SECTION 5: THESIS DETAILS

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DEDICATION

To my family

ACKNOWLEDGMENTS*

First and foremost, I would like to present my truthful gratitude and appreciation to my supervisor Asst. Prof. Dr. Onur Gölbaşı for his marvelous mentorship. In this long road, he taught me not only the research but also the academic environment. I would like to thank him for his belief and support to me in every stage of my master's degree. I believe with all my heart that this thesis would not have been accomplished without his inspiring encouragement and guidance.

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* If you have received project support from TÜBİTAK, you must mention about it.

DEVELOPMENT OF A DYNAMIC MAINTENANCE ALGORITHM WITH MULTIPLE SCENARIOS: A CASE STUDY FOR SURFACE MINING

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

MERVE ÖLMEZ TURAN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
MINING ENGINEERING

JUNE 2019

Approval of the thesis:

DEVELOPMENT OF A DYNAMIC MAINTENANCE ALGORITHM WITH MULTIPLE SCENARIOS: A CASE STUDY FOR SURFACE MINING

submitted by **MERVE ÖLMEZ TURAN** in partial fulfillment of the requirements for the degree of **Master of Science in Mining Engineering Department, Middle East Technical University** by,

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

DEVELOPMENT OF A DYNAMIC MAINTENANCE ALGORITHM WITH MULTIPLE SCENARIOS: A CASE STUDY FOR SURFACE MINING

Ölmez Turan, Merve
Master of Science, Mining Engineering
Supervisor: Assist. Prof. Dr. Onur Gölbaşı

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Surface mining operations such as ore extraction and overburden stripping activities highly depend on machine performance. These machines' operational plan aims to handle required amount of material within a specific period with the lowest maintenance cost and the highest availability. In order to achieve these objectives, the machines should be adapted to the production schedule properly. On this basis, maintenance policies play crucial roles in the sustainability of operations. A maintenance policy is basically a combination of work packages that cover the answers of what, when, and how to maintain a machinery system. It should be determined specifically not only the machine itself but also operational dependencies between machines in the fleet. Although the literature on mining machine maintenance modelling commonly concentrates on corrective and preventive actions, opportunistic maintenance that examines whether an opportunity exists for the preventive maintenance of a running component in case of failure of another dependent component is not discussed as required. On this basis, the current study intends to develop an integrated simulation model that considers mathematical interaction of corrective, preventive, and opportunistic maintenance to stochastic uptime and downtime behaviors of subsystems in Arena® Software. The implementation of the simulation algorithm helps to understand the effect of maintenance policy content on total maintenance cost or annual production amount.

The proposed algorithm is implemented for two different scenarios. In the first example, an operation with three shovels where corrective, preventive, and opportunistic maintenance activities are applied under the policy is simulated for a period of one year. The simulation model is also performed for five different inspection intervals. According to results, the maximum attainable annual production of three shovels was obtained as 7,266,714 m^3. The increase of inspection intervals were detected to have no significant effect on the fleet availability. However, increasing time between inspections caused a shift from preventive maintenance to corrective maintenance that may cause a remarkable jump in the machine deterioration rate. In this sense, sensitivity of corrective maintenance statistics to the inspection intervals for each subsystem were evaluated. In the second case, six different maintenance policies with different combinations of corrective, preventive, and opportunistic maintenance were applied for a dragline system. In addition, effect of inspection intervals on the total maintenance cost was also evaluated for the policies that include preventive maintenance. The result shows that the total maintenance cost is minimized to 913,480 $ by applying just corrective and opportunistic maintenance. This means that opportunistic maintenance, which is applied during corrective maintenance hours, is good enough to prevent approaching failures; and preventive maintenance in inspections is redundant for the system. Moreover, the corrective maintenance statistics explains that the machinery house and movement subsystems are the most sensitive to inspection intervals where this is least for the rigging and hoisting subsystems.

Keywords: Dynamic Maintenance Policy, Inspection Interval Optimization, Discrete-Event Simulation, Dragline, Shovel, Arena ® Simulation Software

ÖZ

ÇOKLU SENARYOYA SAHİP BİR DİNAMİK BAKIM-ONARIM ALGORİTMASI GELİŞRİTİRİLMESİ: BİR AÇIK İŞLETME UYGULAMASI

Ölmez Turan, Merve
Yüksek Lisans, Maden Mühendisliği
Tez Danışmanı: Dr. Öğr. Üyesi Onur Gölbaşı

Haziran 2019, 83 sayfa

Cevher ve örtü kazı üretimi gibi yerüstü madencilik faaliyetleri doğrudan makine performanslarına bağlıdır. Bu makinelerin operasyonel açıdan planlanmaları, belirtilen zamanda hedeflenen üretim miktarına en düşük bakım-onarım maliyetleriyle ulaşmayı hedefler. Hedeflenen amaçlara ulaşabilmek için, makinelerin üretim planına uygun şekilde uyum sağlaması gerekmektedir. Buna dayanarak, bakım-onarım politikaları operasyonların sürdürülebilirliğinde önemli rol oynamaktadır. Bakım-onarım politikası temelde, bir makine sisteminde neye, ne zaman ve nasıl bir bakım-onarım uygulaması yapılacağı cevaplarını kapsayan iş paketlerinin kombinasyonudur. Sadece makinelerin kendisinin değil, filodaki makineler arasındaki operasyonel ilişkilerde da belirlenmelidir. Her ne kadar maden makinalarının bakım-onarım modellemesi ile ilgili literatürde genellikle düzeltici ve önleyici bakım-onarım faaliyetlerine odaklanılmış olsa da, bir bağımlı bileşenin arızalanması durumunda çalışan bir bileşene uygulanan önleyici bakım-onarım faaliyeti için bir fırsat olup olmadığını inceleyen fırsatçı bakım-onarım gerektiği gibi tartışılmamaktadır. Buna dayanarak, yapılan çalışma Arena® Yazılımında alt sistemlerin stokastik çalışma ve arıza süresi davranışları ile düzeltici, önleyici ve fırsatçı bakım-onarım uygulamarının matematiksel etkileşimini kapsayan entegre bir simülasyon modeli geliştirmeyi

amaçlamaktadır. Simülasyon algoritmasının uygulanması, bakım-onarım politikasının toplam bakım-onarım maliyetleri veya yıllık üretim miktarları üzerindeki etkisini anlamanıza yardımcı olmaktadır.

Önerilen algoritma iki farklı senaryo için uygulanmaktadır. İlk örnekte, politika kapsamında düzeltici, önleyici ve fırsatçı bakım-onarım faaliyetlerinin uygulandığı üç ekskavatörle yapılan operasyonun bir yıllık bir süresi simüle edilmektedir. Simülasyon modeli ayrıca beş farklı denetim aralığı için gerçekleştirilmektedir. Elde edilen sonuçlara göre, üç ekskavatör icin yıllık maksimum üretim miktarı 7,266,714 m^3 olarak elde edilmektedir. Denetim aralıklarındaki artışın üretime uygunluk oranlarını üzerinde önemli bir etkisinin olmadığı tespit edilmektedir. Fakat, denetimler arasındaki zamanın artması, önleyici bakım-onarımdan düzeltici bakım-onarıma kaymaya neden oldu. Bu kayma ise makine bozulma oranında gözle görülür bir sıçramaya neden olabilemektedir. Bu anlamda, düzeltici bakım-onarım istatistiklerinin her bir alt sistem için denetim aralıklarına duyarlılığı değerlendirildi.İkinci örnekte, bir dragline sistemine düzeltici, önleyici ve fırsatçı bakım-onarım faaliyet kombinasyonlarından oluşan altı farklı bakım-onarım politikası uygulanmıştır. Ayrıca, denetim aralıklarının toplam bakım-onarım maliyeti üzerindeki etkisi de önleyici bakım-onarım faaliyeterini içeren politikalar için değerlendirilmiştir. Sonuç olarak, düzeltici ve fırsatçı bakım-onarım faaliyetleri uygulayarak toplam bakım-onarım maliyetleri 913,480 $ seviyesine düşürülmektedir. Bu durumda, düzeltici bakım-onarım uygulama süresinde uygulanan fırsatçı bakım-onarım uygulaması yaklaşan arızaları önleyecek kadar iyi olduğu ve denetimlerde uygulanan önleyici bakım-onarımın sistem için fazlalık olduğu anlamına gelmektedir. Bunun yanı sıra, düzenleyici bakım-onarım istatistik verilerine göre makine dairesi ve hareket üniteleri denetleme aralıklarına en hızlı tepkiyi verirken, kaldırma ve dengeleme üniteleri en yavaş tepkiyi vermektedir

Anahtar Kelimeler: Dinamik Bakım Onarım Politikaları, Denetim Aralıklarının Optimizasyonu, Ayrık Olay Simülasyonu, Elektrikli Ekskavatör, Çekme Kepçeli Yürüyen Yerkazar, Arena® Simülasyon Programı

To my family

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ABBREVIATIONS

BO	Dragline Boom Subsystem
BU	Dragline Bucket Subsystem
CBM	Condition-Based Maintenance
CM	Corrective Maintenance
CT	Production Cycle Time
DR	Dragline Dragging Subsystem
IT	Inspection Time
LHD	Load-Haul-Dump
MH	Dragline Machinary House Subsystem
MO	Dragline Movement Subsystem
MTBF	Mean Time Between Failure
OM	Opportunistic Maintenance
OTH	Shovel Other Subsystem
PC	Production Amount of Each Cycle
PM	Preventive Maintenance
RCM	Reliability-Centered Maintenance
RI	Dragline Rigging Subsystem
S	Index of Shovel

SHA	Shovel Air System
SHC	Shovel Crowd Mechanism
SHD	Shovel Dipper System
SHE	Shovel Electrical System
SHH	Shovel Hoist Mechanism
TBF	Time Between Failure
TBI	Time Between Inspection
Ths	Expected Percentage of Subsystem's Lifetime Just Before Defect Arises
TPM	Total Productive Maintenance
TSW	Starting Time of Wear-Out Phase
TTR	Time to Repair

CHAPTER 1

INTRODUCTION

1.1. Background

After the Industrial Revolution, machines have started to be part of production systems in various industries by substituting manpower, and this shift boosted the amount and quality of production. In the mining industry, the effect of these systems on production efficiency is observable since almost all stages of mining require different machines with a high capacity and dependability. In most cases, failure of a machine, especially earthmovers, induces an interruption and delay in scheduled activities of a mining operation. Therefore, any forecasting on the range and control of machine failures may contribute to mine planning more precisely by keeping these massive systems above the intended operational conditions.

