator contains 20 buckets of 530 yd^3 with an average loading performance of 12 tons of material per second. Wheel loaders in open-pit mining are widely used because they can move from one location to another quickly when compared to shovels and draglines. Furthermore, they are more selecting when digging ore material. The bucket capacities of the large wheel loaders vary between 19 and 53 yd^3.

Figure 2. 2. P&H 4100XPC Mining Shovel

Figure 2. 3. Bagger 288 bucket-wheel excavator. From (Mining-Technology, 2018)

Hauling equipment consists of mining trucks and conveyor systems. Mining trucks are used to transport the ore and waste material from the mine to different locations such as lixiviation pads, crusher facilities, stockpiles, waste dump, etc. The largest models have an overall body length of 45 ft and height (body raised) of 50 ft with payload capacities of around 400 short tons. However, highest-payload-capacity haul trucks such as the Belaz 75710 reach 496 short tons capacity but they are designed under specific requests. Another option to transport bulk materials over long distances is belt conveyors, which should be designed accordingly to specific mine conditions, the volume of material, topography, distances, and weather conditions. Nevertheless, it is common in mining to have a combination of both hauling systems; mining trucks transporting material from the mine to designated locations from where belt conveyors carry it to its final destination.

Figure 2. 4. Four haul trucks Komatsu 930 and two truck operators in a Peruvian copper open pit mine

Finally, specialized heavy-duty equipment such as crushers, grinders, classifiers, and concentrators are used for mineral processing. In this case, the size, design, and type of equipment will depend on the characteristics of the material being processed.

The selection of the mining equipment that maximizes productivity and efficiency at the minimum cost is an important task in mining. More importantly, given that some of the equipment used in the mineral industries are custom designed, a tailored maintenance strategy is also required

2.2 Reliability Theory

2.2.1 Failure

Failure can be defined as the incapacity of a piece of equipment or system to perform adequately under specific parameters (Dhillon, 2008). The literature provides additional terms related to failure including defect, fault, and malfunction. However, the most practical definition of failure is described as nonconformity to stipulated performance criterion (Smith, 2017)

Failure rate and failure mechanisms are two terms found frequently in the literature. The former is the ratio of the total number of failures to the total observed time. The latter describes physical, chemical, or other types of processes that result in a failure. A general classification of failures mechanism is proposed by Blischke and Murthy (2011)which considers two main groups: overstress failures and wear-out failures.

According to this categorization, overstress failures consist of failures mechanics such as brittle fracture, ductile fracture, yield, buckling, and elastic deformations. Wear out failures involve mechanisms such as wear, corrosion, dendritic growth, interdiffusion, fatigue crack propagation, initiation, and radiation.

The probability that an item will fail at any time up to t is given by

$$F(t) = \int_0^t f(t)\,\mathrm{d}t \tag{2.1}$$

where $f(t)$ states for the probability density function of failure.

2.2.2 Mean Time to Failure (MTTF) and Mean Time Between Failures (MTBF)

The Mean Time to Failure (MTTF) is the average time that passes until a failure occurs and is used for non-repairable systems. The Mean Time Between Failures (MTBF) describes the average time between successive failures of an item or piece of equipment and is used for repairable systems. The MTBF can be obtained by calculating the total amount of operating hours of the item and divide them by the total amount of failures observed for that period. MTTF can be expressed as the expected value of the failure time T (Elsayed, 2012). Thus,

$$MTTF = \int_0^\infty tf(t)\,dt \tag{2.2}$$

And in terms of reliability, $R(t)$, the MTTF can be written as

$$MTTF = \int_0^\infty R(t)\,dt \tag{2.3}$$

2.2.3 Mean Time to Repair (MTTR)

The MTTR is the average time required to repair a failed item, piece of equipment or system. It involves all of the maintenance tasks performed to the failed equipment in order to restore it to its regular operational mode.

2.2.4 Availability

The likelihood that a piece of equipment or system is operational at the time t when used under specified conditions, and where the overall time t involves operating, logistical, repair, and administrative time (Dhillon, 2008).

Lie, Hwang, and Tillman (1977) classify availability as inherent, achieved, and operational availability.

Inherent Availability, A_i: takes into consideration only corrective maintenance (i.e., time to repair) and excludes ready time, preventive maintenance downtime, as well as logistics and administrative downtime.

$$A_i = \frac{MTBF}{MTBF + MTTR} \tag{2.4}$$

Achieved Availability, A_a: takes into consideration corrective and preventive maintenance downtime, and it is a function of the mean time between maintenance. However, it excludes logistics and administrative downtime.

$$A_a = \frac{MTBM}{MTBM + Mdown} \tag{2.5}$$

where $Mdown$ represents the mean maintenance downtime resulting from corrective and preventive actions. MTBM stands for the mean time between maintenance.

Operational Availability, A_o: considers maintenance and repair time as well as ready time, logistics time, and administrative time and it is expressed as

$$A_o = \frac{MTBM + ready\ time}{(MTBM + ready\ time) + MD} \tag{2.6}$$

where $ready\ time = operational\ cycle - (MTBF + MD)$ and the mean delay time, $MD = Mdown + delay\ time$

2.2.5 Maintainability

It is the probability of completing an effective repair task in a given time for a specific piece of equipment that has already failed. Equipment with a higher level of maintainability will be restored faster and will require fewer complex maintenance tasks.

2.2.6 Maintenance

Group of tasks performed to the failed piece of equipment or system with the objective to restore it to its satisfactory functioning state. This concept is further explained in Section 2.3.

2.2.7 Reliability

It describes the probability that a piece, part, or component of equipment or system will perform its designed functions adequately under routine operating conditions and for a specified period of time (Tobias and Trindade, 2011)

The reliability can be obtained from the probability that an item will fail, $F(t)$, at any time

$$R(t) = 1 - F(t) \tag{2.7}$$

2.2.8 Repairable and Non-Repairable Systems

Engineering systems can be repairable or non-repairable, depending on the nature of their components (Figure 2.5). Non-repairable systems consist of items whose lifetime is a random variable described by a single time to failure (MTTF). After failure, items are discarded or recycled. On the other hand, repairable systems could be restored to operating conditions without replacing the entire systems. This system consists of items whose lifetime are random variables associated with MTBF and the number of failures.

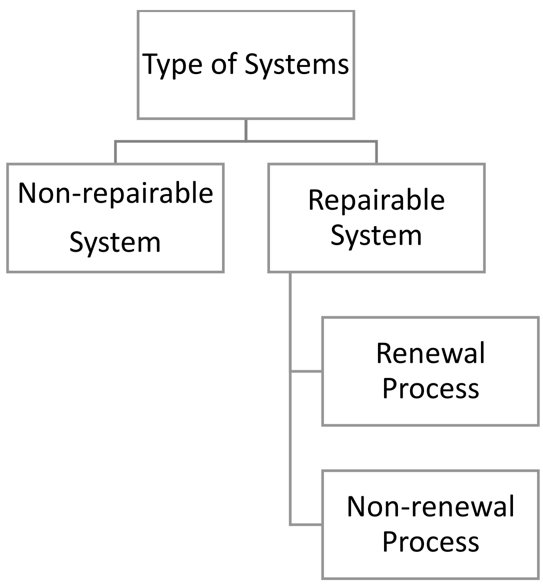

Figure 2. 5. A general classification of systems

As seen in Figure 2.5, repairable systems can be further classified as renewable and non-renewable processes. Renewal processes are associated with independent and identically distributed MTBF. Therefore, the system is as good as new after repairs, and there is no trend or deterioration of the system over time. On the other hand, the non-renewal process considers that the mean time between subsequent repairs is also a function of other variables such as the design of the equipment, operating conditions, environmental conditions, the quality of repair, etc. Therefore, the assumption independent and identically distributed MTBF cannot be held anymore.

2.3 Maintenance Activities

2.3.1 Maintenance Management and Leadership

Maintenance is an integrated process, including engineering and managerial activities, to return or restore to its planned functions throughout the life of the equipment. (Dhillon, 2008). In the mining industry, there is a trend characterized by a transition from traditional reactive maintenance, to preventive maintenance. This trend is furthered by more advanced maintenance strategies: predictive maintenance, prescriptive and cognitive maintenance. The reasons behind the growing interest in advanced maintenance strategies are: (a). The equipment of mining operations gets larger and more complex. Waiting costs associated with a failure can be significant for a company. (b) New statistical and machine learning techniques provide the tools to develop advance maintenance programs.

As Figure 2.6 shows, to be effectively implemented, maintenance management should start from the highest level of the corporation and it should be periodically evaluated using key performance indicators. Moreover, the staff and the labor force should be oriented and periodically trained according to the objectives of the maintenance management program.

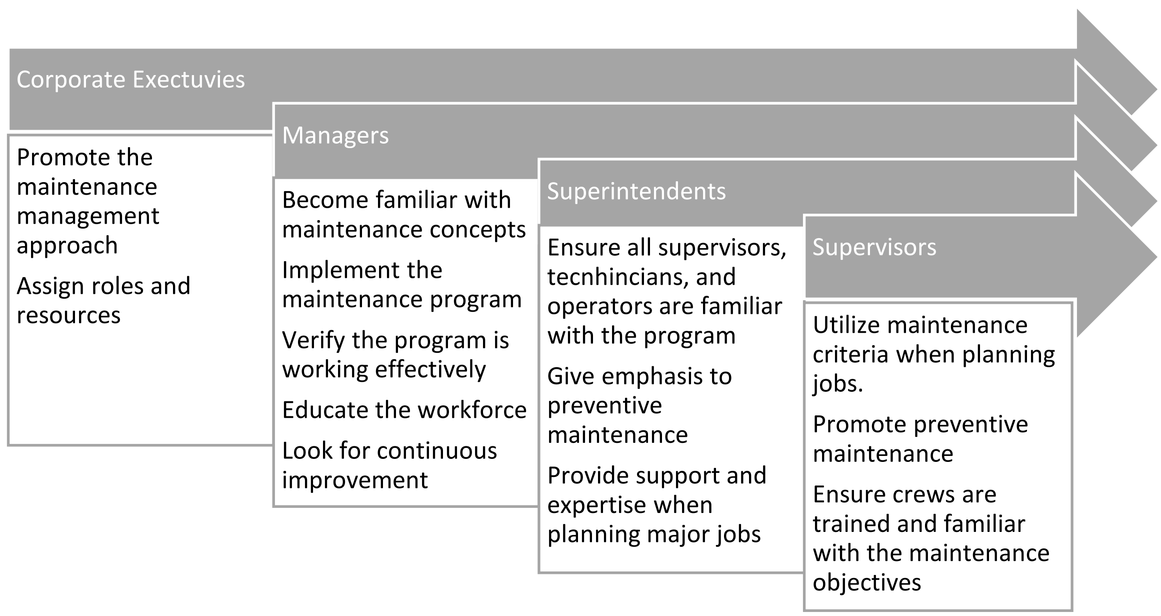

Figure 2. 6. Maintenance management leadership roles Adapted from Tomlingson (2009)

2.3.2 Maintenance classification

Maintenance classification is usually a controversial topic. Some authors, such as Wang (2014), classify maintenance in three categories: corrective, preventive, and predictive. However, others consider predictive strategies a subcategory of preventive maintenance and consider only two main categories: corrective and preventive (Duffuaa, Ben-Daya, Al-Sultan, and Andijani, 2001; Tsang, 1995). This study will consider a general maintenance classification observed in the mining industry and including current trends. This classification is presented in Figure 2.7

This literature review will consider the second classification since it is more used in the industry. Corrective maintenance refers to a reactive approach that aims to restore a system or a piece of equipment after a failure, while preventive maintenance describes a proactive methodology that aims to prevent potential failures by implementing planned inspections and maintenance tasks. In other words, maintenance can be classified based on how the interval between tasks or inspections is determined as well as the objective of the tasks.

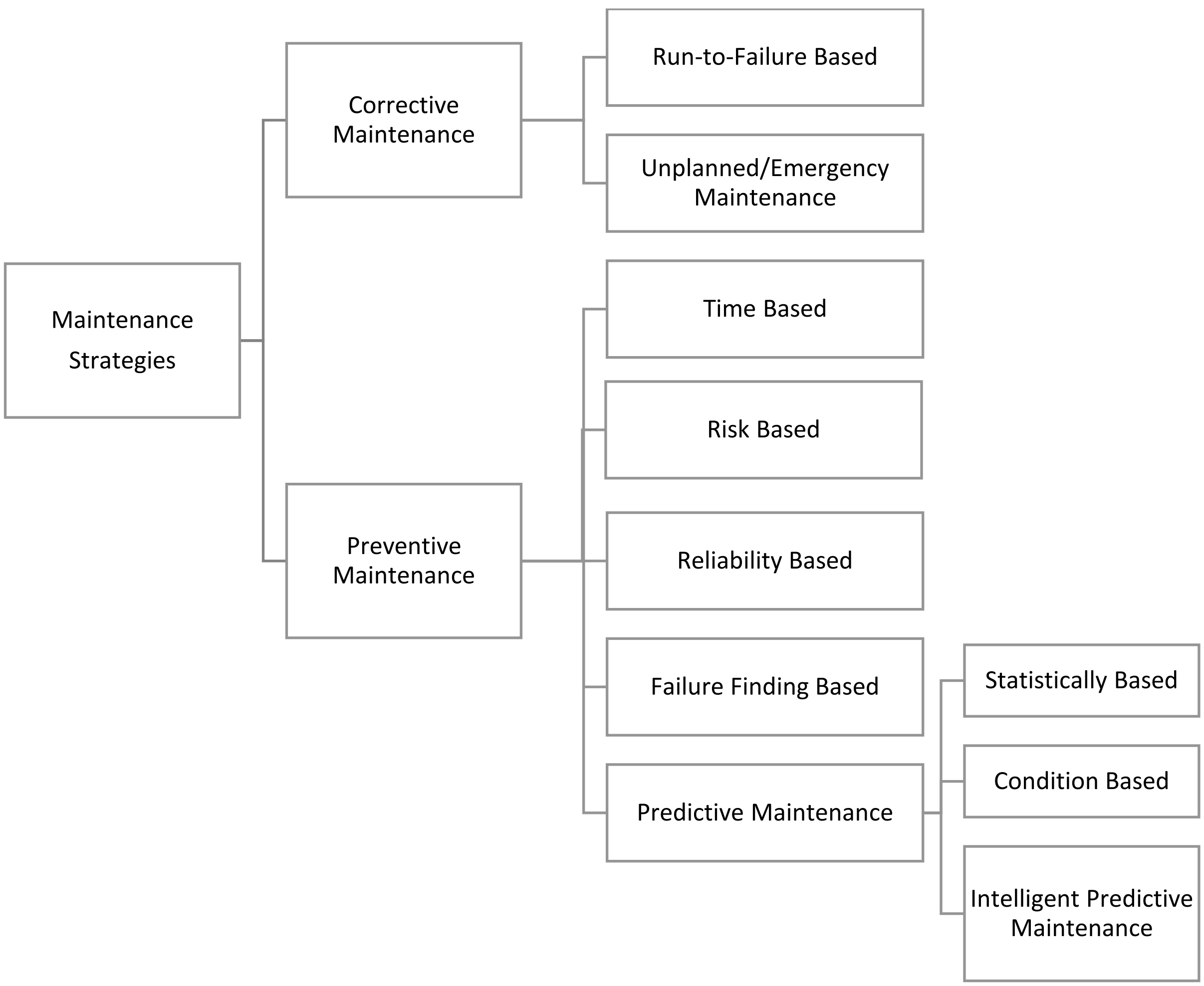

Figure 2. 7. Maintenance classification based on industry practices

2.3.2.1 Corrective Maintenance

Corrective maintenance (CM) is related to maintenance tasks carried out to restore the failed system or piece equipment to its intended function. Even though there is a general understanding that corrective maintenance should be the last strategy when addressing the maintenance of mining equipment, around 55% of maintenance resources and activities are still corrective (Wang, 2014). Moreover, 35% of maintenance tasks of mobile equipment in mining operations are still related to this type of maintenance (Sander, 2011).

There are two subcategories of corrective maintenance: planned CM or run-to-failure strategy and unplanned CM. Also, same classification is named as the immediate and the deferred CM in the literature. Run-to-failure based refers to a planned CM strategy in which failures are expected and acceptable with the consideration that avoiding them is not economical or practical (Hupjé, 2018). A key factor to consider for this strategy is its potential impact or consequences related to environmental, operational or safety aspects. Examples of the implementation of this strategy are those related to disposable or small assets, which are intended to be replaced instead of being repaired, are batteries, light fittings, hand tools, etc. The other subcategory of corrective maintenance is the unplanned maintenance or breakdown maintenance. This type of maintenance is not expected, and it represents a considerable breakdown time if the equipment is not attended to immediately. However, corrective actions can be either completed immediately in case of key equipment or planned for a more appropriate time when it is less disruptive to the operation (Sander, 2011).

From the moment the failure is detected, a corrective maintenance strategy can be typically divided into six stages (Blanchard, Verma, and Peterson, 1995).

1. Preparation for maintenance
2. Localization and fault isolation
3. Disassembly
4. Repair or replace tasks
5. Reassembly
6. Adjustment and condition verification

Failures can be detected by operators or failure detection systems. Most of the time, operators report unusual sounds or vibrations in a specific part of the equipment, which can lead mechanics to find the failure. The first stage of the corrective maintenance cycle is the preparation for maintenance, which goes from the moment the failure was detected until the mechanics arrive at the specific location where the equipment is working. Depending on the urgency of the labor and the magnitude of the operation, the response could be immediately or could be scheduled for later. In the second stage, the localization and fault isolation is generally the most time-consuming activity (Blanchard et al., 1995) and depends on the mechanic expertise as well as the operator's ability to describe unusual working parameters. Consecutively, the system or pieces of equipment are repair or replaced and the system is reassembly. Finally, a condition verification is necessary to guarantee the quality of the repair as well as safety conditions. Generally, CM strategies are associated with reactive responses to failures which are linked to high maintenance costs. This is due to the high cost of restoring a piece of equipment to an operating condition under limited time; supplementary damage to the equipment caused by the failure and the penalty associated with operational disruption (Tsang, 1995).