There are different types of maintenance policies that have been evolved in compliance with political and industrial fluctuations in the related decades. For instance, run to failure maintenance, which stands for repairing after the failure occurrence, was widely used up to the end of mid-forties. This type is also called corrective maintenance (CM). After World War II, market growth and global computation led to a significant improvement of mechanization and mass production, especially in the mining and transportation sectors. In that period, some preventive measures, i.e. preventive maintenance (PM), were started to be included in maintenance policies to increase the system availability and reliability. On this basis, preventive maintenance offers a scheduled activity that is performed without a failure occurrence so as to decrease the risk of failure. The third and the last period of the maintenance evaluation was started when the small-scale and sensitive machines had come into sight in some sectors such as health care, data processing, and telecommunication. In this maintenance approach, the activity scope covers not only reliability and productivity, but also the safety and quality of the production (Moubray, 1997). In this sense, remote monitoring systems with improved sensor technology have been included in maintenance activities. These systems, called condition-based maintenance (CBM), intend to monitor the data flow of machine performance indicators such as vibration, stress, and sound. It is occasionally considered under preventive maintenance work packages. However, there are some other industrial cases where CBM is evaluated and stated apart from preventive maintenance. This is called predictive maintenance. Table 1.1 shows the revaluation and inclusion of maintenance types and their influence areas.

Table 1.1. *Developments in Maintenance (Venkataraman, 2010)*

Period	Types of Market and Manufacturing	Types of Maintenance
Pre 1945	• Assembly lines • Production for stock	CM
1950s	• Economic expansion • Ever-Increasing demand	CM
1960s	• The growing complexity of assets • Innovations • Expanding infrastructure	CM & PM
1970s	• Market saturation Paradigm shift from a vendor to customer	CM, PM, CBM
1980s	• The customers have become the king	CM, PM, CBM
1990s	• Global competition • Implementation of enterprise resource planning, total quality management	CM, PM, CBM, Total Production Maintenance, Reliability-Centered Maintenance

By using the principles of maintenance types, their mathematical interactions, and their effects on production, this study aims to develop an algorithm that evaluates and optimizes multiple maintenance policies with different work packages for mining machineries.

1.2. Problem Statement

In the mining industry, production activities that cover drilling, blasting, loading, and haulage have a serial connection with each other. It means that any interruption in any of those activities may cause an interruption in the production cycle. Among these, earthmoving machineries have an extreme priority and importance since they have a direct effect on production. They are generally complex, expensive, and massive machines. Therefore, maintenance policies and their work packages need to be constituted very carefully. Improper maintenance policies may cause not just high operational cost but also additional production loss. In industries, maintenance cost maybe 15 to 70% of total production cost (Jajimoggala *et al.*, 2011). 30-50 % of the total production cost is constituted by maintenance cost in open pit mines (Krellis and Singleton, 1998). This percentage can change according to machine types and their usage areas (Hall, 1997). Mining machines are used in challenging working environments where the maintenance operation is carried out on field or in maintenance shops, which needs a considerable cash flow. Many other external and internal factors such as ambient temperature, rock type, geological anomalies, operational factors, competency of manpower, and spare part logistic factors may change the deterioration of machines and frequency of maintenance works. In addition, maintenance work packages with different implementation plans affect sustainability and maintainability of the production systems. In this sense, maintenance policies should offer a balance between corrective and preventive measures that minimizes overall maintenance cost (Figure 1.1).

Secondly, the value of a production loss is assessed by the capacity and the unit cost for a given operation. The production rate of a machine is highly affected by the excavated material properties, operator skills, its catalogue capacity, and production plans. There may be catastrophic changes in machine availabilities year by year. For instance, shovel availability in a mine was detected to decrease from 64% to 55% between 2009 and 2010 (Ozdogan, 2012). On the other hand, the production cost is measured by operational expenses and downtime cost that is a function of commodity price and unit production. As seen in Figure 1.2, iron ore fines price has fluctuated between 40 and 100 USD/dry metric ton in the recent five years (Market Inside, 2019). Any change in the commodity price has a great effect on the unit value of production loss.

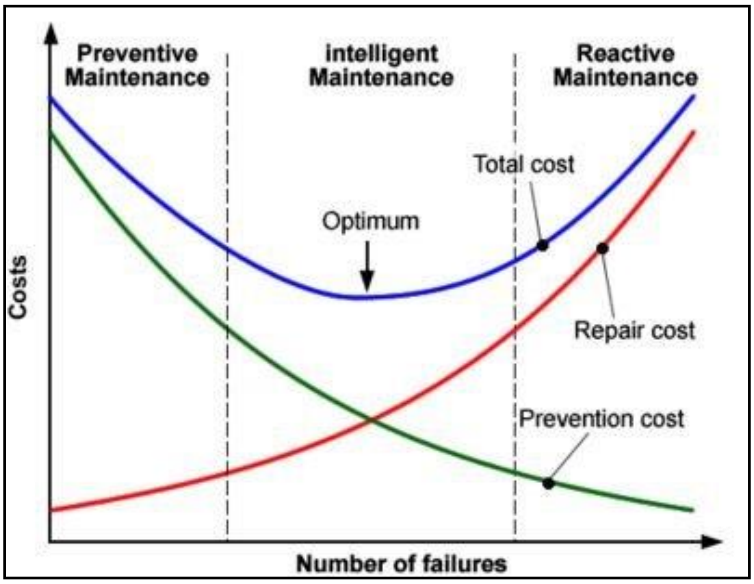


Figure 1.1. Accounting Cost of Maintenance Balance (Jardine, 1973)

Variability of maintenance work packages, their effectivities and financial burdens, uncertainty in the deterioration of machine parts, and time-dependent value of production complicate the constitution of a proper maintenance policy. Therefore, a holistic and dynamic approach that offers a comparative evaluation of production capacity, physical cost, and production loss is required for the optimality of policy.

A comprehensive literature review showed that there is a lack of maintenance algorithm, which correlates the interactions of work packages for mining machineries in both financial and operational manner. In this sense, this research study intends to develop a dynamic model for solving and comparing multiple maintenance policies to find out an optimal way of maintaining mining machineries.

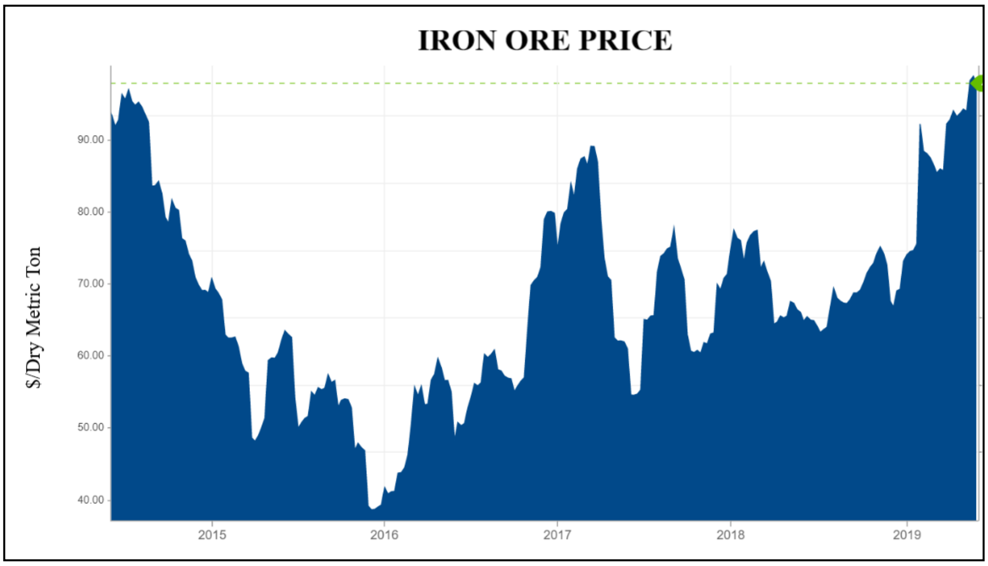


Figure 1.2. A Sample Chart for a Commodity Price Change (Market Inside, 2019)

1.3. Objectives and Scopes of the Study

The main objective of this study is to develop a stochastic algorithm to evaluate different maintenance policies for mining machineries. Sub-objectives of the study entail i) building up mathematical interactions between the work packages in a policy, ii) decomposition of machinery systems, iii) data pre-processing and assessment of algorithm parameters, iv) simulation of the policies in a discrete-event environment, and v) evaluation of simulation results in terms of overall maintenance cost and production outcomes.