Wang (2014) listed several disadvantages related to corrective maintenance strategies:

- Increased labor cost, especially when overtime is required
- Increased cost due to unscheduled downtime of equipment
- Potential to impact other secondary equipment or process due to equipment failure
- Significant spares inventory is needed to guarantee rapid repairs
- Ineffective utilization of staff resource
- There is no record of the state of the equipment

2.3.2.2 Preventive Maintenance

Preventive maintenance (PM) is related to planned strategies implemented to avoid failures and corrective maintenance tasks as much as possible, along with prolonging the useful life of capital assets and auxiliary equipment (Higgins, Mobley, and Smith, 2002). It can be defined as maintenance tasks carried out at determined intervals or following some particular criteria to reduce the possibility of failures or the degradation of the system (Wang, 2014). It has a big impact on improving the overall reliability and availability of systems and pieces of equipment by implementing planned activities such as regular inspections, cleanings, lubrication, adjustment, and replacement of components due to wear out (Usher, Kamal, and Syed, 1998). Preventive maintenance differs from corrective maintenance because it utilizes historical failure data allowing maintenance planners to apply diverse statistical tools.

Preventive maintenance can be classified in Time-based maintenance, predictive maintenance, reliability-based maintenance, failure-finding maintenance, and risk-based maintenance. Regardless of the above classifications, all preventive maintenance approaches share the common purpose of prolonging the useful life of equipment assets as much as possible. A preventive maintenance strategy can be typically divided into four stages (Blanchard et al., 1995):

1. Preparation time
2. Inspection Time
3. Servicing time
4. Checkout time

The application of PM is, generally, conducted through the recommendations of the equipment manufacturer (OEM). In most cases, maintenance activities are implemented through time or condition-based. However, as listed by (Ahmad and Kamaruddin, 2012), there some reasons why PM based entirely on OEM recommendations is not always good enough. The main three reasons are:

1. Each equipment is subjected to specific working conditions related to environment and operational parameters that make a unique environment. Therefore, a maintenance plan cannot be generalized for every operation. It should be customized.

2. OEM manuals are not, in most of the cases, elaborated based on real operating conditions or with the experience of those who operate and maintain them.
3. Possible hidden agenda of maximizing spare components substitution through frequent PMs

Wang (2014) listed several disadvantages related to preventive maintenance strategies:

- Catastrophic failures are still likely to occur
- It is labor-intensive compared to CM strategies
- Possibility to conduct unneeded maintenance

a) Time-Based Maintenance (TBM)

Time-based maintenance is a preventive strategy which prioritizes the maintenance based on a regular schedule (i.e., weekly, monthly, etc.) A general TBM process assumes that failure behavior is predictable, so components are substituted at fixed times or intervals based on failure time data (Mann, Saxena, and Knapp Gerald, 1995).

TBM is based on the bathtub curve (Hupjé, 2018), which describes the failure behavior of most components. As observed in Figure 2.8, this curve has three regions: the early failure period, the stable failure period and the wear-out failure period (Tobias and Trindade, 2011). First, the early failure period describes failures triggered by design defects which become evident after the first operational hours of the component. This period presents a gradual decline in the failure rate as the curve approaches to the second stage. Second, the stable failure period defines a constant failure rate after early failures have been corrected. Finally, the last stage of the curve defines the wear-out period in which component demonstrates a growing failure rate due to wear and fatigue.

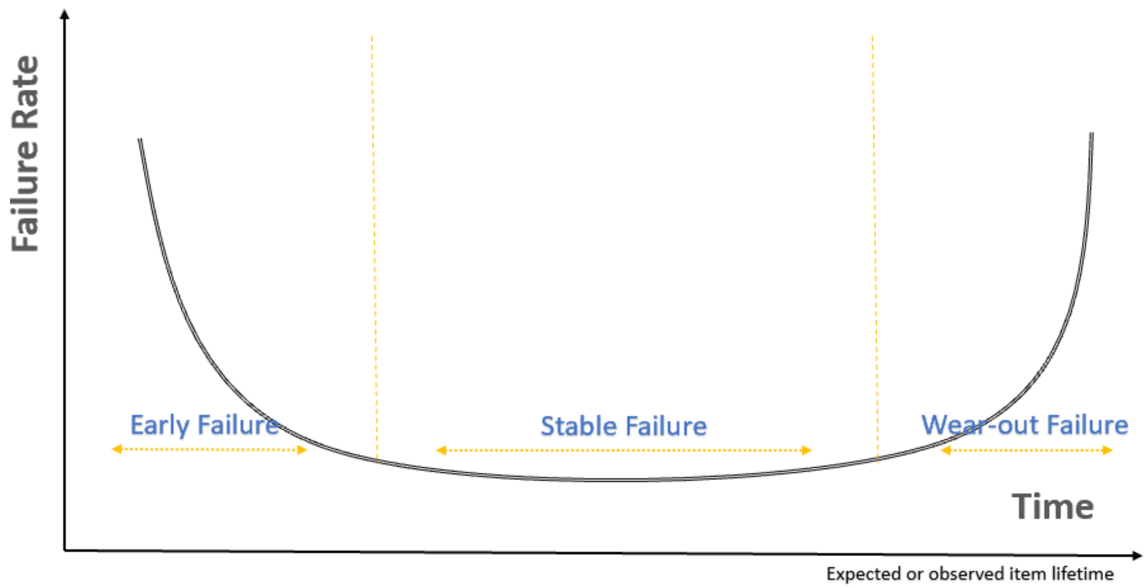

Figure 2. 8. Bathtub curve

b) Risk-Based Maintenance (RBM)

Risk-based maintenance is a type of preventive maintenance that focuses on the assessment of expected failures and consequences. Assessments, based on the likelihood of the failure and its consequences, are performed and a risk rating is elaborated to decide maintenance related tasks. It is expected that maintenance resources will be distributed according to the risk rating, starting with assets that represent the most risk for the operation.

The result of the RBM maintenance policy and the main difference with Reliability Centered Maintenance (RCM) is that RBM allows corporations to find critical assets so that they can effectively allocate their maintenance resources. However, and RBM does not consider which maintenance method is the most appropriate or which failure modes are associated with the asset under consideration.

Chan (2019) details six steps associated with RBM strategies:

1. A dataset containing enough record of historical failure data of components and system should be designed and constantly updated
2. Assess the likelihood of failures
3. Evaluate the potential consequences of failures and quantify losses
4. Design a risk ranking including based on the probability of failure and consequences
5. Design maintenance action plans with a frequency of inspections and maintenance tasks for each system/component
6. Repeat cycle

c) Reliability Centered Maintenance (RCM)

Reliability-based maintenance was implemented for the first time in the aircraft industry in the 1960s. Since then, RCM has been used consistently by the aircraft, defense, space, and nuclear industries where failures are normally associated with large losses of life, national security matters, and environmental impacts (NASA, 2000; Nowlan and Heap, 1978).

Reliability-based maintenance describes a preventive maintenance strategy that focuses on the reliability of components and groups of components working together as systems to reduce failure rates, as well as reducing maintenance costs. RCM defines specific maintenance tasks to prevent failures and increase the component's reliability.

RCM prioritizes the most critical assets which are most likely to fail or suffer larger consequences. It also proposes a maintenance strategy based on functional systems and failure modes listing all the possible consequences. Higgins et al. (2002) defined a typical RCM based on two components: functional units and failure modes. The first refers to components whose failure has the potential to impact the safety, operational, or economic aspect of a specific system, while the second is associated with the cause of failure. Failures modes are identified based on qualitative or quantitative methodologies and ranked according to the probability of occurrence and consequences of failure. Finally, maintenance tasks and procedures are implemented for the most critical units to maintain the system operating with high reliability.

Nowlan and Heap (1978) listed three primary RCM characteristics as follow:

1. Function oriented, it pursues to conserve a system or equipment intended function.
2. System oriented, it prioritizes preserving the system function rather than individual component functions.
3. Failure oriented, it studies the relationship between failure rates and operating age.

d) Failure Finding Based Maintenance

Failure finding based maintenance is a form of preventive maintenance approach aiming to find malfunctions that are not detected during routine inspections (i.e., hidden failures) in equipment that will not be needed to be utilized until some other equipment has failed. This type of maintenance strategy normally requires a complete functional test of the equipment to guarantee that it is in optimal conditions to be used when required (Conachey, 2005). He remarked that this strategy is especially convenient because it guarantees that the component is working safely and allows companies to discover if a repair or spare components are required.

This strategy is heavily used with industrial safety and protection systems designed to be activated upon emergency/operational demands to protect people, environment, or maintain production constant (Lienhardt, Hugues, Bes, and Noll, 2008). Some examples of components associated with the application of this strategy are:

- Smoke detectors
- Switches (pressure or electrical)
- Standby electric generators
- Safety valves

e) Predictive Maintenance (PdM)

Predictive maintenance can be defined as a group of tasks oriented to not only prevent failures but also predict when failures are expected to occur. The fundamental idea behind PdM is that 99% of equipment failures are preceded by certain signs or indications that failures are expected to occur (Wang, 2014). Hence, PdM aims to make the most of this window-opportunity to predict and prevent failures.

There is still controversy related to the classification of predictive maintenance and whether it should be included as a part of preventive maintenance or not. For practical matters of this study, predictive maintenance will be organized in the following three categories: Statistical based Maintenance, Condition Based Maintenance, and Intelligent Predictive Maintenance.

i. Statistical Based Maintenance

This approach represents the first attempt of PdM to predict failures. Statistical based maintenance consists of a group of maintenance tasks based on historical statistical data that was methodically recorder to predict future failures. Statistical models are also formulated for the estimation of the replacement time of components and to estimate the degradation of systems. However, the current trend in PdM is the migration of purely statistical-based approaches into other strategies that allow the use of sensors to estimate the condition of components in real-time and provide valuable information when pursuing failure predictions.

ii. Condition Based Maintenance (CBM)

Condition-based maintenance is a preventive maintenance strategy that relies on the evidence that a failure is about to occur and aims to prevent the system from failing completely or to avoid the failure consequences. The underlying fundamental of CBM is the monitoring of the condition of components and system by the use of sensors or other kinds of indicators such that maintenance is only performed when needed or just before failure (Andersen and Rasmussen, 1999).

(Hupjé, 2018) agrees that an essential notion within CBM is the P-F curve, which is presented in Figure 2.9. This curve describes the behavior of failures between the point where the failure starts manifesting (P) until the point where the failure occurs (F).

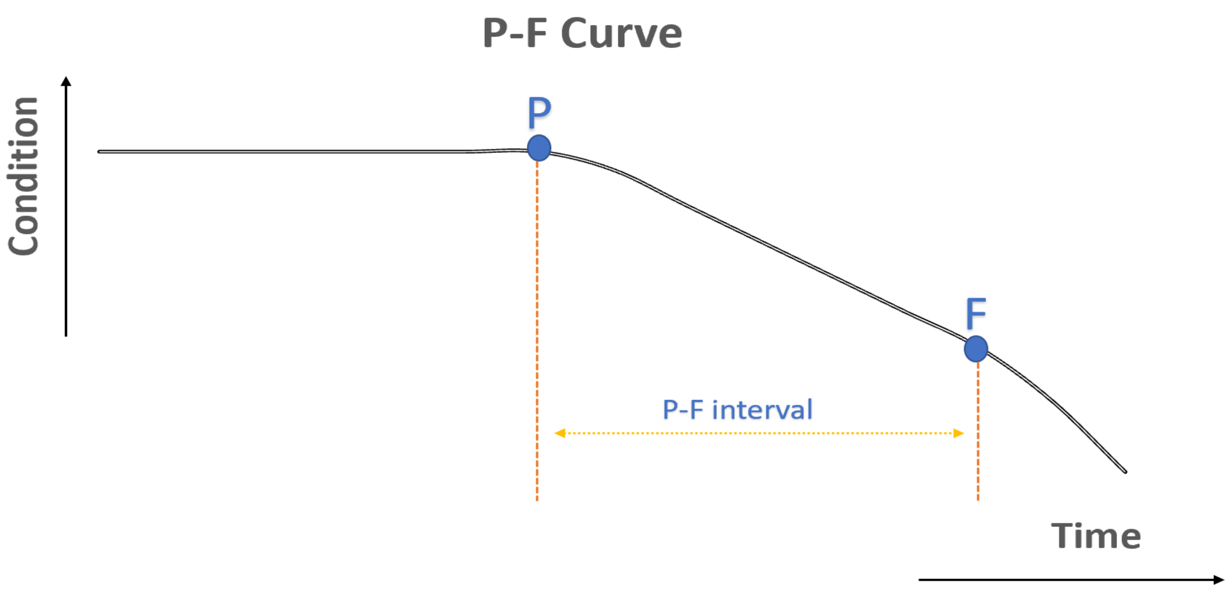

Figure 2. 9. P-F curve

This curve is of vital importance since it presents a window-opportunity of failures to be detected and corrected on time. Hence, for CBM to represent an effective maintenance strategy, effective early inspections in the P-F interval are required. Inspection times should be organized in such a way that they should be capable of capturing the indicators of deterioration between failures starts manifesting point (P) and failure occurrence point (F). Evidence that a failure is about to occur can be represented by anomalies during operation hours or irregularities during visual inspection. Some of the most used techniques to address CBM are:

- Lubricant Analysis: This test is performed to determine the oil's condition and determine whether other particles or contaminants. In most of the cases, the presence of metal particles is a signal of components wear.
- Corrosion monitoring: It is performed to find any signs of corrosion, which has the potential to cause leaks and potential component failures.
- Acoustic emission detection: Related to the detection of gas or liquid leaks, as well as friction and stress of rotating machinery.
- Vibration Analysis: Vibration techniques are generally associated with the degradation of components and it is normally performed on rotating equipment.

iii. Intelligent Predictive Maintenance (IPdM)

Intelligent Predictive Maintenance (IPdM) is also known as cognitive predictive maintenance or simply prescriptive maintenance. It describes a type of predictive maintenance that could be understood as the evolution of CBM since it not only utilizes vital data from sensors, but also combine diverse technologies such as high-end intelligent equipment, smart networks, Internet of Things (IoT), Artificial Intelligence (AI) in such a way that decision making has the potential to optimize asset management in real-time (Wang, Wang, Strandhagen, and Yu, 2018). Recent technologies advances, as well as the constant desire to reduce costs and maximize productivity, has revolutionized maintenance strategies in such a way that the use of AI and Big Data analytics have derived on more reliable maintenance strategies able to significantly impact resource availability and productivity.

This type of PdM can detect any event associated with the use or condition of the equipment and it not only can show when the failure is going to happen but what are the reasons that triggered the failure. Additionally, IPdM analysis all the possible outcomes and make recommendations to mitigate any potential risk associated with the failure with the possibility to send automatically generated tasks to maintenance personnel on the field.

According to Wang (2014), there are five main modules of IPdM:

1. Data acquisition (Sensor data)
2. Signal and data processing
3. Feature extraction, fault diagnosis, and anomaly detection
4. Maintenance decision-making
5. Key performance indicators (KPIs)
6. Maintenance scheduling optimization

To perform maintenance related decision-making, IPdM includes fault diagnostic and prognosis methodologies (i.e., Proactive Maintenance) before it defines the respective KPIs and performs optimizations. Cognitive maintenance considers fault diagnosis methodologies as well as machine learning techniques.

2.3.3 Applications of maintenance strategies

The literature provides diverse studies related to the different strategies of maintenance for different industries. For instance, regarding TBM applications, Das and Acharya (2004) discussed the replacement topic related to TBM. In their study, two replacement models considering scheduled intervals were proposed to obtain an optimal number of unit and replacement times that minimized the expenses costs. Maillart and Fang (2006) studied the replacement problem by proposing an approach to determine optimal replacement time for the multi-systems subject to budget constraints. Similarly, Laggoune, Chateauneuf, and Aissani (2010) expanded the knowledge for multi-systems subjected to random failures to minimize the cost rate. Wu, Ng, Xie, and Huang (2010) examined this topic for finite lifecycle multi-state systems related to degradation and failures to determine optimum replace time. Moreover, Hsieh (2005) developed a maintenance strategy considering aging and random shocks to define optimal operating times and the optimal quantities of essential components that maximized the annual net profit of the production system.

Regarding RBM, Chen and Toyoda (1989) developed a methodology based on this approach for maintenance scheduling based incremental risk categories. Later, Dey (2001); Dey, Ogunlana, Gupta, and Tabucanon (1998) applied RBM for maintenance scheduling and inspections for cross-country pipelines. About RCM, Niu, Yang, and Pecht (2010) proposed a methodology to reduce maintenance costs as well as condition monitoring by introducing two case studies related to induction motors and methane compressors. (Lienhardt et al., 2008) addressed a failure-finding maintenance strategy for repairable systems in the aircraft industry intending to reduce maintenance costs and consider the risk of corrective maintenance. Faut detection approaches are proposed by Ayaz, Öztürk, Şeker, and Upadhyaya (2009); Pedregal and Carnero (2009).

PM strategies were proposed by Ben-Daya and Alghamdi (2000), consisting of two consecutive preventive maintenance models that consider both the age reduction of the system and the PM intervals. Sheu, Yeh, Lin, and Juang (2001) determined optimal an optimal preventive maintenance policy considering Bayesian theory. Bloch-Mercier (2002) considered a PM policy considering a Markov deteriorating system. Later, Bris, Châtelet, and Yalaoui (2003) proposed an optimization method to minimize the PM cost of parallel systems using Monte Carlo simulation.

Chu, Proth, and Wolff (1998) proposed an overall PdM replacement model based on dynamic programming. Hall, Knights, and Daneshmend (2000) presented a cost-saving approach based on oil analysis and CBM of underground equipment in a gold mine. Swanson (2001) introduced a prognostic approach using condition and failure hazard to optimize availability, reliability, and the total cost of ownership of a particular asset. Later, the application of predictive maintenance in the manufacturing industry was examined by McKone and Weiss (2002).

A generalized CBM model able to be applied in different industries was developed by Amari, McLaughlin, and Pham (2006). The approach uses Markov Decision Processes (MDP) to deliver optimal cost-effective maintenance decisions based on CBM. Machine Learning (ML) methodologies for predictive maintenance to minimized downtime and associated costs are also explored by Susto, Schirru, Pampuri, McLoone, and Beghi (2014). ML applications considering vibration and acoustic analysis from milling machinery were studied by Wu, Jennings, Terpenny, Gao, and Kumara (2017) by considering regression trees to represent failures. Similarly, another ML application was the main focus of (Shin, Cho, and Oh, 2018) for the prediction of the abnormal operation of a conveyor belt system considering Supported Vector Machine (SVM).