Scope of the study includes maintenance work packages related to preventive maintenance (PM), corrective maintenance (CM) and opportunistic maintenance (OM) strategies. Direct cost values are included in the model deterministically where production loss and system behavior are handled stochastically.

1.4. Research Methodology

This research study uses stochastic approaches when developing a multi-stage maintenance algorithm. Graphical illustration of the research methodology used in the study can be viewed in Figure 1.3. The main steps of the methodology are as follows:

- Identification of functional dependencies in the systems
  - Identification of the machine’s components and subsystems,
  - Evaluation of quantitative failure and repair datasets,
  - Investigation of expert opinions, machinery catalogs, and related studies,
- Development of a machine-specific maintenance policy in Arena® software.
  - Introducing the configuration of components in the system,
  - Logical adaptation of corrective maintenance, preventive maintenance, and opportunistic maintenance to the system configuration,
  - Defining scheduled breaks other than maintenance activities,
- Optimization of the introduced maintenance policy
  - Monitoring random operating hours and random repairing times, and resultant production losses which variate dynamically with each time increment,
  - Optimizing and reporting inspection intervals, their resultant annual production amount and machine availabilities,
- The sensitivity analysis of the maintenance policy to different work packages
  - Given random operating and downtime behavior of system, evaluating and discussing the sensitivity of various maintenance policies to production rate and maintenance cost.

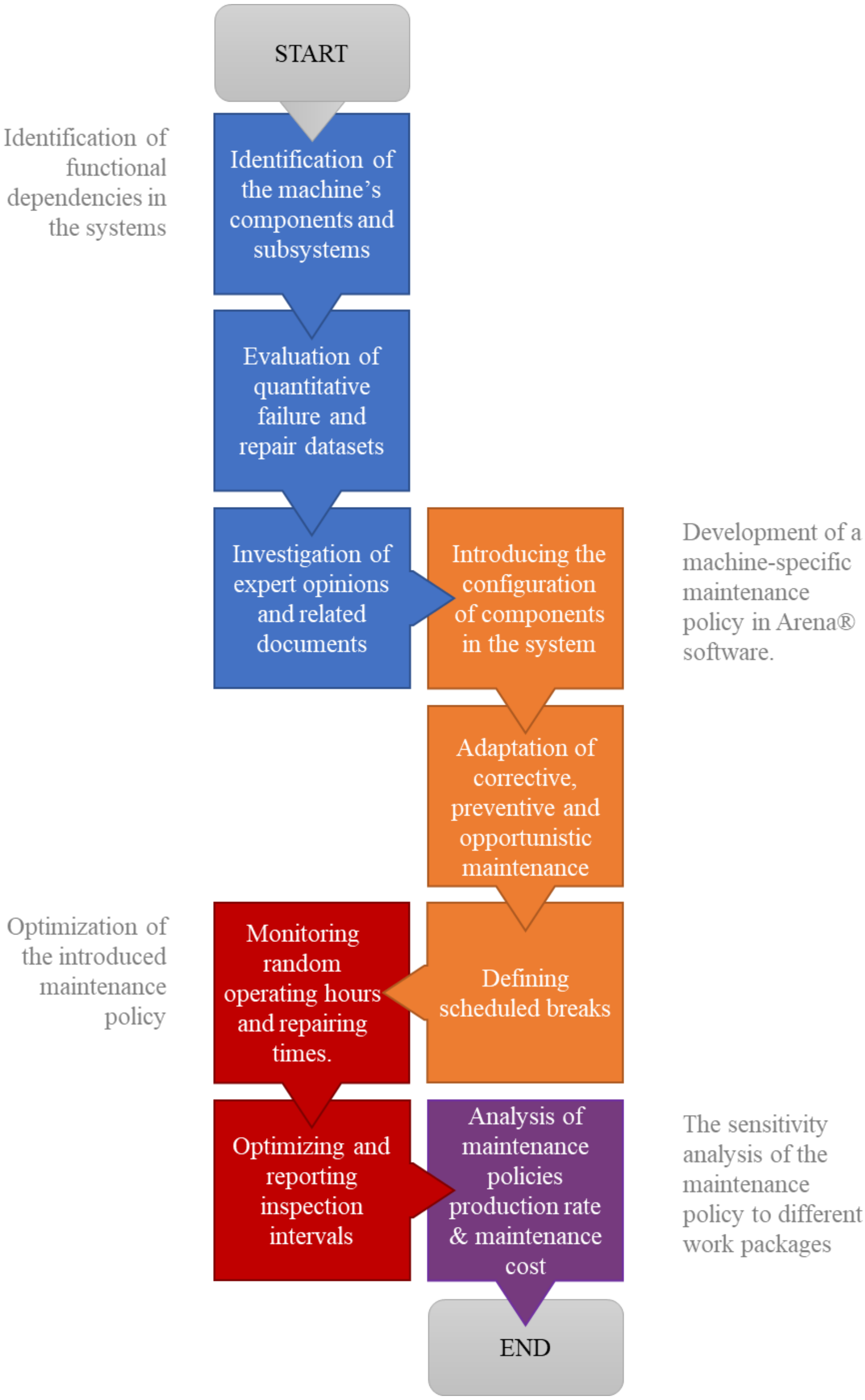


Figure 1.3. Research Methodology of the Thesis Study

1.5. Significance and Expected Contributions of This Thesis

Although there are many studies about maintenance scheduling or planning in the literature, their implementation on mining machines is limited. In addition, mining-related studies generally cover just reliability analysis to highlight the most critical component in the system without any component or subsystem decomposition. Moreover, mathematical modelling of multi-scenarios for maintenance was not studied in detail. In this sense, there is no observed research about the maintenance simulation that covers the interaction between multiple-machines and multi-subsystems. Moreover, the recent studies have generally ignored opportunistic maintenance although it is common in practice. The current dissertation implements a maintenance simulation-optimization model, considering corrective, preventive, and opportunistic maintenance application with random component lifetimes and repair times. Therefore, the research allows investigating the effects of different maintenance policies on total maintenance cost or production availability for changing inspection intervals.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

This chapter briefly explains the terms, theories, and methodologies related to maintenance models. In this sense, the literature survey highlights the topics about maintenance activities, maintenance optimization, modeling, and simulation of maintenance policies and recent maintenance studies in the mining area.

2.2. Classification of Maintenance Activities

Budai *et al.* (2008) defined maintenance as a group of activities required to keep a facility in "as built" condition and therefore it may continue to have its original productive capacity. Ben-Daya *et al*. (2016) categorized maintenance activities in two major groups as PM and CM. Branching of different maintenance work packages under PM and CM can be viewed in Figure 2.1.

Corrective maintenance is implemented after random failure occurrences that happen during operation. In the literature, it also is called run to failure strategy. CM can be divided into two subgroups based on the importance of the failed component. For a critical component, immediate CM needs to be initiated instantly to mitigate or prevent the resultant negative consequences such as injuries, death, high downtime or high cost of production loss. The other type of CM is the deferred CM, which is carried on a non-critical component and can be delayed. Although CM requires low investment and labor skills, the factors such as additional production losses, extra labor hours, extras for repairing and replacement cost, and increasing risk of the accident are the reasons why CM should not be a priority in a maintenance policy. In addition, the production plan can suffer from the unavailability of spare parts and delays in breakdown management. Thus, maintenance activities that include proper PM activities may reduce the total maintenance cost by 8 to 12 % (The US Department of Energy, 2010).

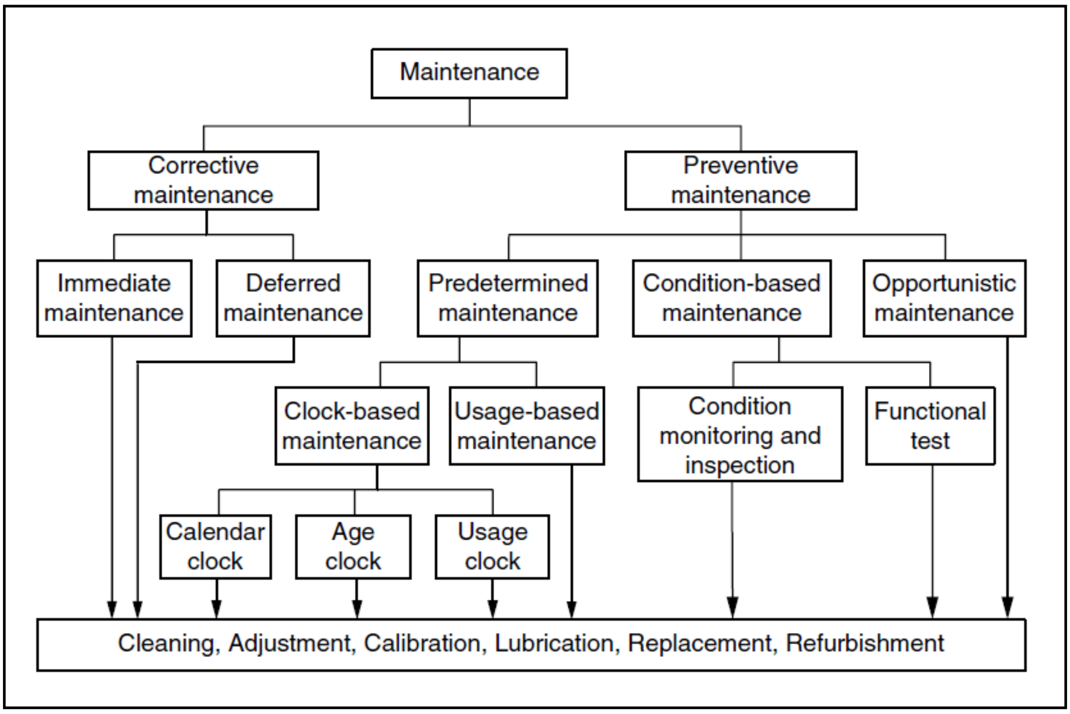


Figure 2.1. Types of Maintenance Activities (Ben-Daya et al., 2016)