2.3.4 Recent developments in maintenance

New technologies have shifted the direction of how data are processed and manipulated for the benefit of safety, operation excellence, and decision-making by processing an enormous amount of data in seconds. These changes have driven the interest in more automatized maintenance systems that can integrate multiple machines. The goal is to achieve near-zero breakdown events by the implementation of embedded cognitive systems with the potential to monitor, diagnose, recommend, and allow equipment to perform its repairs without assistance (i.e., self-maintenance) or with the minimum support as possible from a maintenance crew. Two intelligence software tools with applications in maintenance are described in this section.

2.3.4.1 Watchdog Agent®

Developed by the Center for Intelligent Maintenance Systems (IMS), a leader researching center in topics of Prognostics and Health Management (PHM), e-Maintenance, and Decision Support, this toolbox represents a collection of intelligent software that can be customized for different applications. Some of the most important solutions given by this software are condition assessment, fault detection, and performance prediction. As can be observed in Figure 2.10, the Watchdog Agent® consists of four modules: feature extraction, performance assessment, diagnosis, and prognosis modules. Those modules work with input data from embedded sensors and historical data.

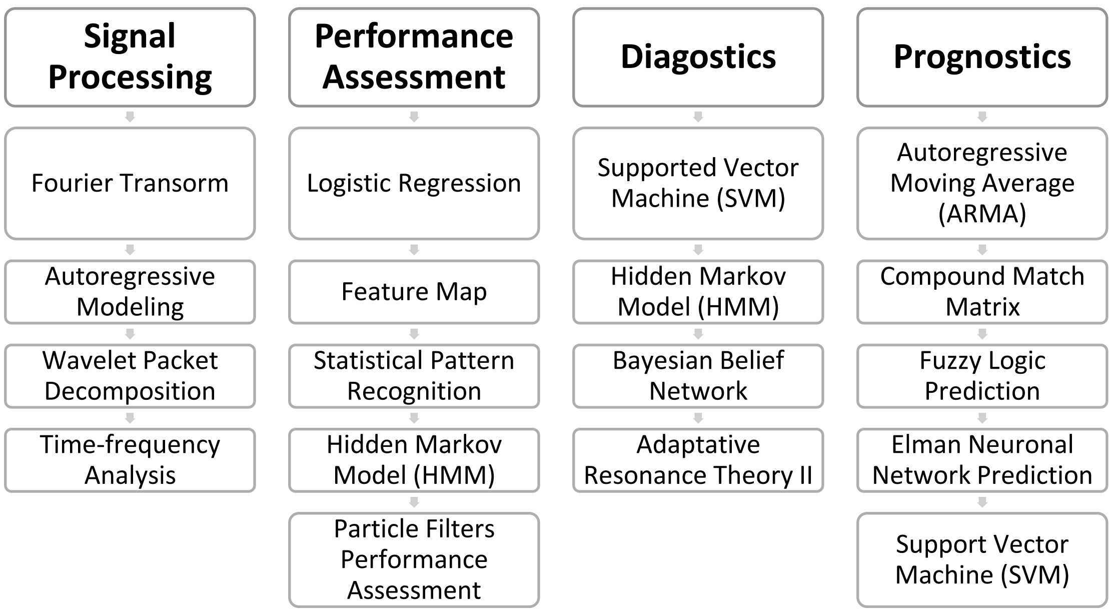

Figure 2. 10. Watchdog Agent® modules. Adapted from Lee and Wang (2008)

First, the sensor and data acquisition systems accumulate raw performance data of specific equipment, and detailed features of data related to the performance of the equipment are extracted and analyzed with signal processing tools. Second, in the performance assessment module, these performance features are then analyzed to compare sensor data results with expected nominal values, as can be observed in Figure 2.11. Next, the diagnostics module reveals the system degradation as well as its proximity to previous faults (Lee and Wang, 2008). Finally, the prediction and prognostic module have the objective to analyze the degradation behavior over time and predict future outcomes.

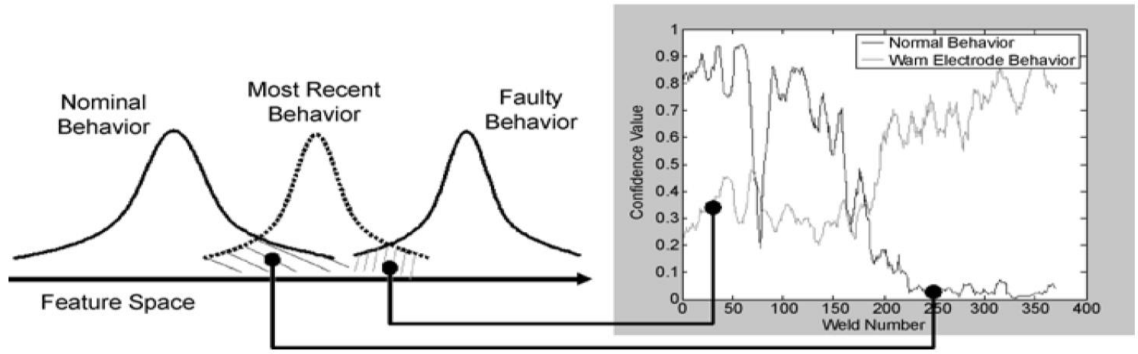

Figure 2. 11. Comparison of sensor data with nominal parameters. From Lee and Wang (2008)

This toolbox has been applied in the mining and construction industry for the performance management, assessment, and prediction of health management of heavy-duty equipment produced by Komatsu. In this case study, it was shown how the Watchdog Agent®, working in conjunction with Komatsu, was able to predict health management based on a specific application of the diesel engine component. Lee, Kao, and Yang (2014) listed and described Watchdog Agent® modules by the following steps:

- The data acquisition module was responsible for storage daily data such measured in the diesel engine such as pressures, fuel flow rate, temperature, and the rotational speed of the engine
- Then, the Huber method was used for the data preprocessing to remove outliers and autoregressive moving average approaches were conducted to predict time series values
- Next, engine patterns were classified using Bayesian Belief Network (BBN) classification technique to understand the irregular engine behavior in the data in such a way that the root cause of the problem was detected at the initial phase of degradation

- Finally, life prediction was estimated by the use of a fuzzy logic-based algorithm, which was a function of both features extracted from data pattens and engineering experience.

2.3.4.2 IBM Maximo® APM

IBM Maximo® is part of the IBM Maximo Asset Performance Management (APM) suite specialized in determining the probability of asset potential failures and determining the reasons that could affect plant or business operations. It uses IBM Watson™ as a cognitive tool to search for models in asset statistics and correlates with any known issues to better foresee failures (IBM, 2020).

Watson™ represents an innovative software that has been used in areas such as finance, education, manufacturing, aerospace, and medicine. For instance, it was applied to improve the reliability and maintenance operation of the U.S. army equipment with the following listed benefits (IBM, 2013):

- Improved repair parts forecasting and supply availability
- Supported mission command with equipment deep insight based on data analytics
- Assisted with the acquisition process and life cycle assessment

The main characteristics of the use of Watson for predictive maintenance are:

- Store and correlate vast amounts of asset data including sensor data
- Builds and expand deep knowledge based on the data
- Predict and diagnose component failures and prescribe maintenance tasks

2.4 Mining equipment and sustainability linkage

The sustainability of a mining operation can be defined as the development of organization, operation and management strategies to extract mineral resources without sacrificing the needs of future generations. The linkage between mining equipment and sustainability is based on three core values: social, economic, and environmental aspects. There is a close relationship between equipment management and the sustainability of mining operations. Regarding the economic aspect, by implementing an effective equipment management policy, the mining companies have the potential to increase their overall productivity and efficiency. High levels of reliability, availability, and maintainability will reduce downtime and will contribute to a more efficient operation. Moreover, potential catastrophic failures could be detected on time and maintenance tasks scheduled in order to prevent equipment failure. Repair costs, non-scheduled tasks, as well as spare inventories, could be reduced and significantly save money.

Social and environmental considerations associated with equipment management could vary depending on several factors such as mine location, proximity to local communities, mining method, type of equipment, etc. Social aspects are related to any potential impact that mining equipment could have on local communities and the general population. For example, the initial disruption in public or local areas to gain general access for construction equipment at the beginning of the operation. Social aspects also involve the safety of the workforce, which will be increased by effective maintenance strategies.

From an environmental standpoint, the impact of mining operations will depend on whether diesel-based equipment is in use, as is still typical within the mining industry. Despite carbon policies such as the carbon tax and Cap and trade being successfully implemented by many governments, gas emissions from mobile equipment and processing plants still represent a meaningful contribution to global warming which may be successfully addressed by effective equipment management policies while migration to greener technologies is gradually implemented.

3 Optimal Inspection Intervals based on an RCM approach and maintenance scheduling based on Virtual Age

As the equipment is a critical asset for mining companies, an appropriate maintenance policy is necessary to ensure excellent performance. Maintenance has a direct impact on availability and reliability, which will impact the economical aspect of a mining operation by reducing costs and maximizing efficiency. Improving the traditional reactive maintenance, which involves waiting until the failure time, has become a high priority for mining companies due to its potential to reduce overall operating costs. Moreover, with larger and more complex mining equipment being produced, maintenance costs such as labor and repair expenses have increased considerably. Consequently, maintenance management has a great impact on the overall costs of mining companies by detecting or reducing the probability of potential failures and suggesting immediate actions. Maintenance management aims to maximize the equipment's useful life while reducing overall operating costs. Therefore, by developing a proper maintenance strategy, mining companies could avoid unscheduled, long-term downtime and productivity losses related to more expensive repairs.

An effective maintenance policy should also consider optimal inspection intervals to detect failures at an early stage and not just depend on reactive maintenance. Inspections are activities that assist in the detection of any latent irregularity or defect in an engineering system. They are generally implemented on an activity checklist proposed by the supplier, designer, or operation-specific standards. The objective of inspections is to avoid possible catastrophic failures through a general examination of the current state of the equipment They allow maintenance planners to decide on whether the equipment needs scheduled maintenance, or if minor replacements and corrections should be executed to guarantee normal operation and safety standards. Inspection activities are of great benefit in terms of asset management, especially for industries that rely heavily on equipment reliability and availability (e.g., mining and construction). In addition to facilitating maintenance scheduling, they also provide vital information about the various issues; these include warranty policies, optimal item replacement timing, and understanding deterioration mechanisms (Gölbaşı and Demirel, 2017).

Moreover, the determination of the best time to inspect an engineering system has a direct impact on operation availability. It can also represent a key decision when a system's breakdown has the potential to represent considerable downtime that can affect other processes. Most of the time, inspection intervals do not receive the importance they should, and they are simply implemented based on recommendations proposed by the OEM. However, they cannot be fixed based on only the type of equipment being analyzed regardless of other specific considerations such as weather conditions, operating conditions, and maintenance policies. Therefore, inspection intervals must be executed at the appropriate time. For instance, if inspection intervals are too short, the overall inspection cost (e.g., labor and resources) would increase considerably due to the execution of more frequent inspections that will be responsible for production losses. Similarly, if inspection intervals are too long, degradations, latent occurrences, and anomalies may not be detected in time. The engineering problem herein is to find the best inspection interval, which represents a trade-off between the inspection costs and benefits obtained by anticipating possible failures in advance.

Optimal inspection intervals provide useful input for preventive maintenance (PM) scheduling that is a fundamental process to maximize the equipment performance. Preventive maintenance consists of a series of activities performed to enhance systems' reliability and repair/replace components before failures. The main difference between inspection and maintenance is that while the former only involves regular activities to detect irregularities, defects, wear, anomalies or corrosion, the latter is related to repair/replacement tasks. By developing a proper maintenance strategy, mining companies could avoid unscheduled long downtime and productivity losses related to more expensive repairs due to unpredicted, and sometimes critical, failures. The PM actions are normally scheduled at convenient points in time to get desired levels of reliability. Based on how well equipment is repaired (i.e., the degree of restoration), Wang and Pham (2006) classify PM in the following way:

a) Perfect repair or perfect maintenance: Maintenance actions that recover the system to "as good as new condition"
b) Minimal repair: Maintenance actions that recover the system to the same condition as it had when it failed.
c) Imperfect repair or imperfect maintenance: Maintenance actions that restore the system in-between "as good as new" and "as bad as old". Imperfect maintenance involves rejuvenation of a system.
d) Worse repair or worse maintenance: Maintenance actions that increase the failure rate of the system.

The literature provides different approaches to analyze inspection intervals in maintenance. For instance, the delay-time based approach is one of the most used methodologies. The delay time can be defined as the period from the defect arrival time to the moment of failure. This concept was first introduced by Christer (1973) as a procedure for the optimization of inspection intervals. Later, Bayesian techniques to optimize inspection intervals and maintenance planning were studied by Apeland and Scarf (2003). Their model proposed the idea of integrating the analyst group judgments into the analysis, so besides all the available data, the engineering expertise and experience are considered into the model to estimate future values. Zhao, Chan, Roberts, and Madelin (2007) used a non-homogeneous Poisson process (NHPP) and delay-time concept to propose an algorithm to optimize intervals of inspections and maximize the reliability of the component under inspection. Specific applications considering delay-time and best inspection intervals were presented in Andrawus, Watson, Kishk, and Gordon (2008); Arthur (2005); Scarf and Majid (2011) regarding topics such as automotive vehicles, wind turbines, and marine systems, respectively.

Li and Pham (2005) developed a generalized condition-based maintenance model relying on multiple competing failure processes, including two degradation processes, and random shocks. The average long-run expected cost was deduced based on degradation and random cumulative shock damage expressions. Mathew (2008) stated that, for the regularity of inspection to be ideal, it must faithfully match the failure rate of the equipment. His model consists of a three-layered structure. In the first stage, a time-dependent model for inspection frequency was proposed. Second, the consideration of the relationship between inspection frequency and the hazard rate behavior was taken into account. Finally, in the last stage, the model accounted for cost optimization. His optimal inspection frequency model was presented as an alternative for forecasting maintenance costs. Later, Wang (2008) discussed a model to estimate the minimum expected cost per unit related to optimal replacement time considering the repair and maintenance durations, as well as the costs related to their repair and loss of production. Barker and Newby (2009) addressed an inspection and maintenance strategy for a system whose state is denoted by a multivariate stochastic process. Other studies that also considered the delay-time concept were Taghipour and Banjevic (2012) to determine optimal periodic inspections and Berrade, Scarf, and Cavalcante (2015) for preventive maintenance scheduling in a single component.

Accordingly, the topic of maintenance scheduling has been largely discussed in recent decades. The p-q guideline is a well-known strategy to show the state of maintenance. Nakagawa (1979) examined imperfect maintenance and proposed a model that suggests that after every PM, a system returns to its previous condition as good as new (perfect repair) with a likelihood p, and as in bad condition as old with a likelihood q=1-p (minimal repair). A comparable methodology was likewise considered by Helvic (1980). Later, Brown and Proschan (1983) examined the p-q guideline and set up aging upholding properties of the imperfect repair model. These outcomes were utilized afterward by Wang and Pham (1996) to acquire ideal imperfect maintenance policies. Lim, Lu, and Park (1998) presented a Bayesian imperfect repair model with the likelihood of a perfect repair expressed as *P*. Accepting that *P* is an arbitrary variable, the dispersion of waiting delays between two successive perfect repairs and its relating inadequacy rate was acquired. Likewise, Cha and Kim (2001) demonstrated Bayesian accessibility where

P is not fixed but on the other hand, an irregular variable with an earlier dispersion. Li and Shaked (2003) supplemented Brown and Proschan (1983) by including stochastic maintenance correlations for the number of breakdowns. A similar idea was introduced by Malik (1979). He expressed that maintenance activities are between minimal and perfect repairs. In other words, imperfect repairs lie between 'as good as new' and 'as bad as old' repairs. At that point, the level of progress in the failure rate was named improvement factor. Lie and Chun (1986) supplemented Malik's model with a general interpretation to determine the improvement factor dependent on maintenance costs and the system's age. Jayabalan and Chaudhuri (1992b) considered the improvement factor in proposing a calculation to limit the normal total expenses for a maintenance scheduling model. Additionally, Jayabalan and Chaudhuri (1992c) talked about an ideal support policy for a system with expanded mean downtime and guaranteed failure rate. Suresh and Chaudhuri (1994), considering the fuzzy set hypothesis and improvement factor, proposed a PM approach to achieve an ideal reliability range. Other studies identified with the improvement factor technique were submitted by Canfield (1986); Chan and Shaw (1993); and Doyen and Gaudoin (2004).

Kijima, Morimura, and Suzuki (1988) developed a stochastic model for repairable systems that are related to general repairs. Later, Kijima (1989) proposed the General Repair Model (GRP), which is a stochastic model able to describe imperfect maintenance by understanding the effects of repairs on the age of the system. A system subjected to failure is analyzed and repaired after each failure. For this model, the age of the system is reduced after repairs. Being the real age (i.e., physical age) of a system its operating functioning time, its virtual age will be a function of the real age. Assume that after each event, repairs are implemented to improve the system performance. The restoration factor represents the improvement of equipment life after each repair. Let *q* be the action effectiveness factor, which can be understood as the opposite of the restoration factor (RF). While the restoration factor is a value between 0 and 1 that describes the percentage to which a system or component will be restored, the action effectiveness factor is defined as *q= 1-RF*. Where RF stands for the restoration factor and q is the action effectiveness factor. An RF of 1 implies that the repaired component is as good as new, while an RF of 0 implies that the component is as bad as old or has the same condition as it had before the repair. Likewise, an RF of 1 would indicate a *q* of 0 and an RF of 0 would indicate a *q* of 1. There are two general repair models (Kijima, 1989).

Type I:

$$v_i = v_{i-1} + qx_i = qt_i \tag{3.1}$$

Type II:

$$v_i = q(v_{i-1} + x_i) = q^i x_1 + q^{i-1} x_2 + \cdots x_i \tag{3.2}$$

where vi is the virtual age of the system right after the ith repair. The main difference between both virtual age models is related to the moment where the damage was incurred. The former considers that the ith repair is not able to remove the damage incurred before the ith failure. The only thing it can do is to reduce the additional age xi to qxi. In contrast, the latter model assumes that the virtual age has been accumulated to vi-1 + xi at the moment when the ith repair is performed. Thus, the ith repair can remove the cumulative damage from current and previous failures by reducing the age to q(vi-1 + xi) (Kijima, 1989).

3.1 Methodology

The first step is based on the analysis of failure data to estimate the desired reliability levels that could be used to suggest optimal inspection intervals. Reliability can be defined as the probability that a system will have a satisfactory performance under normal conditions for a specific time period (Dhillon, 2008). Diverse studies covering topics of reliability could be found in the literature, in which the power-law is selected to fit the data. The power-law is a well-known methodology for analyzing the reliability of repairable systems and determine the system failure behavior. Equation 3.3 describes the power-law mean value function.

$$M(t) = \lambda t^{\beta} \tag{3.3}$$

Where λ and β stand for the shape and scale factor, respectively. They can be estimated by mathematical procedures or by using specialized reliability software such as ReliaSoft. Once the model parameters (λ and β) have been estimated, the reliability of each truck could be easily estimated by considering power or exponential relations (Tobias and Trindade, 2011). Considering the reliability as the probability of zero occurrences in the time interval $(t\ to\ t + s)$, the reliability $R(s)$, can be expressed by as

$$R(s) = e^{-\left(M(t+s)-M(t)\right)} \tag{3.4}$$

Where $M(t)$ is defined as the mean cumulative number of failures and s is the time interval. Inspection intervals can be implemented based on the desired reliability decision-makers would like to maintain. The second step develops optimal preventive maintenance scheduling considering the virtual age of the trucks, which represents the rejuvenation of the equipment after each repair. The methodology for the determination of optimal inspection intervals and PM scheduling is presented in Figure 3.1. When considering the specific effect of CM and PM for the system, the system's virtual age for the Model I could be defined according to Equations 3.5 and 3.6 (Jack, 1998):

$$v_{ij} = v_{i-1,j} + q_{CM}\left(t_{ij} - t_{i-1,j}\right), \tag{3.5}$$

$$v_{0j} = v_{0,j-1} + q_{PM}\left(v_{n_{J-1},j-1} - v_{0,j-1} + t_{0j} - t_{n_{J-1}+1,j-1}\right), \tag{3.6}$$

Similarly, Equations 3.7 and 3.8 for Model II:

$$v_{ij} = q_{CM}\left(v_{i-1,j} + t_{ij} - t_{i-1,j}\right), \tag{3.7}$$

$$v_{0j} = q_{PM}\left(v_{n_{J-1},j-1} + t_{0j} - t_{n_{J-1}+1,j-1}\right), \tag{3.8}$$

where t_{ij} is the time of the $i\ th$ failure in the $j\ th$ PM interval; t_{0j} stands for the time of $(j-1)th$ PM ; v_{ij} is the virtual age following the $i\ th$ repair in the $j\ th$ PM interval; and v_{0j} is the virtual age following the $(j-1)th$ PM. Then, the probability of failure at time t relying only on the system's virtual age and is expressed (Jack, 1998):

$$u(t;H_t) = r[v(t)] = r\left(v_{i-1,j} + t - t_{i-1,j}\right) \text{ for } t_{i-1,j} \le t < t_{ij}\,, \tag{3.9}$$

Where H_t is the history of the failure process up to time t, and r(x) is the hazard rate function for the time to first system failure. The expected failure count function is stated by $M(t) = E\{N(t)\}$, where $N(t)$ is the number of failures occurring up to time t. Then, the rate of occurrence of failures at time t, $m(t)$ is defined (Jack, 1998).

$$m(t) = M'(t) = \lim_{\Delta t \downarrow O} \frac{\Pr\{\, a\ failure\ \ in\ (t, t + \Delta t)\}}{\Delta t} \tag{3.10}$$

It is worthy to note that closed-form expressions for $M(t)$ exist in some special cases. For example, in the case of periodic PMs at times $jT(j = 1,2, \dots)$ and a minimal $CM\ (q_{CM} = 1)$, then for $(j-1)T \le t < jT$:

$$M(t;T) = \ \sum_{i=1}^{j-1} [R(\, v_{0i} + T) - R(v_{0i})] + R(v_{0j} + t - j{-}1T) - R(v_{0j}) \tag{3.11}$$

where $v_{0i} = (i-1)q_{PM}T$ for model I, $v_{0i} = \left(\frac{1-q_{PM}^{i-1}}{1-q_{PM}}\right)\delta_{PM}T$ for model II, and $R_{(x)} = \int_0^x r(u)\, \mathrm{d}u$ is the corresponding cumulative hazard function. Also, for perfect PM $(q_{PM} = 0)$, Equation 3.12 reduces to the simple form presented (Jack, 1998).

$$M(t;T) = (j-1)R(T) + R(t - (j-1)T) \text{ for } (j-1)T \le t < jT, \tag{3.12}$$

Later, the simulated value of $M(t)$ would be required. Some considerations would be given to estimate $M(t,T)$ by simulation. The survivor function of the random variable representing the time between the $(i-1)th$ and the $i\ th$ failure in the $j\ th$ PM interval is expressed

$$Pr\,\{X_{ij} > x | v_{i-1,j}\} = \frac{\bar{F}\left(v_{i^{-1},j} + x\right)}{\bar{F}\left(v_{i^{-1},j}\right)} = exp\,\{-\{R\left(v_{i^{-1},j} + x\right) - R\left(v_{i^{-1},j}\right)]\} \tag{3.13}$$

where $\bar{F}$(x) is the survivor function and R(x) is the cumulative hazard function. Then the generator for failures times is defined (Jack, 1998)

$$T_{ij} = T_{i-1,j} - v_{i-1,j+} R^{-1}\left[R\left(v_{i^{-1},j}\right) - ln\, u_{ij}\right] \text{ for } (j = 1,2, \ldots, k\, ; i = 1,2, \ldots nj) \tag{3.14}$$

where T_{ij} is the generator for system failure times, $T_{ij} = T_{i-1,j} + x$, and u_{ij} represents a uniform (0,1) variate that could be expressed as $u_{ij} = \exp\{-\{R(v_{i^{-1},j} + x) - R(v_{i^{-1},j})\}\}$

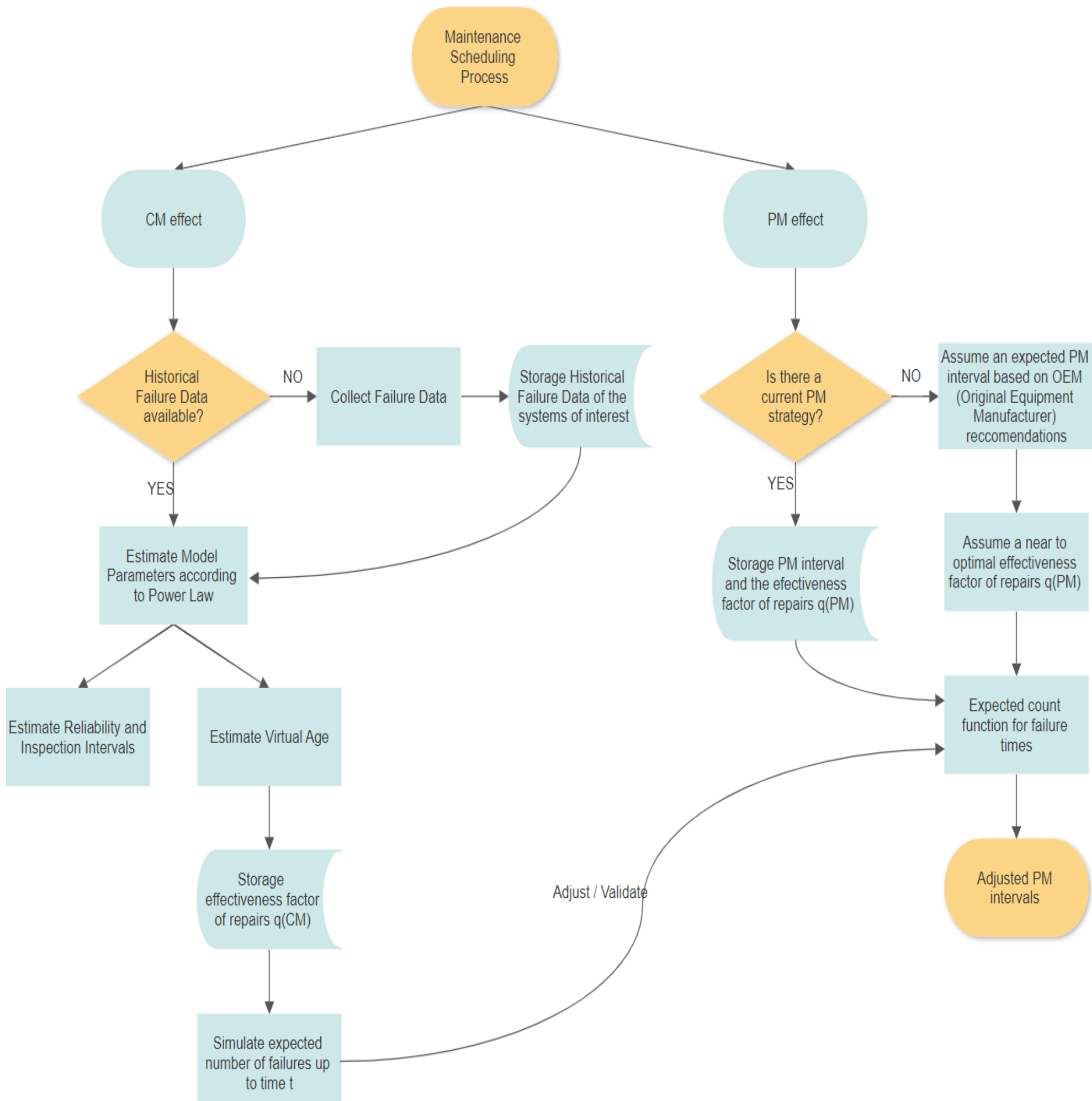

Figure 3. 1. Methodology to estimate optimal inspection intervals and PM Scheduling

3.2 Case Study

3.2.1 Data Collection

In this section, using historical failure data, eight mining trucks have been modeled using specialized reliability software: namely RGA and Weibull++ suites supported by ReliaSoft.

Table 3. 1. Failure times in hours for one of the mining trucks under inspection

Failure Times Truck 1							
364.5	1572.8	3501.8	4707.6	5375.5	5856.7	6715.4	7285.9
368.9	1615.8	3521.4	4716.4	5377.9	5856.9	6851.0	7298.8
471.3	1621.8	3689.2	4717.9	5389.9	5857.9	6851.4	7299.4
478.4	1622.9	3788.5	4944.8	5401.9	5897.4	6853.9	7300.1
478.7	1762.9	3789.0	4945.0	5413.9	5897.8	7021.9	7442.2
773.4	1763.6	3871.5	4945.3	5425.9	5977.8	7022.2	7442.5
773.8	1926.7	3988.4	4945.9	5475.0	5977.9	7096.0	7481.9
776.0	2197.0	4043.6	4955.2	5484.0	5983.0	7105.9	7489.9
776.4	2197.4	4054.6	4955.7	5530.9	5987.2	7117.9	7501.9
778.3	2287.6	4205.7	4957.9	5533.9	5988.6	7121.8	7508.7
800.7	2426.3	4206.3	4974.2	5651.8	5995.8	7129.9	7508.9
964.4	2603.2	4263.0	4979.7	5653.9	5996.0	7141.9	7640.1
988.4	2797.3	4353.4	4981.1	5665.9	6039.5	7145.8	7689.8
1014.4	2797.5	4356.4	4981.9	5677.9	6256.0	7153.9	7980.3
1016.6	2797.9	4357.9	4993.3	5689.9	6289.9	7165.9	8083.8
1022.9	3145.6	4431.0	4993.9	5701.9	6292.0	7177.9	8144.0
1087.7	3145.9	4431.5	5043.7	5713.9	6297.5	7189.9	8148.2
1092.3	3155.7	4456.9	5063.5	5725.9	6298.0	7201.9	8153.5
1094.9	3194.2	4457.2	5080.4	5775.7	6301.9	7213.9	8288.0
1106.9	3269.5	4465.9	5111.2	5780.5	6338.5	7225.9	8288.3
1173.6	3273.5	4534.5	5112.1	5822.3	6350.6	7237.9	8511.8
1220.1	3293.6	4539.1	5126.8	5822.5	6389.5	7249.9	8512.3
1275.8	3297.2	4540.3	5162.6	5823.9	6389.6	7252.7	8681.1
1308.0	3493.5	4545.5	5199.7	5832.5	6606.1	7261.9	8836.4
1310.9	3495.9	4647.7	5246.2	5833.9	6659.8	7273.9	8858.2

Table 3.1. presents historical failure information recorded in one year and related to five of the main systems of each of the trucks was considered. The subsystems under inspection were the tray/body system, braking system, engine system, electrical system, and hydraulic system. In this study, the effect of system rejuvenation due to multiple imperfect repairs after each failure has been introduced, considering the concept of the virtual age.

3.2.2 Results of the optimal inspection intervals based on RCM

After analyzing the failure times for the trucks under inspection, the power-law parameters (i.e., λ and β), are determined as in Table 3.2. The Laplace trend test, which assesses the hypothesis if a trend exists in the data, is evaluated to determine whether the system is deteriorating, improving, or if there is no trend at all. As was expected, it concluded that the mining trucks under consideration are deteriorating. The graphical analysis presented in Figure 3.2 based on failure time is consistent with the system being analyzed. Repairable systems with non-renewable processes are expected to show deterioration over time. As Figure 3.2 shows, as truck ages, the number of failures increases considerably. Figure 3.3. describes a typical reliability curve of one of the trucks under consideration.

Table 3. 2. Parameter estimation results for one of the trucks under consideration

Parameters	
Model	Power Law
Analysis	Estimation
Beta	1.311246
Lambda(hr)	0.001333

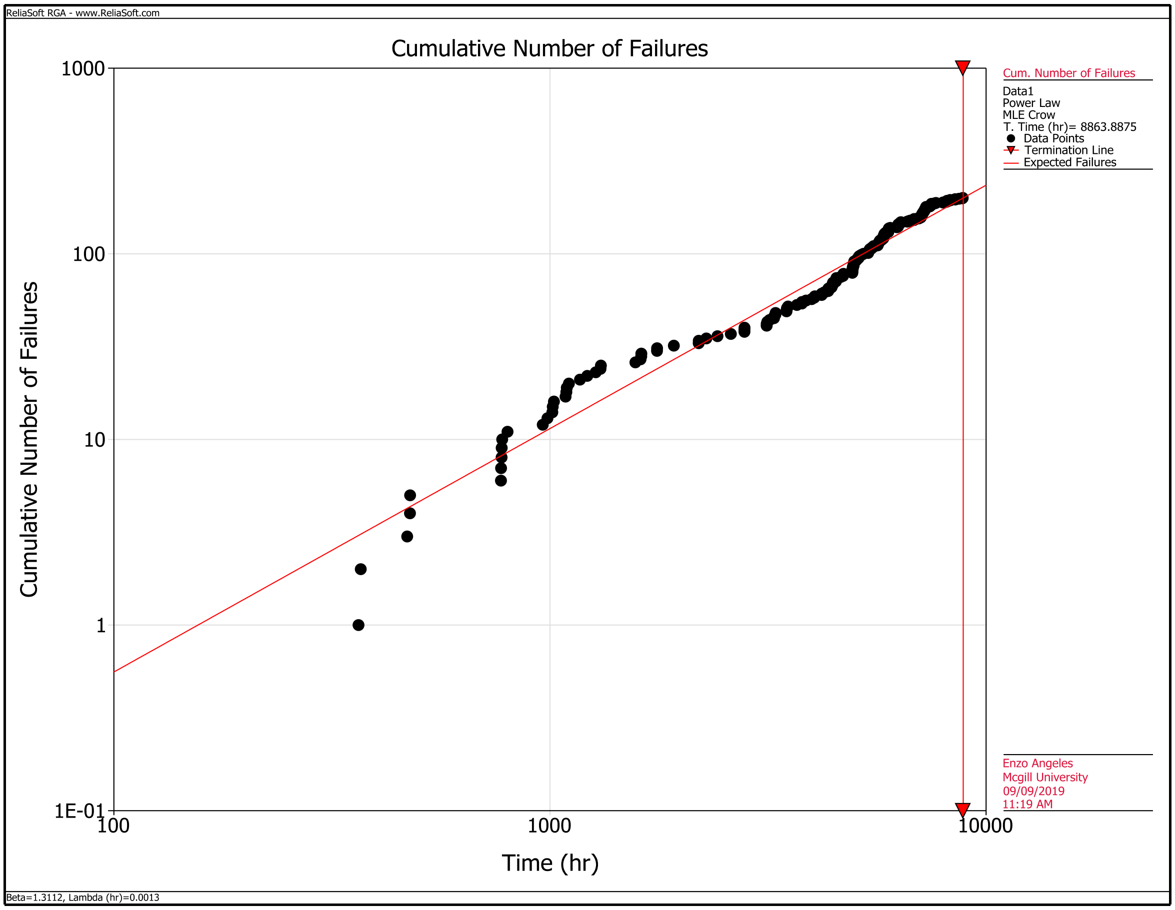

Figure 3. 2. Cumulative number of failures for one of the trucks under inspection

Since repairable systems may exhibit dependent and not identically distributed failures, where past and current repairs may affect the future failure process, the general repair process (GRP) was selected in this case study. Given that the objective is to determine the virtual age associated with the repairable system being studied, the exact occurrence event of each of the failures should be available to apply Equations 3.1 or 3.2, which describe types I and II of the virtual age respectively. However, the failure time would be unknown until the event occurs. Therefore, closed-form expressions to represent the total failure time and failure intensity are not available since they are functions of failure times and virtual age. Hence, multiple simulations must be performed to forecast these values.