On the other hand, preventive maintenance (PM) is performed before a failure occurrence to minimize the impact of a sudden breakdown by detecting the approaching failures and/or finding hidden defects. PM can be grouped as predetermined, condition-based, and opportunistic. Predetermined maintenance, sometimes called preventive maintenance interchangeably in the literature, is carried out considering the focus of time and usage. Time can be continuous (i.e. calendar or age clock) or intermittent (i.e. usage clock). Because of dynamic operation schedules and environment changes, predetermined maintenance may sometimes be ineffective, and its convenience needs to be validated. On the other hand, CBM is applied only when the system is suitable for such an adaptation. Condition monitoring systems such as sensors or regular inspection and functional tests are used to control the machine’s condition. When a specific measurable parameter of system degradation, which can be heat, vibration or oil level, reaches the warning threshold level, the risk of failure is assumed to be beyond the acceptable limit. These threshold levels trigger the maintenance crew for a proactive response. CBM reduces not only downtime but also cost of spare part and labor. However, the installation of condition monitoring is generally required high capital investment.

In brief, as illustrated in Figure 2.2, CM is applied after failure when degradation level reaches breakdown threshold where PM is applied before the threshold level. On the other hand, CBM is applied when degradation reaches a specific warning threshold which is always less than the expected failure point (Alrabghi and Tiwari, 2015). Opportunistic maintenance (OM), as a specific type of preventive maintenance, is carried out for deteriorated but non-failed components preventively where the failure of another component provides an opportunity for such a maintenance. Additionally, administrative breaks may also provide such an opportunistic time for maintenance. OM offers a cost-effective way of maintenance only if there is enough amount of implementation time and resource.

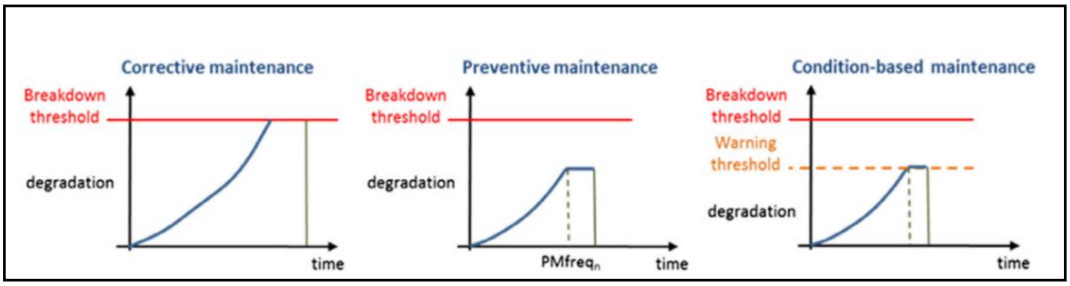


Figure 2.2. Trigger Points of Different Maintenance Types (Alrabghi and Tiwari, 2015)

In literature and industry, the most common maintenance activities were detected to be PM, CM, and CBM. Alrabghi and Tiwari (2015) stated that PM models were investigated most in the literature. On the other hand, The US Department of Energy (2010) report showed that the majority of maintenance activities is performed correctively with CM in the US industry. Figure 2.3 shows the comparative weights of maintenance types in the literature and the industry.

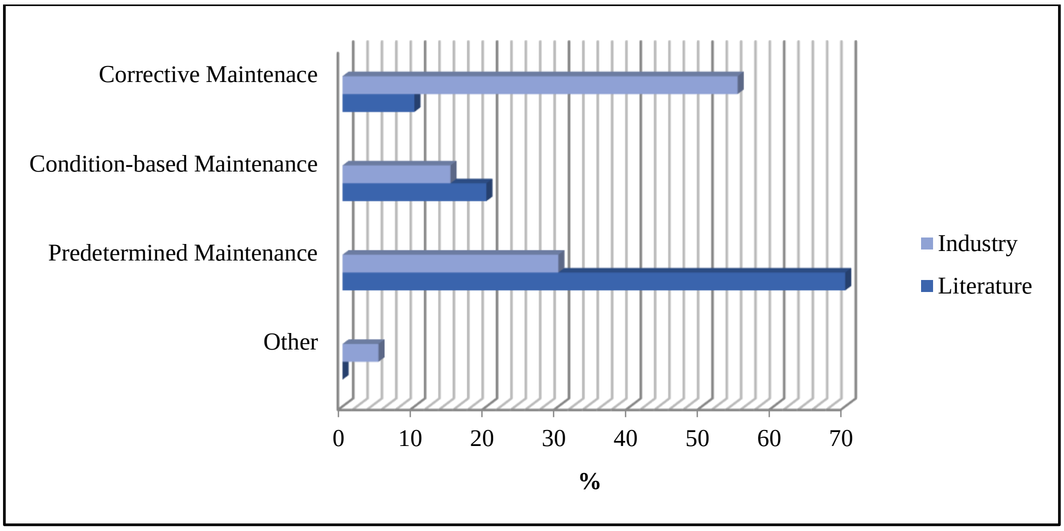


Figure 2.3. Maintenance Application in Literature and US Industry (Alrabghi and Tiwari, 2015; The USA Department of Energy, 2010)

There are two popular maintenance approaches in practice, which are called reliability-centered maintenance (RCM) and total productive maintenance (TPM). TPM was introduced by Nakajima (1988) and defined as a maintenance management approach that combines total quality management philosophy and maintenance techniques. TPM focuses on involving all employees in an organization to improve an equipment performance by defining six major losses due to equipment failures. The aim of this strategy is to eliminate these losses and maximizing overall equipment effectiveness. On the other hand, Reliability-Centered Maintenance is a methodology that defines the actions to be considered so as to ensure that the system continues fulfilling its functional capacity in its present condition. The purpose of RCM is the optimization of preventive maintenance depending on systems and functionalities of their components (Budai et al., 2008). The methodology can cover the combinations of corrective, preventive, and condition-based actions. RCM application areas can be examined in Figure 2.4.

Moreover, maintenance actions may contribute to the operation age of a system or a component differently. As shown in Figure 2.5, Pham and Wang (1996) give an overview of the different possible degrees of restoration:

- Perfect repair or perfect maintenance: The operating condition of the system is restored to an as good as new state, which means that the lifetime distribution, degradation level, and failure rate are same with a new component.
- Minimal repair or minimal maintenance: The system is restored to the condition just before the maintenance action, which stands for as bad as old state.
- Imperfect repair or imperfect maintenance: The system is restored to somewhere between as good as new and as bad as old conditions.
- Worse repair or worse maintenance: The system failure rate or actual age of the system increases after performing a maintenance action. Worse repair means that the repair type or maintenance implementation is inappropriate for the related system.

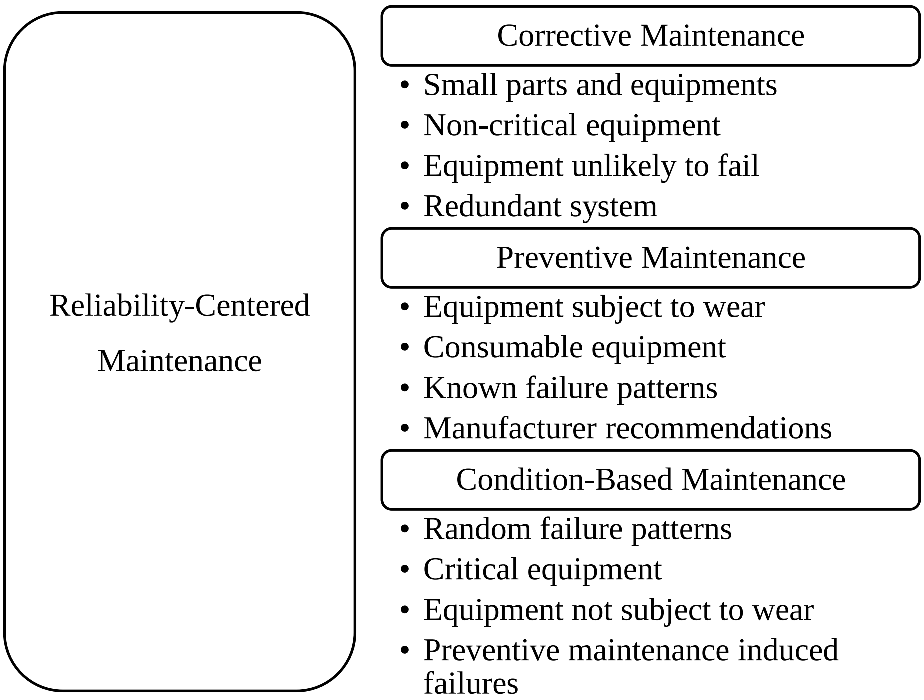


Figure 2.4. Reliability-Centered Maintenance Application Areas (Moubray, 1997)

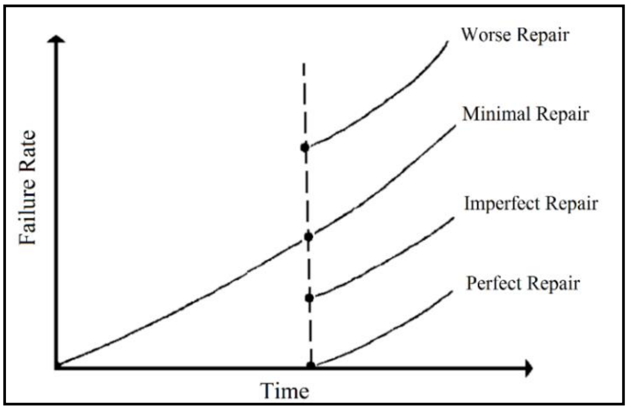


Figure 2.5. Effect of Repair Types on Failure Rate (Blischke and Murthy, 2000)

2.3. Simulation and Modelling of an Engineering System

This section makes a brief introduction about the modelling steps of engineering systems and simulation types that can be used to mimic the system operations in a computational environment.