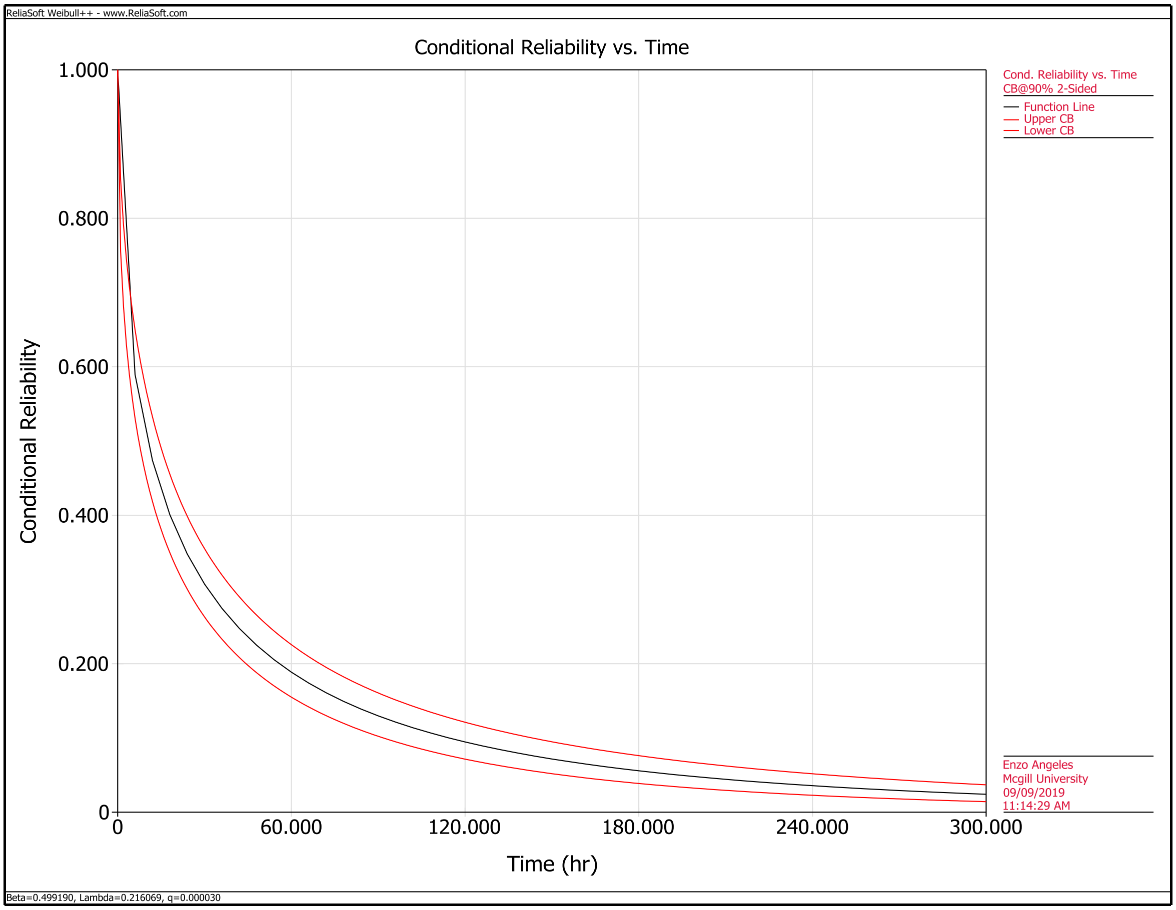

Figure 3. 3. Reliability curve of one of the trucks under inspection

The first step is to determine which virtual age model provides the best statistical fit for the given data. In order to do so, both types of virtual age presented in Equations 3.1 and 3.2 are tested. The Likelihood Function Value (Lk) is a parameter that can be used for model selection. The model containing the greater value of Lk (the closest to zero in the case of negative values) would represent the best statistical fit for the data (Schwarz, 2011). Table 3.3. shows the result of the test obtained in ReliaSoft for one of the trucks under consideration. The eight trucks present similar results, where Model I is chosen because it presents a larger LK value. Later, using Equation 3.1 and the value of the effectiveness factor, q, previously simulated with Monte Carlo (500 simulations), the value of the model parameters considering the effect of virtual age and the effectiveness factor are presented in Table 3.4

Table 3. 3. Analysis summary for virtual age type I and type II corresponding to one of the trucks under consideration

Parameters Model I		Parameters Model II	
Model	Power Law	Model	Power Law
Beta	1.630270	Beta	1.230343
Lambda(hr)	0.000043	Lambda(hr)	0.000850
Lk Value	-178.8386	Lk Value	-179.5067
RF	0.861379	RF	0.999399

Table 3. 4. Estimated parameters considering virtual age (VA)

Trucks	Considering Virtual Age (VA)		
	Lambda	Beta	Effectiveness factor
1	0.000043	1.63027	0.06864
2	0.000441	1.29904	0.07840
3	0.000059	1.49349	0.42548
4	0.000020	1.69391	0.20155
5	0.000027	1.58352	0.07995
6	0.000738	1.23744	0.09731
7	0.000261	1.31744	0.11332
8	0.000084	1.41070	0.27682

Figure 3.4 shows the virtual age of each of the mining trucks under consideration. As can be observed, small values of the effectiveness factor, q, presented in Table 3.4 are associated with small values of the virtual age. For instance, an effectiveness factor of 0.06, which was found for truck 1, is associated with a virtual age of 877 hours while an effectiveness factor of 0.42, which was found for truck 3, is related to a virtual age of 3640 hours. To sum, the closer the effectiveness factor is to 1 the older the virtual age is expected.

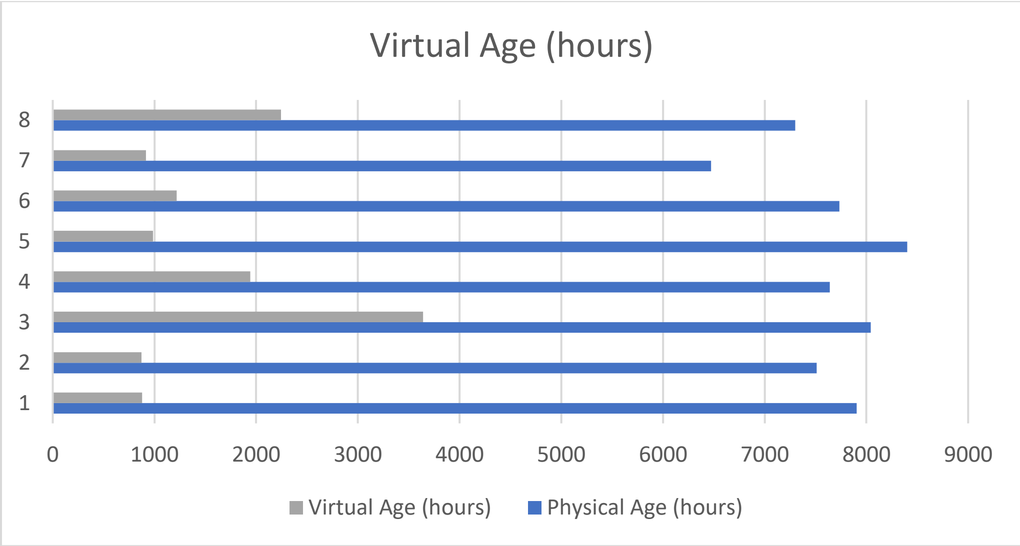

Figure 3. 4. Virtual age (hours) vs Physical age (hours) of the mining trucks under inspection

The reliability of each truck could give an idea of the necessity of establishing regular inspection intervals, which could prevent potential failures. Hence, based on the desired reliability, optimal inspection intervals can be proposed depending on the age and rejuvenation of the trucks. Figure 3.5 describes the reliability behavior for each of the mining trucks as well as the fleet's reliability (red curve). As can be observed, each truck presents different reliability behavior, which is related to its historical failure data, quality of repair actions, as well as other factors such as the system's age and operational conditions.

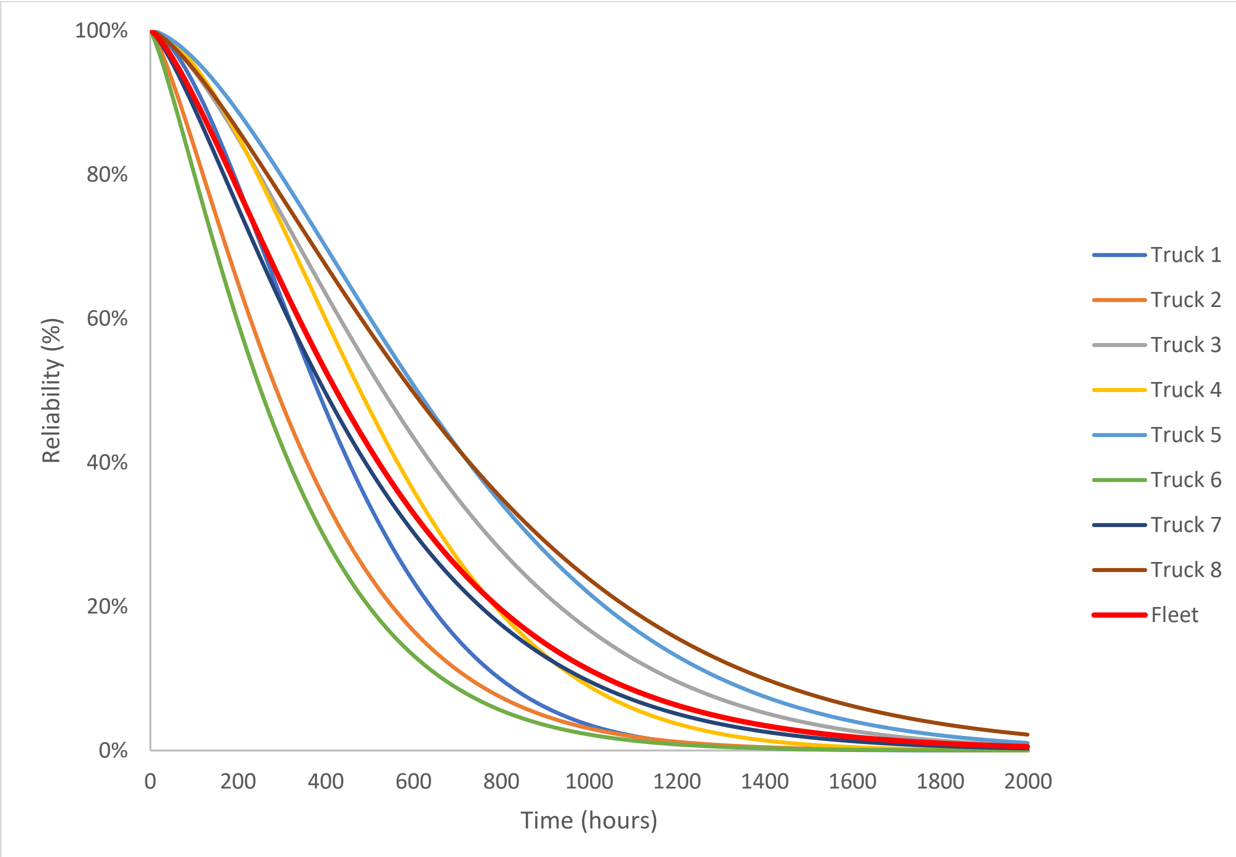

Figure 3. 5. Reliability curves of the mining trucks under inspection

Table 3. 5. Inspection intervals based on desired fleet reliability

Time interval (hours)	Reliability (%)
0 - 24	99.99 – 98.63
24 - 48	98.63 – 96.52
48 - 72	96.52 – 94.03
72 - 96	94.03 – 91.29
96 - 120	91.29 – 88.38
120 - 144	88.38 – 85.35
144 - 168	85.35 – 82.24
168 - 192	82.24 – 79.08

Considering the fleet's reliability, Table 3.5 shows the attainable reliabilities for given inspection intervals. With this information, decision-makers can establish optimal inspection intervals based on the desired reliability. For instance, the results suggest that if the operational target is to maintain the fleet reliability indicator over 96.5%, inspection intervals should not be longer than 48 hours, which implies that inspection should be carried out every 2 days assuming non-stop operation. If the inspection is carried out between 96 and 120 hours of non-stop operation, then the expected reliability would be between 91.29 % and 88.38%. Finally, if desired fleet reliability is 80% then the inspection interval could be carried out between 168 and 192 hours, implying a weekly inspection.

3.2.3 Results of the Optimal Maintenance Scheduling based on Virtual Age

Assuming that the time to first failure (in hours) has a specific distribution, the expected failure count function $M(t;T)$ can be calculated, as was described in Equations 3.11 and 3.12. For this calculation, the age-reduction factors q_{CM} and q_{PM}, PM interval T, and system lifetime distribution parameters, λ and β, would be necessary. Minimal CM (q_{CM} = 1) was assumed at the beginning of the study.

With the estimation parameters previously calculated in Table 3.2, the time to the first failure has a Weibull distribution with $R(x) = (0.001333x)^{1.311246}$, $T = 1{,}000\,h$, and minimal CM, $q_{CM} = 1$ ("bad as old"). Figure 3.6 shows the results of the function $M(t;T)$ for the Model I for different values of q_{PM} when holding a period T=1,000 hours and k =9, where k means the average number of preventive maintenance in one year. As can be observed, while q_{PM} values increase, the expected failure count also increases. When increasing the PM period from T=1,000 to T=2,200 (or quarterly), Figure 3.7 shows higher expected failures $M(t;T)$ obtained for the same span time. Accounting for a general assumption of PM intervals of one month for each truck, Figure 3.8 shows the results when considering T=720h (PM interval each month), k=12, and different values of q_{PM}. This configuration seems to be optimal when compared with the previous two models due to its lower number of expected failures. Table 3.6 presents the expected count function $M(t;T)$ for three different values of q_{PM} when considering the optimal scenario of one PM each month (T =720h).

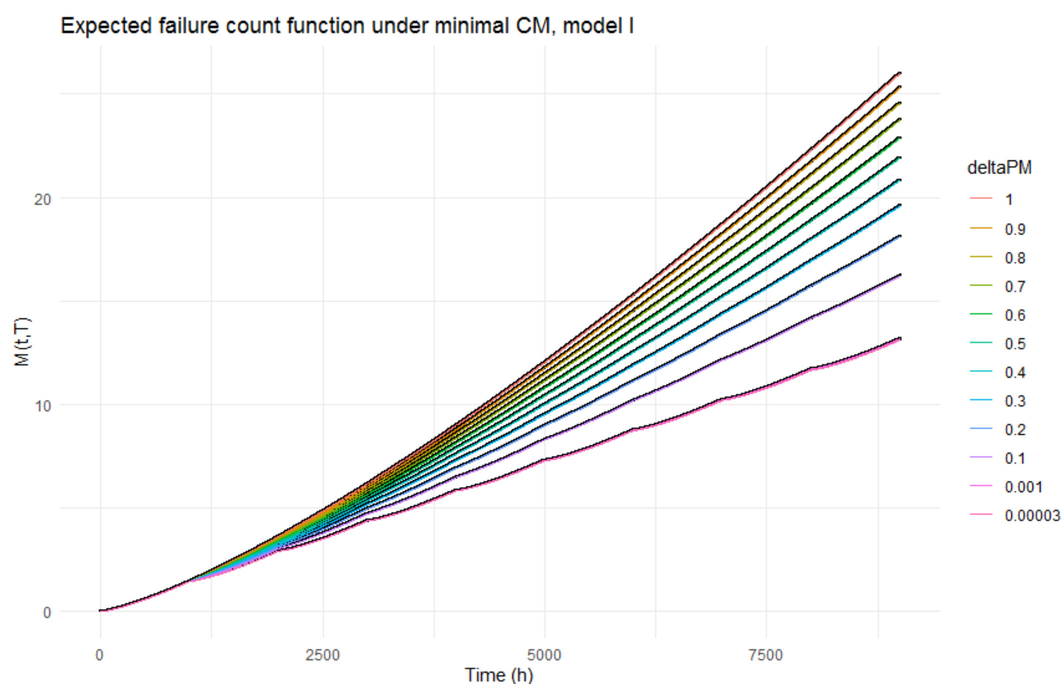

Figure 3. 6. Expected failure count function for T=1000, k=9, and different values of q_{PM}.

Both minimal repair and perfect repair are considered to see the difference in such extreme values. However, since one of the objectives of this thesis is to present an optimal maintenance scheduling, a ‘near to a perfect PM’ ($q_{PM} = 0.001$), found in the graphical analysis previously discussed, can be assumed.

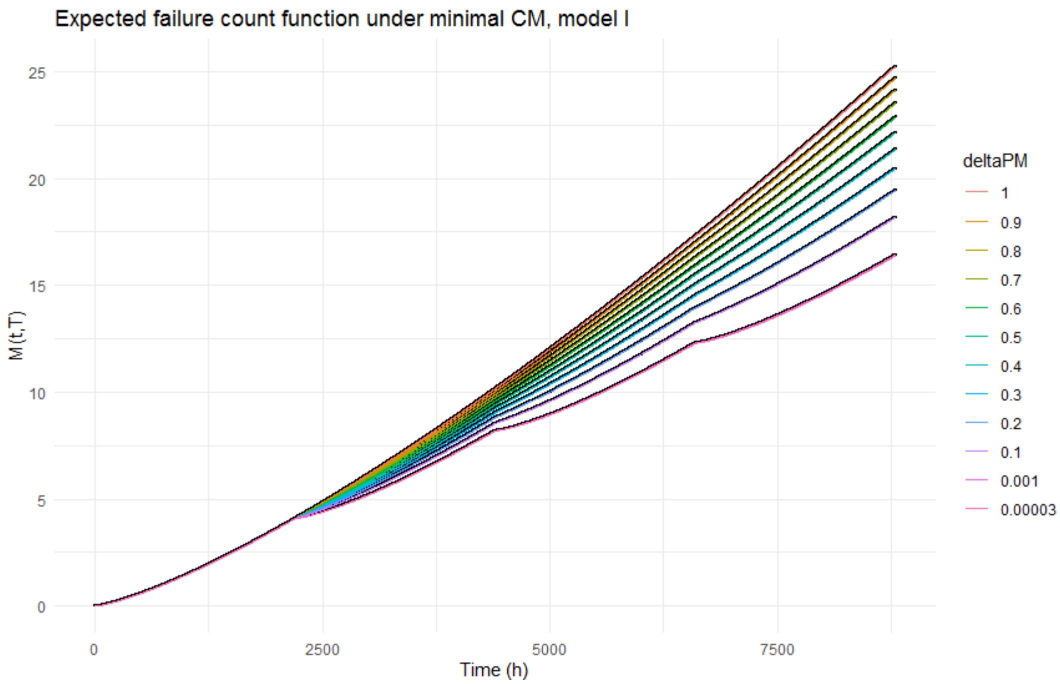

Figure 3. 7. Expected failure count function for T=2200, k=4, and different values of q_{PM}.