2.3.1. Modeling of an Engineering System

The system is like a black box although input and output of it can be observed. This means that the system cannot be understood exactly, and the model is a miniature representation of the real system, so it tries to enlighten the underlying mechanism of the system. Observation of input and output and phenomena behind the system are used to build the model. In case that the model's prediction is highly correlated with the real system's outputs then the model can be utilized to simulate and analyze other scenarios. The basic steps used for building a model can be listed as follows (Dym, 2004):

- Identification of the requirements for the model
- Listing the required data set in the model
- Identification of available relevant data
- Identification of the circumstances that apply
- Identification of the leading physical principles

- Identification of the equations that will be used, the calculations that will be made, and the answers that will outcome
- Validation of the model.

Schematic view of how a model should be developed with which questions are given in Figure 2.6.

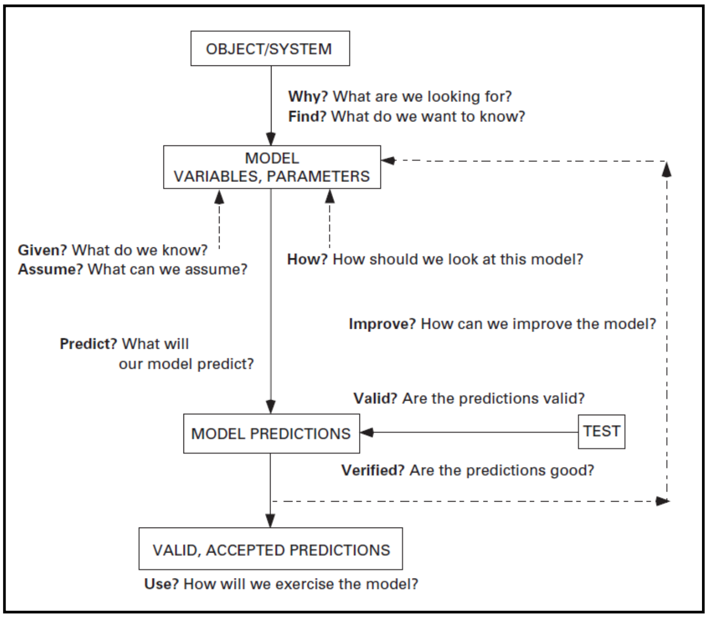


Figure 2.6. Follow Chart of Model (Carson and Cobelli, 2001).

In a maintenance system, assets, production dynamics, and maintenance resources constitute the three pillars of the model. Production dynamics are buffer capacities where maintenance resources include spare parts, maintenance crew, and capacity of the maintenance shop. On the other hand, assets can be explained in three main parts as number of components, number of stages, and relationship between assets.

In the literature, systems are defined as single-unit or multiple-unit. Single-unit means that the system can be defined without any decomposition or only one component is considered. For instance, Gilardoni *et al.* (2016) concentrated only on haulage truck engine maintenance where Elevli *et al.* (2008) studied shovel maintenance without component classification.

On the other hand, multi-unit systems, which consider two or more components, were analyzed in the literature with different configurations. These configurations can be series, parallel, K-out-of-N and standby (Figure 2.7). In a series configuration, failure of any component can stop the whole system. This type is commonly observed in the subsystems of different machines (Roy *et al.*, 2001). In a parallel configuration, the system keeps on production until all components are failed. This type of configuration is used in manufacturing production lines (Zahedi-Hosseini *et al.*, 2018). Furthermore, systems can include both series and parallel configurations as also shown in Figure 2.7. Truong Ba, *et al.* (2017) built a method to optimize the opportunistic maintenance strategy for the series-parallel system. Moreover, in K-out-of-N configuration, if K number of components works in N number of components in a system, the system keeps working. For example, the earthmoving ability of a shovel is active even though two out of four hydraulic pumps in the system are operationally healthy (Samanta *et al.*, 2002). In standby systems, some of the identical components wait in passive mode. When a working component fails, one of these passive components switch with the failed one in milliseconds. Levitin *et al.* (2018) implemented an optimization model for a power station's coal transportation system where subsystems were constructed with stand-by components.

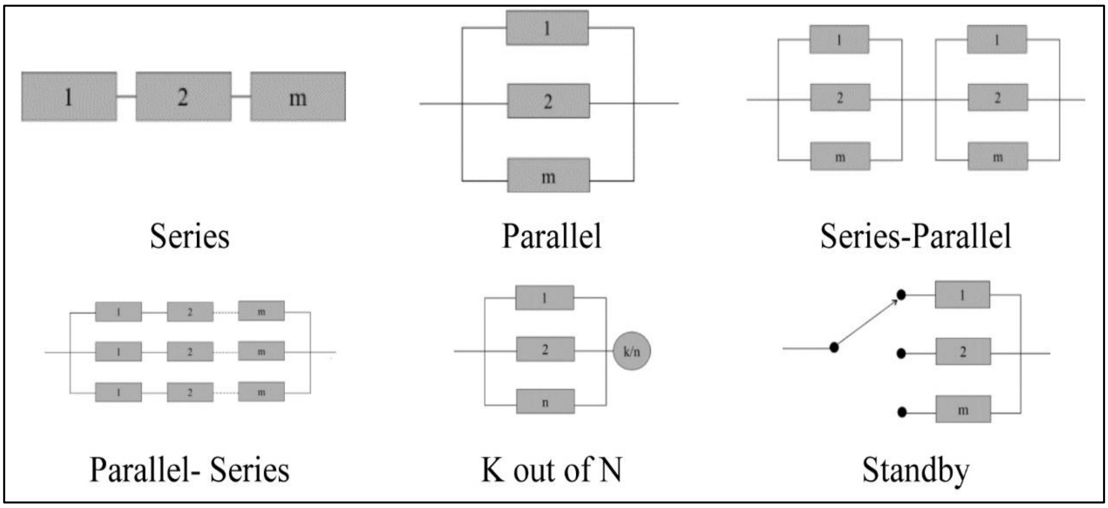


Figure 2.7. System Configuration Types (Kumar et al., 2006)

In any configuration, for measuring performance of the system, global mining companies use their internal standard time usage model. Although all calendar time structures are created by same logic, their time component names are different form each other. For example, Figure 2.8 illustrates The Glencore time usage model (Ritter and Stoyan, 2018). The components of a system can be in a stage of working, unscheduled stoppage or external idle time. External idle is caused by an administrative or weather condition. On the other hand, the working time covers available time and maintenance time. Maintenance model contains planned or unplanned stoppage. How and when a maintenance activity will be performed with which content may also change depending on the model scopes. While CM and OM strategies consider as unplanned maintenance time, PM strategy considers as planned maintenance time.

<table>
<tr><td colspan="11">Calendar Time (CT)</td></tr>
<tr><td colspan="10">Scheduled Time (ST)</td><td rowspan="5">Unscheduled Time (UT)</td></tr>
<tr><td colspan="8">Working Time (WT)</td><td colspan="2">External Idle Time (IT)</td></tr>
<tr><td colspan="6">Available Time (AT)</td><td colspan="2">Maintenance Time (MT)</td><td rowspan="3">Other External Idle Time (OE)</td><td rowspan="3">Weather External Idle Time (WE)</td></tr>
<tr><td colspan="2">Operating Time (OT)</td><td colspan="4">Operating Delay Time (OD)</td><td rowspan="2">Unplanned Maint. Time (UM)</td><td rowspan="2">Planned Maint. Time (PM)</td></tr>
<tr><td>Dynamic Operating Time (DT)</td><td>Non-dynamic Operating Time (NT)</td><td>Process Delay Time (PD)</td><td>Unplanned Delay Time (UD)</td><td>Labour Delay Time (LD)</td><td>Standby Delay Time (SD)</td></tr>
</table>

Figure 2.8. The Glencore time usage model (Ritter and Stoyan, 2018)

2.3.2. Simulation Types

Simulation is defined as “experimentation with a simplified imitation of an operations system as it progresses through time, for the purpose of better understanding and/or improving that complex system” by Robinson (2004). For complex maintenance problems, analytical, and mathematical approaches are limited in solving. In this sense, Rezg *et al.* (2005) developed both analytical and simulation models to solve identical complex problems and the results showed that the simulation model provided more flexibility and simpler estimations. In this sense, the advantages of the simulation may be listed as follows (Sharma *et al.*, 2011):

- Simulation allows to study and experiment with a complex system in a more practical manner.
- Simulation enables the feasibility testing of any hypothesis about how or why certain phenomena occur.
- Flexibility in time handling as it can be compressed or expanded to allow for a speed-up or slow-down of the phenomena under investigation.
- Evaluating the different circumstances of simulation by changing the inputs and observing the resultant outputs can produce a valuable insight into which variables are the most important.
- Simulation helps in the formulation and verification of analytical solutions.

In addition to these advantages, simulation also has some disadvantages as:

- Special training is required to build simulation models.
- Since much randomness is associated with simulation, so it can be hard to distinguish whether an observation is a result of system interrelationships or of randomness.
- Simulation modeling and analysis can be time consuming and expensive.

Simulation modeling can be categorized into three main types based on the progress of time, as shown in Figure 2.9:

✓ *Time-slicing Simulation:* Model is simulated in every constant time-step (ΔT). There are two main problems with the time-slicing approach. There are redundant data produced since the system is generally in the same condition between the increments. Secondly, the determination of ΔT is critical.

✓ *Discrete-event Simulation*: Model is simulated at a time point when any value or situation changes. Model is created in chronological orders of the change points, called an event. The system is updated when an event occurs. Otherwise, the system remains unchanged and time is advanced to the next scheduled event. Although this approach gives a chance to analyze the model efficiently, it may lead to a more complex structure and a need for additional controlling.

✓ Continuous *Simulation*: Model is simulated in a continuous timeline. This is suitable for a condition where system changes continuously through time.

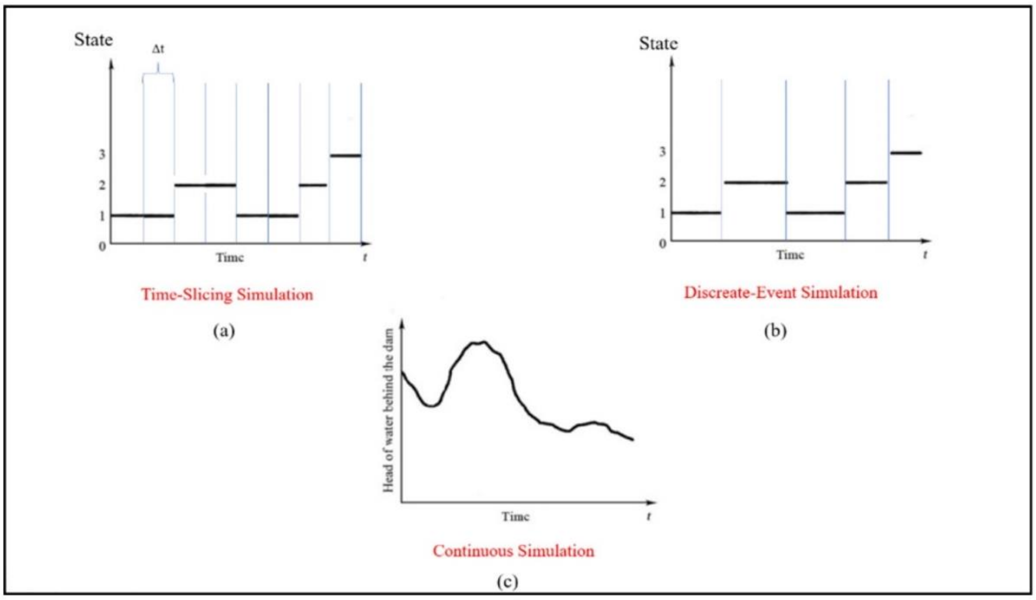


Figure 2.9. Sample Illustration of Time-Slicing Simulation (a), Discrete-Event Simulation (b), and Continuous Simulation (c)

In brief, discrete-event simulation (DES) offers less computational time compared to the other simulation types. In addition, since a maintenance model requires consecutive and discrete decision-making process when the system state is turned to either of failure, corrective maintenance, preventive maintenance and opportunistic maintenance, DES is selected as a simulation type in this research study.

2.4. Maintenance Policy Optimization

A maintenance policy should give an answer to what, when, and how questions for maintenance activities (Budai et al., 2006). The work on maintenance optimization was initiated in the early 1960s by McCall (1965), Barlow and Proschan (1965), and Pierskalla and Voelker (1979). Maintenance optimization model which is defined as "the procedure of finding and comparing feasible solutions until no better solution can be found" by Deb (2001), has three main stages as objective, decision variables, and constraints. Constraints in a maintenance policy can be inventory limits, budget, labor, minimum reliability level or physical capacity of maintenance shop (Alrabghi and Tiwari, 2015). In following the parts, the objective of model and decision variables will be explained in detail.

2.4.1. Optimization Objective

The objective of an optimization model for maintenance policy can be as follows (Wilson, 2002):

- Minimizing the cost,
- Maximizing quantity of products,
- Maximizing availability,
- Maximizing work safety.

The cost item consists of two parts that are account costs and opportunistic costs. They are also called direct and indirect costs. In maintenance operations, accounting costs are the real expenditure of labor, material and spare parts, contractors, infrastructures and the related tax. On the other hand, Boyes and Melvin (1991) defined opportunistic cost as the best alternative that we give up or sacrifice by using the same amount of resource. Opportunistic costs of maintenance actions cover loss of revenue due to the downtime, cost of accidents, demurrages and insurance policies (Ben-Daya *et al*., 2016). Bartholomew-Biggs *et al.* (2006) intended to schedule PM to minimize account cost which reflects repair and replacement costs and PM itself. Also, Kuntz *et al.* (2001) developed a model that finds out the optimal inspection frequency by minimizing cost which covers inspection, CM, PM, and customer reliability costs as opportunistic cost items.

One of the system performance evaluation parameters is availability which is the rate of success at a stated instant of time or over a stated period. Roux *et al.* (2013) identified maximizing machines availability as an objective function. They claimed that the availability is a more adequate criterion than the maintenance costs where production costs are higher than maintenance costs. Some researchers optimized cost and availability in the same model. Alrabghi and Tiwari (2015) proposed a model to estimate the optimal inspection frequency for six-components manufacturing system by minimizing the cost and maximizing the availability. Moreover, a system's availability is directly related to the required quality output and the revenue of the system. Arab *et al.* (2013) developed a model with system parameters of cycle times, buffers' capacity and mean time to repair of machines in order to maximize the throughput. In another view, Yang *et al.* (2008) intended to determine an optimal maintenance strategy among four alternatives such that system profit including availability factor was maximized.

In this thesis, the objective function will be minimizing overall cost of maintenance policy. In addition, two case studies will be performed for a shovel fleet and a dragline to reveal the effects of different maintenance strategies on the systems.

2.4.2. Decision Variable

Decision variable is a pre-specified system parameter that has an effect on the objective function to minimize or maximize its value. In maintenance studies, researchers generally focused on inspection frequency, spare parts, maintenance threshold, priorities, and buffer sizes (Alrabghi and Tiwari, 2015).

Preventive maintenance activities of inspections are carried to control the system in regular intervals to detect possible anomalies in systems. These activities may cover: (i) controlling of system components conditions and their thresholds , (ii) repairing or corrective replacement of hidden failed components, (iii) lubrication, (iv) overhauling, and (v) preventive replacement of specified wear-out components (Gölbaşı and Demirel, 2017). By estimating an optimum inspection interval, the unit cost of maintenance activities can be reduced, and availability and sustainability of systems can be kept in desired levels. Roux et al. (2013) tried to estimate inspection intervals of preventive replacement actions by using simulation and optimization-based model. While the priority was given to maximize the availability of the system, it was intended to minimize the maintenance cost. The results showed an inspection intervals difference of 48 hours can increase the availability by 5 %. In the current study, the decision variable will be defined as inspection interval.

Spare parts are essential inputs of maintenance actions. Out-of-stock spare parts can cause additional downtime. Therefore, proper inventory management can (i) reduce the unnecessary waiting time and anticipatory payment, (ii) increase the system availability, and (iii) decrease indirect and labor cost. Xu et al. (2012) generated a Monte Carlo simulation model for minimizing the total cost of a preventive replacement policy of the multi-component system. The proposed policy reduced the cost values between 3.41% and 10.47%.

Maintenance threshold that triggers maintenance actions is the major decision variable for CBM and OM. Xiang et al. (2012) estimated full lifetime distribution of single-component systems operated under a Markovian environment where the system's instantaneous deterioration rate highly depends on the environment, by using simulation and optimization-based approach. In the study, age-based and CBM policies were developed for the defined systems and a large numerical experiment was conducted to evaluate the cost benefits of the CBM. The results showed that average cost savings with a shift from scheduled maintenance to a CBM were between 23.17% and 44.88%.

Finally, in some studies, maintenance queuing that is the order of maintenance actions to restore in shortest time were optimized for different assets. In other words, systems in a bottleneck should have a higher priority to enhance the total outputs. Hani et al. (2008) developed a simulation model to optimize the scheduling in a railway maintenance facility. The results indicated that the capacity was improved by more than 18%, and that the mean duration of immobilization was reduced by 18.5%.

2.5. Maintenance Studies in Mining Area

In the literature, various maintenance policies have been studied for mining machines such as, shovel (Elevli *et al*., 2008; Pascual *et al*., 2009; Samanta *et al*., 2001, 2002), Load-Haul-Dump (LHD) (Dindarloo, 2016), drilling machine (Al-Chalabi *et al*., 2014), haulage truck (Gilardoni *et al*., 2016; Jafari *et al*., 2017), process plant machines (Wang et al., 2007; Dandotiya and Lundberg, 2012), and dragline (Gölbaşı and Demirel, 2017). A brief discussion on some of these studies are given below.