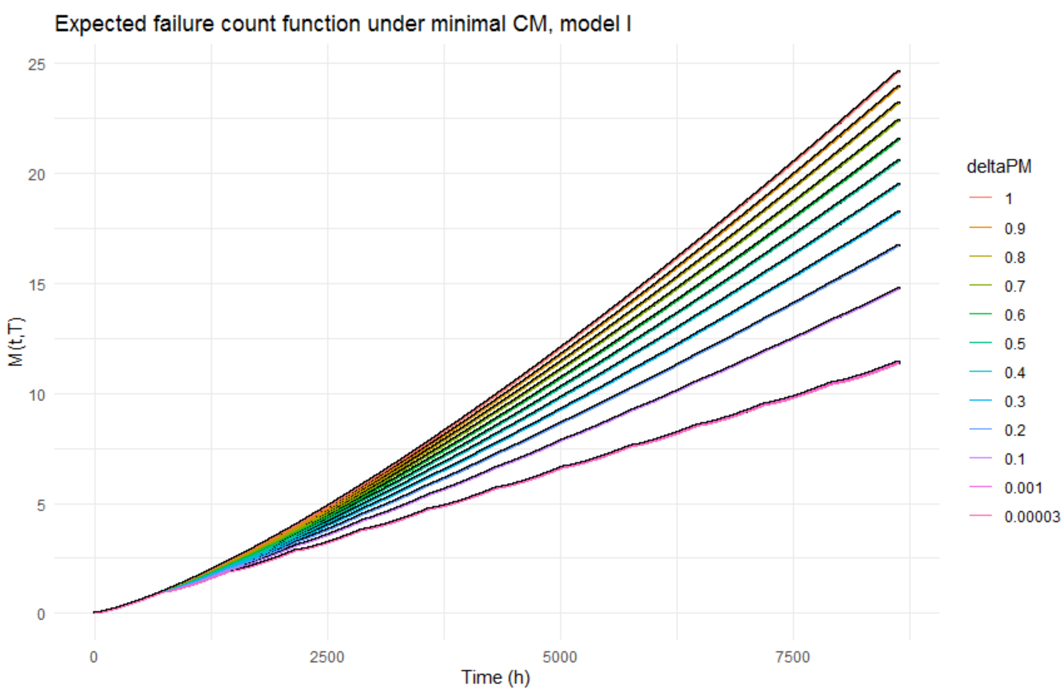

Figure 3. 8. Expected failure count function for T=720, k=12, and different values of q_{PM}

Table 3. 6. Expected $M(t;T)$ failure count functions for different values of q_{PM}

T (hours)	$M(t;T)$, $q_{PM} = 0$	$M(t;T)$, $q_{PM} = 0.001$	$M(t;T)$, $q_{PM} = 1$
720	0.948	0.95	0.948
1440	1.895	1.90	2.351
2160	2.843	2.85	4.002
2880	3.790	3.80	5.835
3600	4.738	4.75	7.819
4320	5.685	5.70	9.930
5040	6.633	6.66	12.155
5760	7.581	7.61	14.481
6480	8.528	8.57	16.899
7200	9.476	9.52	19.402
7920	10.423	10.48	21.985
8640	11.371	11.44	24.642

The last step is to simulate the system behavior $\widehat{M}(t;T)$ and to obtain the generator for the system failures. Equation 3.14 is required to compute these desired values. First, system failure times T_{ij} should be generated. Then, a large number of independent simulations should be performed and the average number of failures occurring up to time t could be computed depending on the values of q_{PM}, the result of this simulation is presented in Table 3.7.

Optimal maintenance scheduling based on the effectiveness factor of the corrective maintenance is presented in Table 3.8 with the assumption of a 'near to perfect' PM ($q_{PM} = 0.01$). While optimal maintenance scheduling should assume a high-standard degree of repair, which is associated with effectiveness factors near to 0, it should not be assumed to be perfect. Hence, effectiveness factor values ranging from 0.1 to 0.4 are considered in the analysis. The choice of the appropriate effectiveness factor (q_{CM}) relies on specific conditions under consideration such as the historical failure data, maintenance policy, as well as the type of mining equipment.

Table 3. 7. Simulated $\widehat{M}(t;T)$ failure count functions for different values of q_{CM}

T(hours)	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
720	0.98	1.04	1.06	1.08	1.05	1.06	1.08	1.07	1.11	1.12	1.13
1440	2.16	2.33	2.42	2.46	2.50	2.57	2.63	2.67	2.71	2.75	2.79
2160	3.37	3.67	3.86	3.99	4.10	4.24	4.36	4.47	4.53	4.68	4.74
2880	4.56	5.05	5.40	5.61	5.84	6.04	6.22	6.41	6.55	6.73	6.86
3600	5.73	6.47	6.99	7.33	7.65	7.91	8.19	8.46	8.69	8.94	9.12
4320	6.92	7.91	8.62	9.05	9.49	9.89	10.27	10.62	10.94	11.22	11.51
5040	8.10	9.39	10.29	10.86	11.41	11.93	12.45	12.85	13.28	13.61	13.98
5760	9.30	10.90	11.99	12.74	13.41	14.08	14.67	15.17	15.65	16.08	16.52
6480	10.49	12.47	13.74	14.64	15.51	16.28	16.94	17.58	18.11	18.64	19.16
7200	11.69	14.07	15.50	16.61	17.63	18.55	19.30	20.06	20.72	21.26	21.89
7920	12.86	15.66	17.33	18.62	19.80	20.89	21.73	22.58	23.31	24.00	24.70
8640	14.03	17.30	19.22	20.71	22.01	23.24	24.26	25.19	25.98	26.79	27.60

Table 3. 8. Maintenance Scheduling for different values of q_CM when considering an optimal q_PM=0.01

q_{CM}	T(hours)	k
0	604.32	14
0.1	528.53	16
0.2	490.66	18
0.3	467.71	18
0.4	451.05	19

Table 3.8 provides five categories of optimal maintenance scheduling starting with the perfect CM assumption ($q_{CM} = 0$) which was found to be associated with an optimal

maintenance scheduling of every 604.32 hours of operation (14 times per year assuming continue operation). Considering ‘near to perfect’ effectiveness factors such as 0.1 and 0.2 would represent a maintenance scheduling with shorter intervals of maintenance since previous repairs are no longer perfect.

3.3 Conclusion

A two-step maintenance strategy was proposed: (i) inspection frequency based on desired reliability levels and (ii) development of preventive maintenance scheduling utilizing the virtual age concept. As discussed, optimal inspection intervals lead to a reduction in maintenance costs, which represent a big share of total operating costs in mining industries due to equipment dependency. The effect of the virtual age after repairs and its interaction with potential failures has been the focus of this study. In doing so, the rejuvenation of the system represented by effectiveness factors for eight mining trucks has been estimated to study the behavior of the trucks after repairs. The magnitude of these factors has a direct relationship with the quality of repair trucks have been subjected to. Moreover, optimal inspection intervals have been proposed as a methodology based on the desired level of reliability for a specific truck’s fleet. Given the optimal inspection intervals, maintenance planners and decision-makers could determine better maintenance tasks and prevent catastrophic failures.

The second section discussed maintenance scheduling considering the virtual age concept. The findings propose comparisons between expected failure events versus computer-generated values to address maintenance scheduling for different effectiveness factors. It has been shown that while considering high-value effectiveness factors for PM, more failures are expected in the model. Similar results are obtained when considering high values of the effectiveness factors for CM, which require shorter intervals of maintenance since repairs are no longer assumed to be perfect. Results shown in Table 3.8 could be used to suggest the maintenance scheduling under specific circumstances where the choice of the best effectiveness factor q_{CM} relies on parameters such as the historical failure data, maintenance policy objectives, and type of equipment under consideration

4 A sustainable approach based on the estimation of gas emissions

4.1 Sustainability in the mining industry

Hauling activities play a fundamental role in mining operations as they are responsible for final deliveries of ore and waste materials to different locations in a mining area. The selection of mining equipment depends on whether the operation is carried out above or below ground, production rate, and the type of material being extracted. Some of the mining equipment are large mining trucks, hydraulic mining shovels, draglines, rotary drill rigs, motor graders, dozers, and wheel loaders. Equipment manufacturers are producing bigger equipment to decrease operating costs and maximize productivity. For instance, the Caterpillar 797F truck can carry 400 short tons of payload compared with its predecessor model 797, which could carry 360 short tons of payload.

Because most of this equipment is still diesel-powered, they are associated with significant Greenhouse Gas (GHG) emissions. There are several factors affecting diesel mining equipment emissions such as age, model, engine power, and fuel quality. Also, factors related to specific work conditions such as altitude, weather, operator skills, and equipment maintenance can alter the total amount of GHG emissions. As for equipment maintenance, inspection intervals and the degree of repair (i.e., how well the equipment is repaired) are important from a GHG emissions perspective. A poor maintenance strategy would not only lead to higher operating costs but also would increase emissions. Due to the direct relationship of these gases with climate change and global warming, it is necessary to control and mitigate GHG emissions. However, there is not a specific approach to calculate GHG emissions in the mining industry. GHG emissions are generally estimated using emission factors that are documented for diverse applications. For instance, the Intergovernmental Panel on Climate Change (IPCC) guidelines proposes several approaches to calculating GHG emissions (EPA, 2017).

Due to the direct relationship of these gases with climate change and global warming, there is a necessity to control and mitigate GHG emissions. However, there does not yet exist a specific approach to calculate GHG emissions in the mining industry. Gas emissions are generally estimated using emissions factors that are documented for diverse applications. For example, the Intergovernmental Panel on Climate Change (IPCC) guidelines discuss several methodologies and approaches to calculating GHG emissions. (EPA, 2017). Another important concept to discuss is the carbon footprint, which could be defined as the direct or indirect quantification of the total amount of carbon dioxide emissions released or accumulated on time due to a specific activity (Wiedmann and Minx, 2008).

The IPCC defines three tiers to estimate CO_2, CH_4, and N_2O emissions from fuel combustion depending on the quantity of information required and the degree of complexity. The uncertainty associated with estimation and complexity increases from tier 1 to 3. The Tier 1 method simplifies the process by considering a gain-loss method explained in IPCC guidelines IPCC (2006). This approach is fuel-based and considers all sources of combustion and average emission factors from national energy statistics. Tier 2 is an extension of Tier 1, but it additionally considers country-specific emission factors that better suit specific characteristics of the study. Tier 3 approach considers well-detailed emission models for specific data at the individual plant level. Further information related to the selection of tiers can be found in IPCC (2006). Regarding mining trucks, emissions can be estimated as for general mobile sources, and the Tier selection will depend on the uncertainty associated with the emission-related information available.

Figure 4.1 describes a decision tree proposed by IPCC for estimating emissions for off-road vehicles.

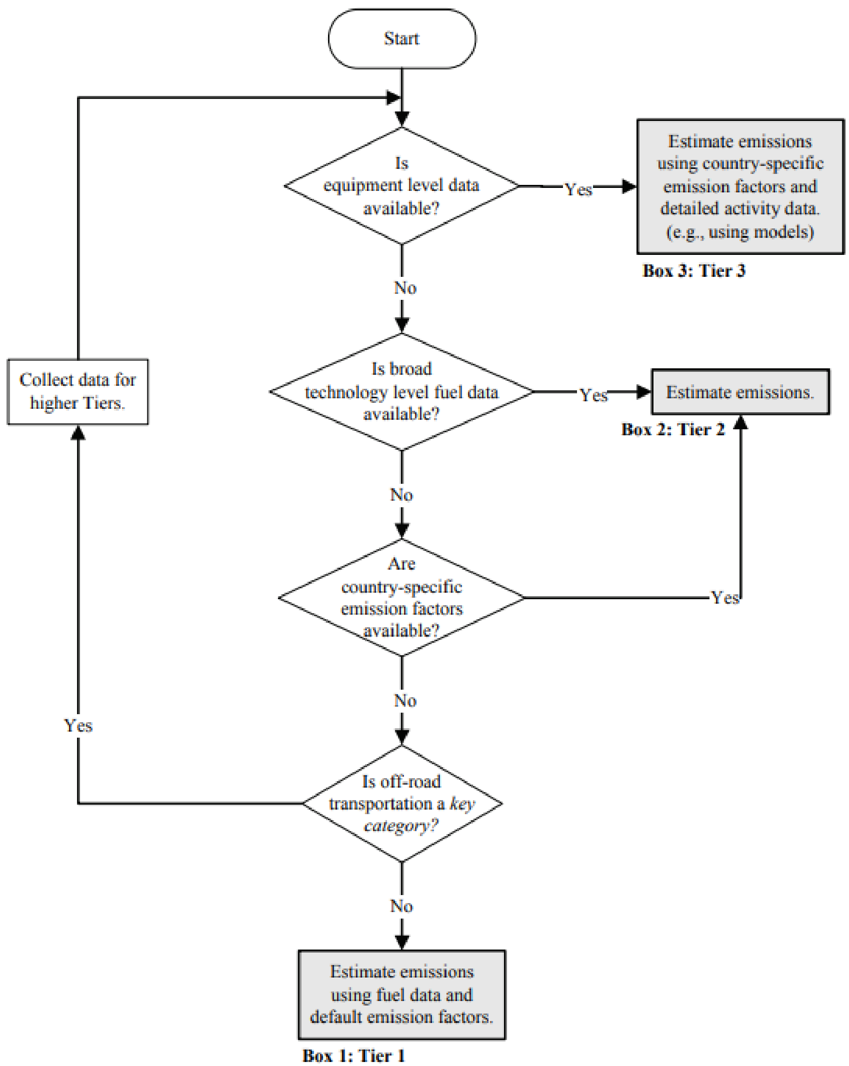

Figure 4. 1. Decision tree for estimating emissions for off-road vehicles

A current trend adopted by governments to reduce greenhouse gas emissions and mitigate climate change is the carbon tax. This measure means to apply a price per each ton of carbon dioxide (CO_2) emitted from burning carbon-based fuels. The objective of the carbon tax is to motivate industries to be aware of the environmental impacts caused by GHG emissions and to reduce them considerably. The price is normally set up for one year and it increases each year to progressively allow industries to adopt less carbon-heavy processes. The federal carbon pollution pricing system of Canada concluded that pricing carbon has a considerable impact on reducing pollution at the lowest cost to businesses and consumers while providing an incentive to satisfy green targets in the long run.

Figure 4.2 illustrates one of the key findings of this study in which was concluded that a price on carbon could cut carbon emissions by 90 million tons in 2022, which is equivalent to shutting down 23 coal-fired power plants for a year (Canada, 2018). Taking this into consideration, mining companies will have to adapt their operations to new regulations. The general trend is to transition from diesel-powered to electricity-powered equipment. However, given that many mining operations are in remote areas, access to electricity is not a given. However, as aforementioned, implementing effective equipment maintenance strategies can reduce GHG emissions. Therefore, the quality of preventive maintenance may contribute to a reduction in gas emissions.

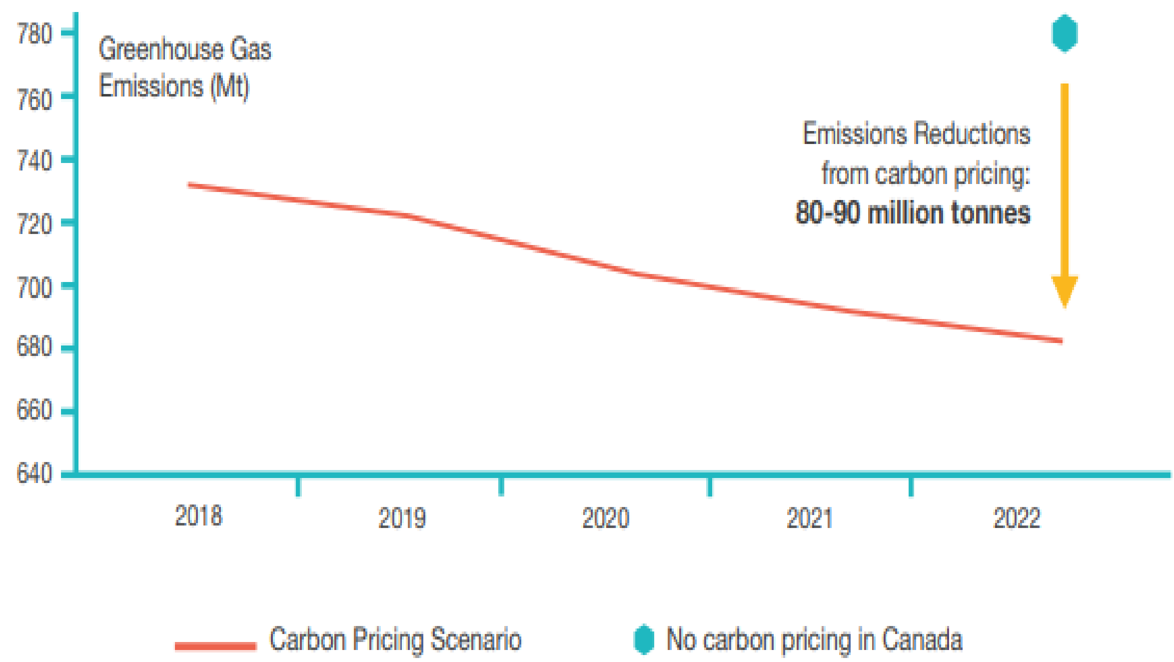

Figure 4. 2. Key findings Government of Canada (Canada, 2018)

The cap-and-trade policy is an alternate measure to reduce the carbon tax. The main motive behind the cap-and-trade policy is to create a new market such that the corporates are forced to reduce their GHG emissions. The main difference between a carbon tax and a cap-and-trade policy is that the former imposes a price per ton of greenhouse gas emissions to companies producing them while the latter set a total of emission allowances each year. These allowances can be traded on secondary markets between companies and a carbon price is established. The fact that there is just a certain number of allowances per year, which are reduced over time, encourages companies to invest in innovation and renewable energies. Throughout the world, many successful examples of the implementation of this policy have been identified. For instance, in the European Union's Emissions Trading System, a decrease of 26% of capped emissions between 2005 and 2016 was observed while a decreasing of 6.2% is expected between 2020 and 2030 (EEA, 2017).

A variety of studies addressing sustainability in asset management have been proposed considering environmental impacts in the specific industries. One of the most well-known methodologies to manage environmental impacts has been life cycle assessment (LCA), which is defined as an environmental assessment tool related to all the stages of a product's life. This methodology consists of four separate stages as can be observed in Figure 4.3: Scope definition, inventory analysis, impact assessment, and interpretation (ISO 14040, 2006). The first stage, scope definition, clearly defines the context of the study and should be consistent with the expected application of the assessment.

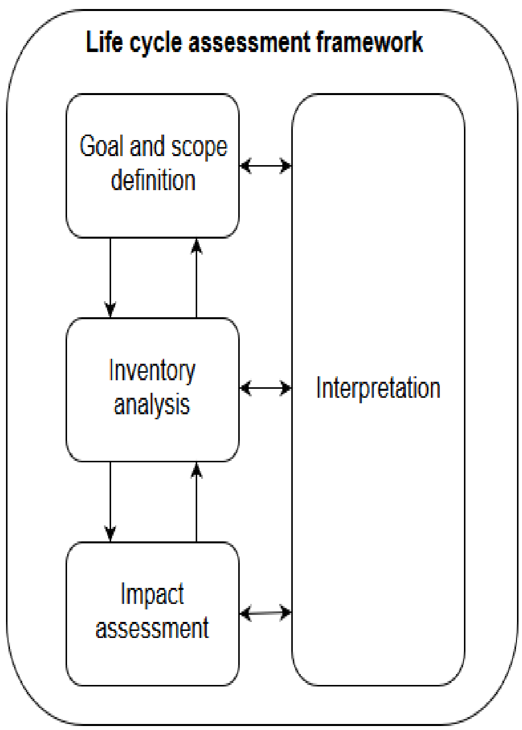

Figure 4. 3. Typical Life Cycle Assessment Framework

The second stage consists in elaborating an inventory of inputs and outputs for the product being evaluated. This stage is usually represented by a flowchart or diagram representing the boundaries and flow to and from the environment from all the units considered for a specific product. The third stage is vital for the study since it defines the impact categories and parameters for the assessment. Finally, the last stage identifies data elements to contribute substantially to every single impact category previously identified in the third stage.

Even though LCA has not been applied extensively in mining, researches have conducted some studies based on this methodology. According to Durucan, Korre, and Munoz-Melendez (2006), one possible reason why LCA methodology is not widely used in mining industries is that generic data, which is often inadequately utilized for mining LCA, should not be used as an accurate account of mining environmental burdens. They stated that the common practice to consider predefined data to represent mining environments fails in represent specific characteristics of mining environments such as exploration, development work, mining, and processing method, ore losses, and other factors that have a direct relation to the nature of discharges to the environment. In their study, they presented several tools to better represent mining environments considering different mining, processing, and environmental scenarios.

Some researchers who proposed studies based on LCA methodologies are Forbes, Von Blottnitz, Gaylard, and Petrie (2000), for a nickel refinery; Mangena and Brent (2006), to evaluate environmental performances of supplied coal products; Awuah-Offei, Checkel, and Askari-Nasab (2009), to study the global warming potential (GWP) and the acidification potential (AP) related to belt conveyors and truck haulage systems in a hypothetical gold open-pit mine; and Burchart-Korol, Krawczyk, Czaplicka-Kolarz, Turek, and Borkowski (2014). They proposed an algorithm to evaluate aspects related to sustainable development for hard coal mines using LCA and considering the cost-efficiency of mining production processes.

Gas emissions and energy consumption are also addressed in the literature. For instance, Kecojevic and Komljenovic (2010) studied haul truck fuel consumption and CO_2 emission under various engine load conditions and presented a model that links truck's fuel consumption, power, and engine load factors. Giustozzi, Crispino, and Flintsch (2012) considered the eco-effective advantage of adequate maintenance activities regarding sustainability assessment and presented a case study to evaluate the environmental impact of preventive maintenance, considering parameters such as cost, performance, GHG emissions, and energy use.

Carmichael, Bartlett, and Kaboli (2014) focused their study on surface mining operations and explored the link between the optimal unit cost of a surface mining operation and the optimal unit emissions operation. Parameters such as payload, truck size, travel distances are considered and tested with real field data. They concluded that conventionally efficient approaches in surface mining operations lead to the least environmental impact (i.e., unnecessary emissions are generated when not operating at the minimum unit cost). Peralta, Sasmito, and Kumral (2016) discussed the benefits of minimizing carbon emissions while maximizing equipment availability. They studied the relationship between equipment reliability and energy consumption through a case study that considers fleet data from six open-pit mining trucks. Besides reliability, the variables such as operating hours, travel distance, gross mass weight, and payload were also considered in a multivariate regression model. In this thesis, the research is extended to add the effects of two new independent variables; namely, season and road conditions to the modeling. Furthermore, different regression models used in the machine learning area are tested to explain the fuel consumption of mining trucks in a more accurate way.

According to the Intergovernmental Panel on Climate Change (IPCC): In the case of Tier 1, where emissions are simply calculated by using fuel-specific emission factors of national statistics, the total amount of emissions (kg) could be estimated as:

$$Emissions(kg) = \sum_{j} \left(Fuel_j + EF_j\right) \tag{4.1}$$

where $Fuel_j$ represents the fuel consumed in terajoules (TJ), EF_j is the emission factor (kg/TJ), and j stands for the fuel type (e.g., petrol, diesel, natural gas, LPG, etc.). More information about the emission factors could be found in IPCC (2006).

Similarly, Tier 2 takes into consideration data on the amount of fuel combusted and country-specific emission factors related to the carbon content of the fuel. These country-specific emission factors are developed by taking into consideration country-specific data such as carbon content of fuels used, carbon oxidation factors, and fuel energy content. For Tier 2, if data are available, the emissions can be obtained from annual hours of use and equipment-specific considerations such as rated power, load factor, and emission factors based on power usage.

$$Emissions(kg) = \sum_{ij} \left(Fuel_{ij} * EF_{ij}\right) \tag{4.2}$$

where $Fuel_{ij}$ represents the fuel consumed in terajoules (TJ), EF_j is the emission factor (kg/TJ), i stands for the vehicle or equipment type, and j stands for the fuel type.

Finally, Tier 3 is the most complex and requires the most specific data. This approach splits the fuel combustion statistics according to variables such as the amount of fuel combusted, country-specific emission factors for each gas, combustion technology, operating conditions, control technology, quality of maintenance, and the age of the equipment used to burn the fuel. Also, equipment-specific parameters, including load factors, rated power, and emission factors based on power usage, should be considered. However, for off-road vehicles, this data may not be available or may not be systematically collected, and may have to be estimated using a combination of the data and assumptions based on experience IPCC (2006). The total amount of emissions for Tier 3 could be calculated as

$$Emissions(kg) = \sum_{ij} \left(N_{ij} * H_{ij} * P_{ij} * LF_{ij} * EF_{ij} \right) \tag{4.3}$$

where N_{ij} is the equipment population factor related to pollution control technologies, H_{ij} represents the annual hours of use of vehicle i, P_{ij} is the average rated power of vehicle i (kW), LF_{ij} is the typical load factor of vehicle i (fraction between 0 and 1), EF_{ij} represents the average emission factor for the use of fuel j for the vehicle i (kg/kWh), i is the off-road vehicle type, and j stands for the specific fuel type being used in the equipment.

Estimation of CO_2 according to the Environmental Protection Agency (EPA): The EPA methodology addresses CO_2 emissions for mobile combustion under the assumption that almost all the carbon is converted to CO_2 during combustion, and CO emission is insignificant compared to CO_2 emission. The methodology to estimate CO_2 emissions from a gallon of fuel consists of multiplying the carbon emissions by the ratio of the molecular weight of CO_2 (44 g/mol) and divide it by the molecular weight of carbon (12), which is 44/12. Equation 4.4 defines the CO_2 emission from diesel fuels in t/hr (EPA, 2017).

$$CO_2 = FC \times EF \tag{4.4}$$

where FC is fuel consumption, and EF is the emission factor. For diesel, the emission factors for CO_2 were estimated to be 2730 (g/L), according to the Guidance Manual for Estimating Greenhouse Gas Emissions (Canada, 2004). The literature provides some models to estimate fuel consumption, which is fundamental to estimate CO_2 emissions. One of the most accepted models to estimate fuel consumption was proposed by Hays (1990) He defines fuel consumption based on field studies. Equation 4.5 states fuel consumption in liters per hour.

$$FC = (CSF \times P \times LF) / FD \tag{4.5}$$

where FC (L/hr) is the hourly fuel consumption; CSF is the engine-specific fuel consumption at full power, kg fuel / bkW-h; P is the rated brake power, kW (hp); LF is the engine load factor, the portion of full power required by the truck in decimal units; and FD is the fuel density, kg/L (lb/ per gal). Depending on the type of truck and manufacturer, mining trucks present different brake kilowatt (horsepower) and different fuel consumption. Diesel fuel density varies from 0.84 to 0.96 Kh/L (7.0 to 8.0 lb per gal). Another similar well-known estimation was proposed by Runge (1998), who stated that fuel consumption for most diesel-powered motors working at 100% load factor is, on average, 0.3 l/kW per hour. Diesel consumption is defined as

$$FC = P \times 0.3 \times LF \qquad (4.6)$$

where FC (L/hr) is hourly fuel consumption, P (kW) is engine power, 0.3 is a unit conversion factor (L/kW/hr), and LF is engine load factor (the portion of full power required by the truck).

The originality of this work rests on the prediction of the fuel consumption for a fleet of mining trucks based on variables such as reliability, road condition, season, and payload. The predicted value of fuel consumption can be used then to estimate CO_2 emissions based on existing methodology.

4.2 Methodology

This study aims to model the fuel consumption of mining trucks to estimate CO_2 emissions. In doing so, several linear and non-linear models were used. The models considered for this study were Multivariate Linear Regression (MLR) optimized with Lasso and Ridge regressors, Stochastic Gradient Descent Regressor (SGD), Random Forest Regressor (RFR), and Gradient Boosting Ensemble Regressor (GBR).

MLR is utilized to predict the value of a dependent variable (i.e. a predictand) as a function of a set of so called independent variables (i.e. predictors). The general form of the model (Yan and Su, 2009) is

$$y_i = \beta_0 + \beta_1 x_{1i} + +\beta_2 x_{2i} + \cdots \beta_k x_{ki} + \varepsilon \mathrm{i} \qquad (4.7)$$

where y_i represents the dependent variable, x_{ki} represent the independent variables, $\beta_{1,}\beta_2,$ and β_k are regression coefficients, β_0 is the intercept term, and ε_i is the error term.

To fit this regression equation, regression coefficients (i.e., $\beta_1, \beta_{2\ldots,}\beta_k$) should first be estimated. However, these coefficients are not mutually comparable (Tacq, 1997). To evaluate the effects of these coefficients, they need to be standardized in order to convert them to values, which must not be greater than one (Tacq, 1997).

$$b_{yx} = \frac{covariation\, X, Y}{variation\, X} \tag{4.8}$$

where X represents independent variables, Y the dependent variable, and the coefficient b_{yx} represents the beta coefficient describing the effect of X in relation to Y. Once these standardized coefficients are estimated, the importance of each of the predictors can be evaluated.

Ridge and Lasso's regressors are extensions of the linear regression framework. Ridge regression was initiated by Hoerl and Kennard (1970), and it considered penalty estimators for the first time. It allows the minimization of the least-squares subject to a penalty. Ridge regression imposes a penalty depending on how large these coefficients are, so instead of removing coefficients from the model, they become insignificant. Similarly, the Least Absolute Shrinkage Selection Operator (LASSO) could be used to estimate and select the parameters of a given regression model. Lasso allows consideration of coefficients with a zero value if they are not relevant for the model (Saleh, Arashi, and Kibria, 2019).

SGD technique is widely used in machine learning (ML). An iterative approach is generally employed to obtain values of various parameters of a function that minimizes the cost function, which could be the difference between predicted and actual values, as much as possible (Hauck, 2014). In this methodology, the parameters are started from specific values chosen from random samples and those SGD simulations are initiated to find optimal parameters. In other words, SGD initializes parameters and then allows them to descend along the gradient of the error to reach the minimum error (Carpenter, 2008).

Other regression techniques considered in this study are ensemble methods such as RFR and GBER. The former was considered with the objective to average several unbiased models to reduce the variance, which represents the general idea of bagging (Trevor, Robert, and Jerome, 2009) while the latter has shown to be a powerful approach on real-life datasets when trying to optimize functions (Frery, Habrard, Sebban, Caelen, and He-Guelton, 2017).

The accuracy of the models was assessed using a test set by calculating the R-squared (R2) measure, which is widely used to determine the quality of a regression model. Besides the R2, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were also considered in this study. While the MAE computes the average absolute deviance (i.e., the average absolute error), the RMSE is used for scoring an algorithm since it allows us to calculate larger errors (Shukla, Agrawal, Sharma, and Tomer, 2019). MAE and RMSE can be defined as

$$MAE = \frac{\sum_{n=1}^{N} |\hat{r}_n - r_n|}{N} \tag{4.9}$$

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N} (\hat{r}_n - r_n)^2}{N}} \tag{4.10}$$

where $\hat{r}_n$ is the predicted value, r_n is the observed/recorded value from the testing data set, and N stands for the total number of pairs (Wang and Lu, 2018). Ideally, lower values of MAE and RMSE and higher values of R-squared are indicative of good model performance.

4.3 Case study

Fuel consumption is a significant factor that needs to be optimized in mining operations. It is dependent on loading and hauling activities, which have a considerable impact on mining costs. GHG emissions can be calculated using the fuel consumption. The methods used are well documented and broadly implemented in statistics and data science areas.

A case study considering data from 8 mining trucks working in a Canadian open-pit mine is proposed considering a one-year dataset. Fuel consumption was modeled as a function of the following four independent variables: Truck's payload, Truck's reliability per cycle time, Road condition, and Season.

Truck's payload accounts for the real payload measured in the field for a fleet of 8 Komatsu 930 trucks; this value is around 284 short tons for the type of truck being analyzed. In this case study, reliability is defined as the probability that a system will have a satisfactory performance under normal conditions for a specific time, which is equal to the cycle time, which records the time starting in the loading areas and finalizing in diverse dumping locations in the mining operation. The road condition is an ordinal variable with values of 1 to 3 (1 for bad condition, 2 for standard condition and 3 for well-maintained condition). Similarly, the season is also an ordinal variable with values 0 and 1 and it accounts for seasonal weather variations. Trucks consume more fuel during winter conditions (Ozdemir and Kumral, 2018). A value of 1 represents the winter season, while a value of 0 is used for all other seasons.

4.3.1 Data Analysis

Descriptive statistics of the dataset show a relatively low standard deviation for the numerical variables and mean reliability of 70.21% for the truck fleet. The results are shown in Table 4.1.

Table 4. 1. Descriptive statistics of dependent (fuel consumption) and independent variables (payload, reliability, road condition and season)

	Payload	Reliability	Season	Road	Fuel
Mean	283.98	70.21	0.14	2.37	16.51
Std deviation	12.23	6.71	0.35	0.55	1.84
min	228.02	48.14	0	1	11.29
25%	277.19	65.33	0	2	15.18
50%	286.43	70.21	0	2	16.46
75%	293.63	75.04	0	3	17.8
max	299.98	90.31	1	3	22.34

The histograms of all variables are shown in Figure 4.4. These histograms show that the fuel consumption and reliability conform closely to a normal distribution, while the payload skews to the right. The payload is a bounded variable with the left bound at zero and the right bound at 300.

The road condition, that can be treated both as a discrete numerical or an ordered categorical variable, shows a very low frequency for not well-maintained roads (i.e., road condition=1), and a very high frequency for normal and well-maintained roads (i.e. road condition values of 2 and 3, respectively). Similarly, the frequencies of the season variable show a lower frequency for winter season conditions. Correlations of all variables were assessed, and it was found that the most correlated variables to fuel consumption are road condition and reliability; the respective coefficient of correlation values are 0.85 and 0.82. These two variables are also correlated with each other, with a value of 0.69 for the coefficient of correlation. This is an indication of a potential multicollinearity issue. The Variance Inflation Factor (VIF) and its respective tolerances are presented in Table 4.2. If the VIF value is more than 5 for any variable, then there could be an issue of multicollinearity in the model (Mehmetoglu and Jakobsen, 2016). It can be seen from this table that none of the VIF values are greater than 5.