Samanta et al. (2001) aimed to analyze the three shovels, operated in an open cast coal mine, with a reliability approach. For this purpose, they collected TBF data set in the mining area. Then, they grouped it regarding the sub-systems of the shovel, which were hydraulic, engine, transmission, bucket, track, and others. Each group of datasets were tested for data dependency and being identical. Because all datasets were identically distributed and independent, the renewal process was used to find the probability distribution functions. According to these functions, the most critical sub-system in the shovels was detected to be hydraulic. The authors suggested that the hydraulic system should be taken into consideration first for improving the performance of shovels.

Louit and Knights (2001) developed a DES model for the analysis of the maintenance performance which covered fleet availabilities, the proportion of preventive maintenance performed in scheduled times, and the percentage of unplanned maintenance. Simulation scenario involved the changes in stock planning, repair standards, additional demand for labor and workshop area, organizational changes, transferring of maintenance staff to operation process, and maintenance contracting. The model indicated that a significant improvement could be achieved through initiatives designed to reduce the frequency of unplanned failures and the times to repair. Two initiatives of relevance are the elimination of breakdowns by root-cause failure analysis and generating repair standards. The model was implemented in a mining company that operates two gold and silver mines in the north of Chile.

Crespo Marquez (2005) evaluated maintenance strategies aimed to cope with a critical failure of a repairable system by using continuous simulation modeling. The objective function of the model was to reduce the total cumulative expected cost of maintenance that was spent for employee, spare parts, rescheduled operations, testing process. The simulation model was implemented for 18 diesel engines installed in the same number of haulage trucks, used for open pit metallic mines.

Gupta *et al.* (2006) analyzed the reliability of a longwall shearer, which had a significant role in the production as a cutter and loader, by decomposing it into subsystems. The analyses showed that 15% of the shearer components reached to their wear-out phase. This means that the preventive replacement could be more economical than corrective repairing for these components. Moreover, they created a fault tree map to find out the most critical component in the system.

Barabady and Kumar (2008) studied on reliability and availability characteristics of a crushing plant, which was located at Jajarm Bauxite Mine in Iran. On this basis, six subsystems` lifetimes of the plant were estimated by using best-fit distributions and non-homogenous Poisson process for lifetimes with non-trend and trend behavior, respectively. According to these analyses, the conveyor subsystem and the secondary screen subsystem were detected to be most critical in point of reliability where the secondary crusher subsystem and conveyer subsystem were critical in point of availability.

Gupta *et al.* (2009) developed a scheme for maintenance policy decisions through a time-based control chart, called t-chart that monitors the failure process of the component or system under investigation. The authors defined the components` time between failure (TBF) data with Weibull and Lognormal distribution functions. The proposed t-chart gives a warning when the observed failure is out of the boundaries defined by the acceptable error limits. According to the failure patterns, they proposed boundaries that explain the required maintenance actions and the cause of TBF patterns. For example, if all TBF points are in the limits and no systematic pattern exists, then the performance of the present maintenance schedule is assumed to be satisfied. They applied the model to Armored Flexible Conveyor in an underground coal mine in India; and they collected data for 2 years. They divided Armored Flexible Conveyor to twenty-three components. Each component`s TBF Weibull distribution function was estimated. Due to the result of the model, nine components get into zone II. For these components, two suggestions were given. The first one is that preventive replacement policy should be applied when it reaches the wear-out phase it should be waited for some more time before fixing up its maintenance schedule if it is new. The other one is the investigation of whether there is any assignable cause leading to significant process deterioration.

Vayenas and Wu (2009) analyzed the maintenance and reliability of LHD by using reliability-based approaches. This analysis was based on the breakdowns and accompanying repair hours of 13 LHD vehicles from January 2006 to May 2007 at a hard rock underground mine in Canada. The results showed that the mechanical breakdown and planned maintenance activities consumed most of the repair times. It means that preventive maintenance did not appear to cause a major improvement on the mechanical availability of equipment.

Uzgören *et al.* (2010) evaluated the reliability of two draglines by using Renewal Process. Reliability values were estimated for different time intervals by using Weibull distribution. The study results showed that mean time between failures (MTBF) for Dragline-1 and Dragline-2 were found to be 97.0 and 75.8 hours respectively. Moreover, the study focused on estimating the required maintenance intervals for various reliability levels. According to the result, 23.8 and 19.1 hours maintenance intervals were required to keep Dragline-1 and Dragline-2 above 75% reliability level, respectively.

Al-Chalabi *et al.* (2014) proposed a model to minimize the total cost that included machine purchase price, maintenance cost, and operating cost. The model was based on artificial neural network and it was used to find the relationships between the costs and the optimal replacement time of drilling machine. The authors studied three different cases for the sensitivity of increasing purchase price, decreasing operating cost, and decreasing maintenance cost. In the model output, the most important parameter influencing the optimal time replacement of the drilling machine was detected to be decreasing maintenance cost, followed by increasing purchase price and decreasing operating cost.

Gilardoni *et al.* (2016) compared two PM policies that were applied periodically and dynamically. The selection of policies was based on minimizing the expected cost. They used 208 failure data of 193 off-road engines that were used in a Brazilian mining area. They used maximum likelihood estimation as a statistical tool. In addition, they assumed that the maintenance activities were imperfect in order to be more realistic. The application result stated that the expected operating cost per unit of time might be much lower if a dynamic policy is used in case of a high maintenance and repair cost.

Said and Taghipour (2016) built a model to define the effects of different PMs, and CMs. The assumption of the model was that the effect of CM was minimal while a PM could reduce the operating age of the system. A likelihood function was used to estimate the failure process and PM effects. Moreover, the reliability function was determined to find out the expected number of failures over a period between two consecutive PMs by using Non-Homogenous Poisson Process. The proposed model was implemented on two haulage trucks that were used in an underground copper-nickel mine located in Canada. The trucks were decomposed into two subsystems as mobile and electrical. Three types of PM were applied every 250, 500, and 1000 hours on the subsystems. According to the results, the mobile subsystem was in the wear-out phase and the expected number of failures and the observed number of failures are relatively close. PM-1 had minimal repair effect while the PM-2 and PM-3 reduced the operating age of the mobile subsystem effectively. Moreover, PMs with three different implementation intervals were detected to turn the electrical subsystem into almost as good as new condition.

Jafari *et al.* (2017) aimed to select an optimal maintenance policy, which covered OM, PM, and CBM to minimize the cost per unit time in the long term. Mean residual lifetime, as an input of the system, was found by using a semi-Markov decision process framework. In the policy, instead of a PM activity, maintenance policy combining CBM and age information was used with a proportional hazards model. This model and a computational algorithm were applied on the haul trucks in a mining company by considering transmission and clutch as two main units. Finally, two maintenance approaches were compared by the developed model. Firstly, the policy did not include OM where no opportunity was considered to perform PM on transmission upon clutch failure. Secondly, the traditional CM was performed. The combined model was detected to be more economical than the conventional approach.

Finally, Gölbaşı and Demirel (2017) developed a simulation algorithm, called the time-counter, to optimize the inspection intervals of draglines by minimizing total direct and indirect maintenance cost. This algorithm was used on two different draglines that operate in Tunçbilek coal mine in Turkey. Firstly, the draglines were decomposed into seven sub-systems and thirty components with a top-to-down approach. Probability distribution functions for TBF and time to repair (TTR) dataset of each component were generated to create a random data input for the algorithm. The simulation results became more realistic when random TBF and TTR values were used instead of the mean values. The algorithm also considered the administrative halts that are shift changes, lunch breaks and holidays, as well as maintenance stops. The current maintenance policy in the mine is that draglines are stopped for 8 hours every 160 h for regular inspection. According to simulation results, the time between inspections (TBI) should be 232 h and 184 h for Dragline-1 and Dragline-2. If the inspections are rescheduled according to the study outputs, the cumulative of direct and indirect costs may be dropped by 5.9 and 6.2 percent for Dragline-1 and Dragline-2, respectively.

According to the literature review, it was observed that there is no research study that evaluates, compares, and optimizes different maintenance policies with different work packages for the mining machineries. This study intends to fill this gap in the literature.

CHAPTER 3

DEVELOPMENT OF THE MAINTENANCE ALGORITHM

3.1. Introduction

This study aims to develop a dynamic maintenance algorithm to find out system availabilities, production rates, contribution of components/subsystems to system failure behavior and total maintenance cost, and optimal policy among different maintenance policy alternatives. The algorithm includes random lifetime and repair time behaviors of system components and scheduled administrative halts in the decisions. The model can be adapted to different production systems that operate coordinately to achieve a production in a certain period. For a clear illustration of the algorithm, the model steps are discussed with two different cases in this chapter. Details of the case studies and the simulation results will be discussed more in Chapter 4.

In the case studies, the model will simulate i) an operation with three electric rope shovels decomposed into subsystems and ii) a dragline decomposed into its working components. Each shovel covers six main subsystems with a serial connection: Air system (SHA), crowd mechanism (SHC), dipper system (SHD), electrical system (SHE), hoist mechanism (SHH) and other subsystem (OTH) as illustrated in Figure 3.1. Second, the dragline is composed of six subsystems in a serial connection where twenty-seven main components are available. These subsystems are called machinery house (MH), rigging (RI), dragging (DR), bucket (BU), movement (MO), boom (BO) as illustrated in Figure 3.2.