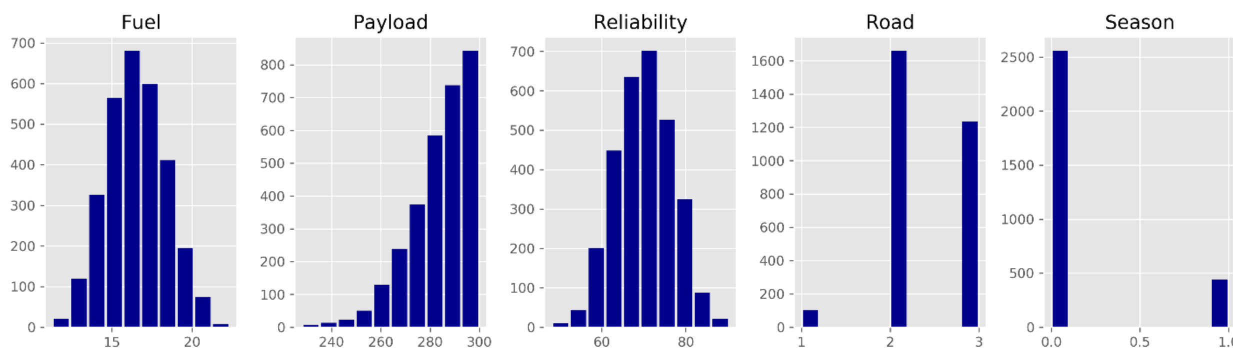

Figure 4. 4. Histograms of all variables under consideration

Table 4. 2. Variance inflation factor (VIF)

	Tolerance	VIF
Intercept		
Payload	0.941	1.063
Reliability	0.414	2.414
Season	0.635	1.576
Road	0.511	1.957

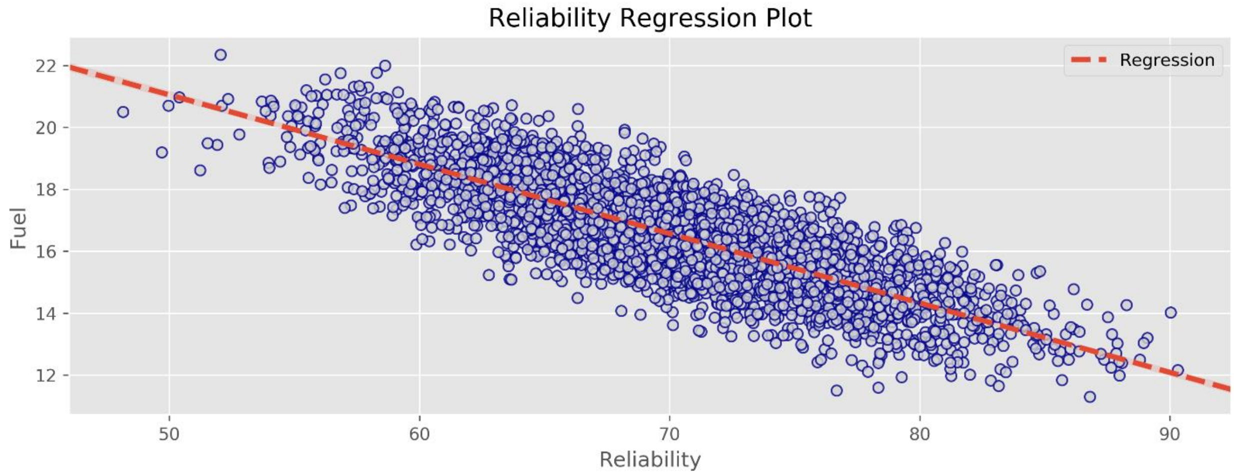

Figure 4. 5. Relationship of reliability and fuel consumption

A linear relationship between reliability and fuel consumption was found (see Figure 4.5). The reliability seems to hold a linear relationship with the dependent variable, without any obvious non-linear areas. This variable was also tested for the presence of heteroscedasticity, which implies the absence of homoscedasticity. Homoscedasticity pertains to the presence of constant variance in the error term of the model as described in Equation 4.11 (Mehmetoglu and Jakobsen, 2016)

$$var(\varepsilon_i|X_1, \dots, X_n) = \sigma_u^2, \qquad 0 < \sigma_u^2 < \infty \tag{4.11}$$

A simple way to analyze heteroscedasticity is to simply study the plot of predicted values versus the residuals of the model. To quantify the degree of heteroscedasticity in the model, the Goldfeld-Quand test was evaluated. Since the p-value was greater than 0.05, the null hypothesis of assuming homoskedasticity could not be rejected, and therefore it was inferred that heteroskedasticity does not exist in the model.

4.4 Modeling Results

As aforementioned, both linear and non-linear approaches were used to model the fuel consumption of mining trucks. The models evaluated for the dataset are Lasso and Ridge regressors, SGD, RFR, and GBR. The results of these models were compared with a base model, i.e. MLR, which assumes the relationship between dependent and independent variables is linear.

Lasso and Ridge regressions were optimized based on a 10-fold cross-validation method. Model performance indicators and the regression coefficients were identical to the base model, confirming that the simple multivariate linear model is accurate enough for this data. Similar results were obtained for the SGD, considering a regularization term (i.e. 'alpha' parameter), optimized to 0.0001. The performance metrics for the SGD were identical to the base model. Finally, the RFR and GBR were analyzed based on a 10-fold cross-validation method. Results show that these models for the test set were slightly worse than the base model. Table 4.3 presents the results of performance measures for all models. These results demonstrate that the predictor-predictand relationship for the analyzed data can be represented by a multivariate linear regression, without losing prediction accuracy.

Table 4. 3. Performance measures for the five selected modeling choices

Model	R^2	MAE	RMSE
Lasso	0.8403	0.5967	0.7393
Ridge	0.8403	0.5967	0.7393
SGD	0.8403	0.5967	0.7393
RFR	0.8371	0.6027	0.7467
GBR	0.8359	0.5969	0.7419

For evaluating the performance of various models, 33% of data was employed and the rest was used for training and estimating model parameters. The values of R2, MAE, and RMSE were calculated using the trained/fitted model. Additionally, the k-fold cross-validation was used, with k=10, for optimizing parameters from the training data. Table 4.4 illustrates the application of a two-way analysis of variance (ANOVA) to determine whether there are significant differences in predicting fuel consumption. Interaction effects among the independent variables can be evaluated effectively with ANOVA.

Table 4. 4. ANOVA results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	12776.73854	4	3194.185	5663.5	.000[b]
Residual	2531.197478	4488	0.563992		
Total	15307.93601	4492			

a. Dependent Variable : Fuel_consumption
b. Predictors: Road, Payload, Season, Reliability

Since the significance of the model is less than 0.05 (Table 4.4), it can be concluded that the proposed model performs well. In other words, the predictor variables considered in the model (i.e., road condition, payload, season, and reliability) are good predictors of the target-dependent variable (i.e., fuel consumption). Moreover, a multi-factor ANOVA analysis was also conducted to quantify the effect of each factor. The results are given in Table 4.5. The “road condition” accounted for 36%, while the “reliability” accounted for 29% of the variability in “fuel consumption”. On the other hand, the “season” accounts for 17%, while the payload only 2% of the variability in “fuel consumption”.

The results of MLR are presented in Table 4.6. This model was also the base model of this study. The results suggest an R2 value of 0.84, while the values of MAE and RMSE are close to 0.60 and 0.55, respectively, for the test set. So, 84% of the variance of fuel consumption can be explained by the proposed model, considering payload, season, road condition, and reliability as predictors. The results of R2, MAE, and RMSE are also shown in Table 4.6 for the training part.

Table 4. 5. Multifactor ANOVA

Source	DF	Sum of Squares	F Ratio	Prob > F
Road	2	5,435.90	9951.776	<.0001
Reliability	1	4,365.36	2497.458	<.0001
Season	1	2,635.33	248.9187	<.0001
Payload	1	341.7	15.8265	<.0001
Error	4487	2529.64		Prob > F
C. Total	4492	15307.936		<.0001

Table 4. 6. Performance measures of the multivariate linear model for training and testing parts

	R^2_Train	MAE_Train	RMSE_Train	R^2_Test	MAE_Test	RMSE_Test
Metric	0.8317	0.6082	0.5723	0.8403	0.5968	0.5465

Figure 4. 6. Graphical analysis of model residuals

Graphical analysis of model residuals is shown in Figure 4.6. The results show that the distribution of residuals of the trained model resembles a normal distribution. The statistics of residuals also indicate the suitability of the linear model since the mean of the residuals is zero, the quantiles are symmetrical, the residual density plot conforms to a normal distribution, and the residual scatter plot does not show any trend.

Table 4.7 provides values of unstandardized and standardized partial coefficients (i.e., beta values) along with regression results. Based on a statistical analysis of these coefficients, the most important feature is the road condition and the second most important feature is the truck's reliability. The season is also significant as it also affects fuel consumption. Payload has a minor impact on the prediction of fuel consumption, but this needs to be verified further because only one specific truck model was analyzed in this case study. Additionally, all considered features are statistically significant for predicting fuel consumption since all p-values are either zero or close to zero.

Table 4. 7. Regression results

Model	B	Std. Error	Beta	t	Sig
(Constant)	26.5270	0.3314		80.04	0.0000
Payload	0.0037	0.0009	0.0249	3.97	0.0001
Reliability	-0.0976	0.0026	-0.3523	-37.36	0.0000
Season	0.6439	0.0398	0.1233	16.18	0.0000
Road Condition	-1.8151	0.0281	-0.5479	-64.52	0.0000
a. Dependent Variable : Fuel_consumption					

The beta weights allow determination of relative importance of each predictor with the predictand (Tacq, 1997). The road condition has the greatest effect on fuel consumption since it is associated with the greatest absolute value of the beta coefficients (i.e. 0.54). Nevertheless, the reliability variable still has an important effect, as it suggests a 0.35 unit decrease in fuel consumption for every unit increase in the reliability variable. The fitted model is shown in Equation 4.12, where the fuel consumption is in liters/cycle time.

$$\begin{aligned} Fuel\ Consumption \\ = 26.5270 + 0.0037 * Payload - 0.0976 * Reliability \\ + 0.6439 * Season - 1.8151 * Road\ conditions \end{aligned} \tag{4.12}$$

The payload variable, which was found to have an effect of only 2%, has not an important interaction with fuel consumption since this study considered only one type of truck (i.e., all of them with the same capacity). After predicting fuel consumption, Equation 4.4 can be used to predict CO_2 emissions as follows:

$$\begin{aligned} CO_2 = 2730 * (26.5270 + 0.0037 * Payload - 0.0976 * Reliability \\ + 0.6439 * Season - 1.8151 * Road\ conditions) \end{aligned} \tag{4.13}$$

The predicted values of CO_2 are shown in Table 4.8 and plotted in Figure 4.7, considering an average cycle time of 37.6 min/cycle, which was calculated considering all observations. Similarly, the average fleet's payload was around 284 short tons. For practical reasons, four levels of reliability going from 60% to 90% were evaluated as well as the two seasonal variables, and three road condition variables.

Results show that poorly maintained roads and lower levels of equipment reliability are responsible for the highest CO_2 emissions. For the season variable, winter is associated with higher CO_2 emissions when compared with other seasons. It was found that a 10% increment in equipment reliability accounts for a reduction of 6% in CO_2 emissions, irrespective of season and road conditions. Likewise, going from poorly maintained roads to well-maintained roads will lead to a 23% reduction in CO_2 emissions.

Moreover, a 49% increase in CO_2 emissions was noticed in the case of poorly maintained roads and equipment reliability of around 60%, when compared to well-maintained roads and equipment reliability of around 90%, independent of the season.

Table 4. 8. Predicted CO_2 emissions

Payload (tons)	Reliability (%)	Season	Road	Fuel.Cons (L/h)	EF (gr/L)	CO_2 (ton/h)
284.00	60	0	1	31.766	2730	0.087
269.00	60	0	2	28.781	2730	0.079
282.00	60	0	3	25.961	2730	0.071
273.00	60	1	1	32.729	2730	0.089
270.00	60	1	2	29.814	2730	0.081
285.00	60	1	3	27.007	2730	0.074
292.00	70	0	1	30.256	2730	0.083
275.00	70	0	2	27.259	2730	0.074
269.00	70	0	3	24.327	2730	0.066
279.00	70	1	1	31.207	2730	0.085
288.00	70	1	2	28.363	2730	0.077
284.00	70	1	3	25.443	2730	0.069
279.00	80	0	1	28.622	2730	0.078
286.00	80	0	2	25.766	2730	0.070
289.00	80	0	3	22.888	2730	0.062
269.00	80	1	1	29.590	2730	0.081
278.00	80	1	2	26.747	2730	0.073
285.00	80	1	3	23.892	2730	0.065
275.00	90	0	1	27.041	2730	0.074
273.00	90	0	2	24.132	2730	0.066
276.00	90	0	3	21.254	2730	0.058
282.00	90	1	1	28.109	2730	0.077
286.00	90	1	2	25.237	2730	0.069
286.00	90	1	3	22.340	2730	0.061

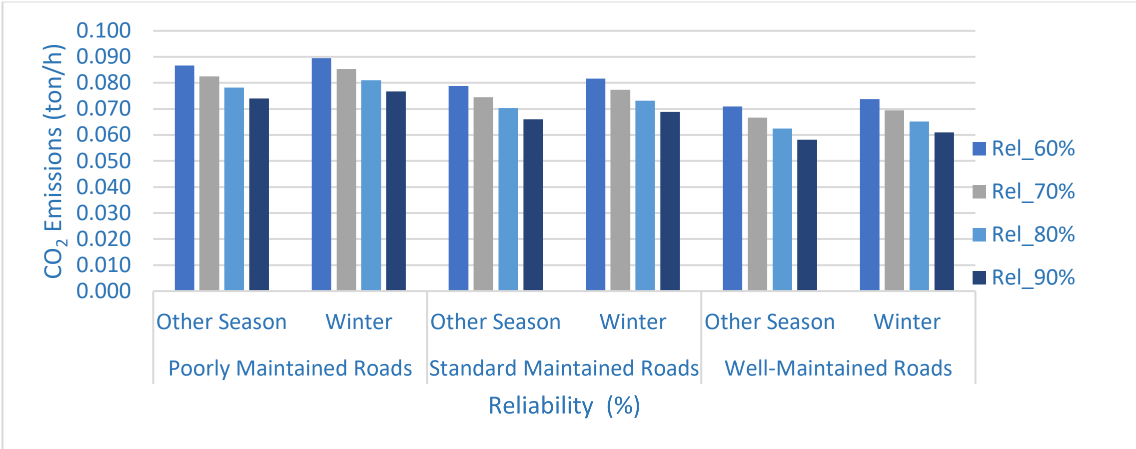

Figure 4. 7. Predicted CO_2 emissions for 60, 70, 80 and 90% reliability levels and poorly, standard and well-maintained road conditions

4.5 Conclusions

In this study, 4,493 observations were considered to propose a predictive model for fuel consumption of mining trucks considering payload, weather condition, road condition, and reliability as predictor variables. Both linear and non-linear models were tested. It was found that an accurate prediction can be obtained through a multivariate linear regression model. This model was able to explain 84% of the variance of the dependent variable.

The analysis of feature importance based on standardized coefficients (i.e., beta values) concluded that the most significant variables of the model are road conditions and the truck’s reliability compared to payload and weather conditions, which were found less significant. It was also found that reliability has a considerable effect (about 29%) on fuel consumption, so this variable is of vital importance for mining companies.

The case study revealed that an increment of 10% on equipment reliability accounts for a 6% reduction in CO_2 emissions, while a decision to improve roads from poor to well-maintained conditions is responsible for a 23% reduction in emissions.

5 Conclusions and Future Work

It is usual for mining companies to rely on a variety of machinery to carry out activities such as drilling, blasting, loading, hauling, and mineral processing. Equipment represents one of the most important assets in the mining industry; it is the main driver of operational performance and efficiency. The maintenance activities aim to increase the efficiency of processes related to mineral extraction and mineral processing while minimizing safety incident rates.

With the objective to take advantage of economies of scale and reduce costs, equipment manufacturers have been producing increasingly large equipment for the past 70 years. Due to this trend, maintenance and operating costs have increased considerably constraining the profit obtained from mineral resources. In this context, concepts such as equipment availability and reliability have the potential to play a key role to reduce costs while maximizing equipment productivity.

This thesis outlined the cornerstones of equipment management and focused on the link between equipment availability, reliability, and GHG emissions. As the equipment is a critical asset for mining companies, an appropriate maintenance policy is necessary to ensure excellent performance. Maintenance has the potential to contribute to the sustainability of mining operations in two ways. First, maintenance has a direct impact on availability and reliability, which will impact the economical aspect of a mining operation by reducing costs and maximizing efficiency. Second, maintenance has the potential to reduce environmental impacts by the utilization of well-maintained equipment. Environmental aspects of a mining operation such as the carbon footprint and gas emissions could be addressed by an adequate maintenance policy. Consequently, equipment fleets with high levels of reliability as well as with minimum greenhouse gas emissions are a high-priority mission for the mining industry.

A reliability-based approach was proposed to determine optimal inspection intervals in such a way to detect and prevent potentially catastrophic failures at an early stage. A case study considering data from 8 mining trucks working in a Canadian open-pit mine was proposed considering the idea of the virtual age. By doing so, trucks' virtual age was obtained considering the effect and quality of repair tasks. The suggested inspection intervals can be selected based on engineering experience and decision-makers' preference for specific reliability levels.

Next, a preventive maintenance scheduling based on the same case study was proposed considering the effects of virtual age for both CM and PM strategies. The rejuvenation of the systems was addressed by the consideration of the effectiveness factor representing the quality of repair actions for both types of maintenance strategies. Expected failure times were obtained based on the consideration of near to optimal PM effectiveness factors and typical inspection intervals proposed by the OEM. Next, these values were compared and adjusted based on the difference of the expected number of failures obtained from the PM and the computer-generated values of failures time obtained from the CM effectiveness factor. It has been shown that while considering high values for effectiveness factors for PM, more failures are expected in the model. Similar results are obtained when considering high values of the effectiveness factors for CM, which require shorter intervals of maintenance since repairs are no longer assumed to be perfect. This methodology can be used to suggest a practical maintenance scheduling plan under specific circumstances where the choice of the best effectiveness factor q_{CM} relies on parameters such as the historical failure data, maintenance policy objectives, and type of equipment under consideration

Finally, Chapter 4 focused on the relationship between reliability and GHG emissions. Having compared various linear and non-linear regression approaches for the prediction of fuel consumption of mining trucks such as Lasso and Ridge regressors, Stochastic Gradient Descent Regressor, Random Forest Regressor, and Gradient Boosting Ensemble Regressor, a multivariate linear regression model was the best fit for the dataset with a potential to explain 84% of the model's variance

Variables containing information about payload, weather conditions, road conditions, and reliability were considered as the independent variables to predict fuel consumption, which was then used to calculate CO_2 emissions. The analysis of the feature importance based on the standardized coefficients (i.e., beta values) concluded that the most significant variables of the model are road conditions and the truck's reliability, while payload and weather conditions are less significant. It was also found that reliability has an effect of 29% on fuel consumption, so it should be a variable of vital importance for mining companies. This case study revealed that an increment of 10% on equipment reliability accounts for a 6% reduction on CO_2 emissions, while a decision to improve maintenance roads from poorly to well-maintained conditions is responsible for a 23% reduction of the same type of emissions.

Future research should consider repair and inspection costs to optimize the determination of optimal inspection intervals and maintenance scheduling. Moreover, the same methodology can be applied to other types of mining equipment such as shovels, front end loaders, mineral processing equipment, etc. Regarding the regression model for the prediction of CO_2, future studies should consider the investigation of the reasons behind the unexplained part of the model as well to extend it to other mining equipment. Variables such as the seasonal variable can further be analyzed for the presence of rain, snow, etc. Similarly, the payload variable can better be addressed, including different kinds of truck models in the analysis (i.e., different capacity). Incorporating more specific constraints in the model, such as the human effect or the road grade, could also result in a considerable improvement in the prediction of fuel consumption

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