In both cases, a combination of preventive maintenance, corrective maintenance, and opportunistic maintenance was introduced for a dynamic and appropriate allocation of maintenance work packages. The simulation steps and logic were clarified in detail in Chapter 3.2 where Arena® implementation was explained in Chapter 3.3.

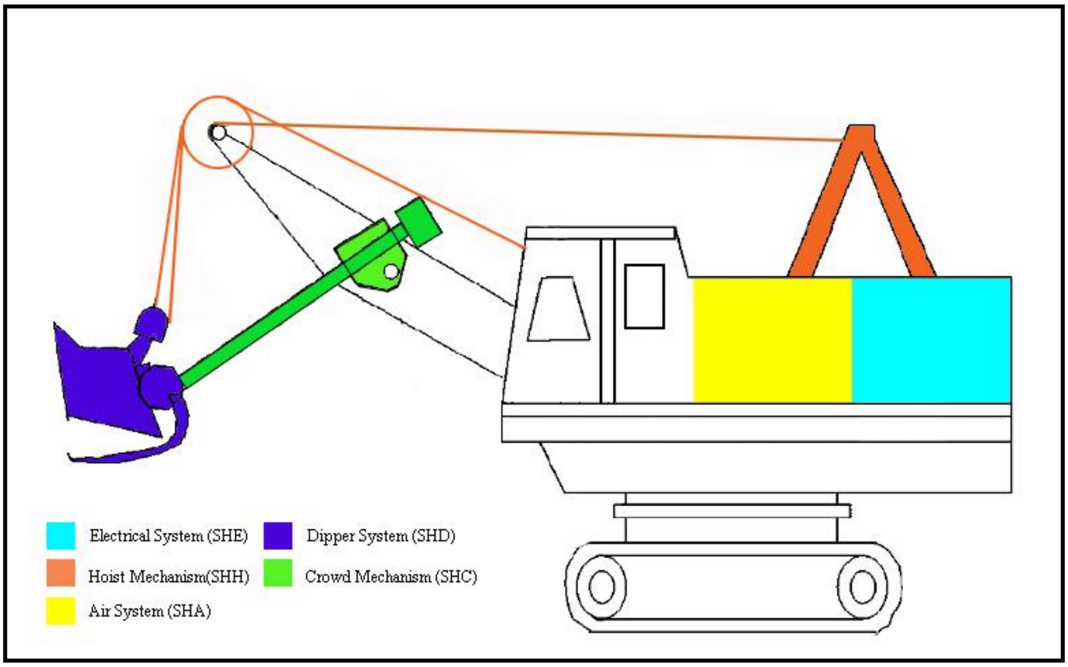


Figure 3.1. Schematic View of Electric Rope Shovel's Subsystems

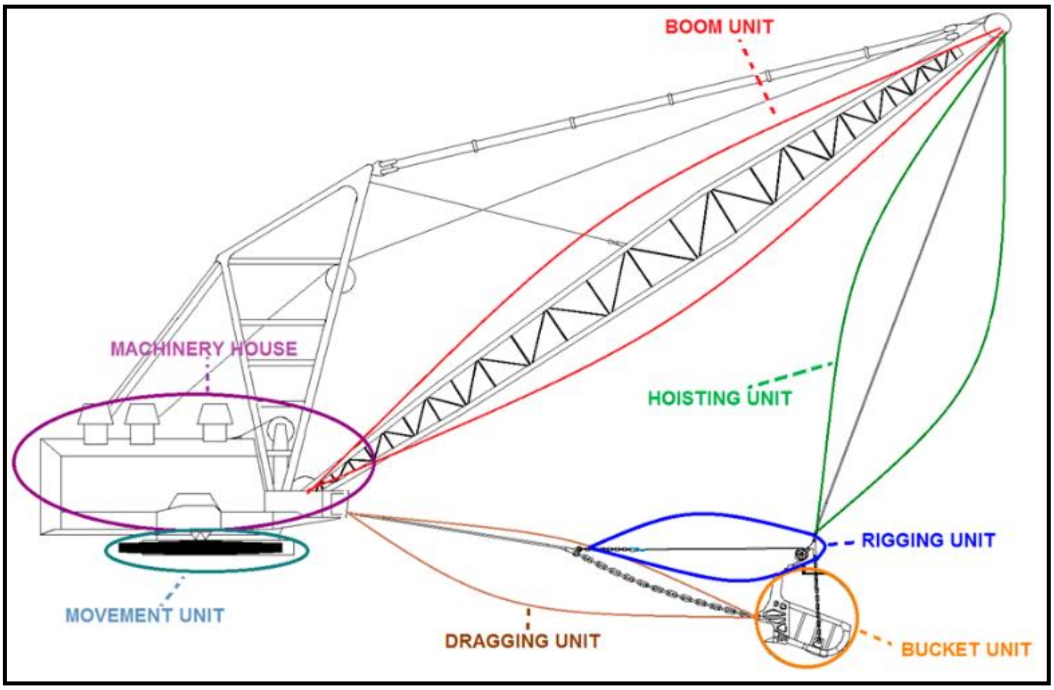


Figure 3.2. Schematic View of Dragline's Subsystems (Demirel & Gölbaşı, 2016)

3.2. Algorithm Logic and Components

The simulation model is built up by using three main time parameters: Time between failures (TBF), time to repair (TTR) and the starting time of wear-out phase (TSW). These parameters are dynamically determined regarding mutual interaction of component parameters. In the simulation model, TBF and TTR values stand for random time between failures (operating time) and random time to repair (corrective maintenance duration) of system components. They are assigned when activated by using the related TBF and TTR probability distribution functions of subsystems or components. On the other hand, TSW values refer to wear-out phases of subsystems or components with a recognizable indication of approaching failures. This type of variable is also called delay-time in the literature, and it takes the value of zero if a component fails suddenly without any warning or indication. In other words, it is the expected portion of the subsystem/component lifetime where the indication is appeared. According to these parameters, change of system state and the required action that can be either of corrective maintenance (CM), preventive maintenance (PM), opportunistic maintenance (OM) or of regular inspection are decided in a discrete-event simulation. In case of no change in the system state, production is allowed to continue. In addition, administrative halts such as shift changes, breaks and regular maintenance activities, the system state and condition of production are also evaluated. In the algorithm, working hour per shift is taken eight hours and equipment are assumed to operate three shifts a day.

As stated, the algorithm will be applied to a shovel fleet and a dragline. In the shovel case, lunch break was assumed an hour at midday and shift breaks were taken half an hour at the end of each shift. On the other hand, for dragline, only shift breaks with half an hour were assumed that means 1.5 total compulsory break a day. According to these actions, the algorithm finds out annual direct and indirect maintenance costs and availabilities of shovels and dragline for different maintenance scenarios. Detailed view of the algorithm flowchart is given in Figure 3.3. These algorithm steps are explained in detail as follows:

i. When the simulation time reaches the target time then the algorithm is ended.
ii. When the simulation time reaches any scheduled shift end, then all equipment parts are stopped, and production is halted until the next scheduled shift start.
iii. When the simulation time reaches the next inspection, the equipment parts and production are stopped during the inspection duration. After inspection, the equipment parts will continue to operate in as bad as old condition except for the condition where the subsystems/component are to be in wear out phase. In this situation, PM is applied to the equipment parts in deterioration and this action is assumed to turn them to as new as good condition as illustrated in Figure 3.4. In case of any decision for PM, the related preventive maintenance cost is generated and accumulated in the total direct preventive cost item (see dragline case).
iv. When any of i^{th} equipment part's lifetime ends, the concerned equipment is stopped until the failed part is correctively maintained. After corrective maintenance, the part is assumed to turn to as good as new condition and the component's corrective maintenance cost is accumulated under the total direct corrective cost is item.
v. Any CM activity for the failed component may create an opportunity for preventive check and repair of the other non-failed components. During a CM application, the non-failed components are controlled to check whether they are in a wear-out period or not. If such components are detected and their preventive maintenance durations are good enough to be performed within the corrective maintenance duration of the failed component, then they are recovered under opportunistic maintenance action. Figure 3.5. can be examined to see how SHD subsystem of Shovel-1 is activated in the failure of SHE subsystem. Then, the part is assumed to turn to as good as new condition and direct

opportunistic maintenance is added to total preventive maintenance cost of the part.

vi. Out of the maintenance times, the equipment makes a production of '*Pro_cycle*' amount in each '*Cycle_shov*' time. If any of i th equipment part is broken in the production cycle, then this cycle is not completed, and the previous cycle is assumed as the last cycle in the current simulation time. On the other hand, inspection or shift breaks do not halt the production cycle. For example, when the simulation time reaches next inspection time and the production cycle is continuing, then equipment will complete production cycle before inspection. Also, idling time of equipment is assumed zero. It means that the haul truck will always be available for the loading.

Considering the given assumption and the algorithm dynamics, time limits, and minimum amount of the production need to be introduced as model constraints. System availabilities and the required inspection intervals are computed regarding the interactions between CM, PM, OM, and random characteristics of the subsystems. By using the model, it is tried to find out the optimal TBI that minimizes the overall maintenance cost while keeping the production above the intended level. The model was created in Arena® simulation environment that is a discrete event simulation software. In the next section, implementation of the algorithm in Arena® will be explained in detail.

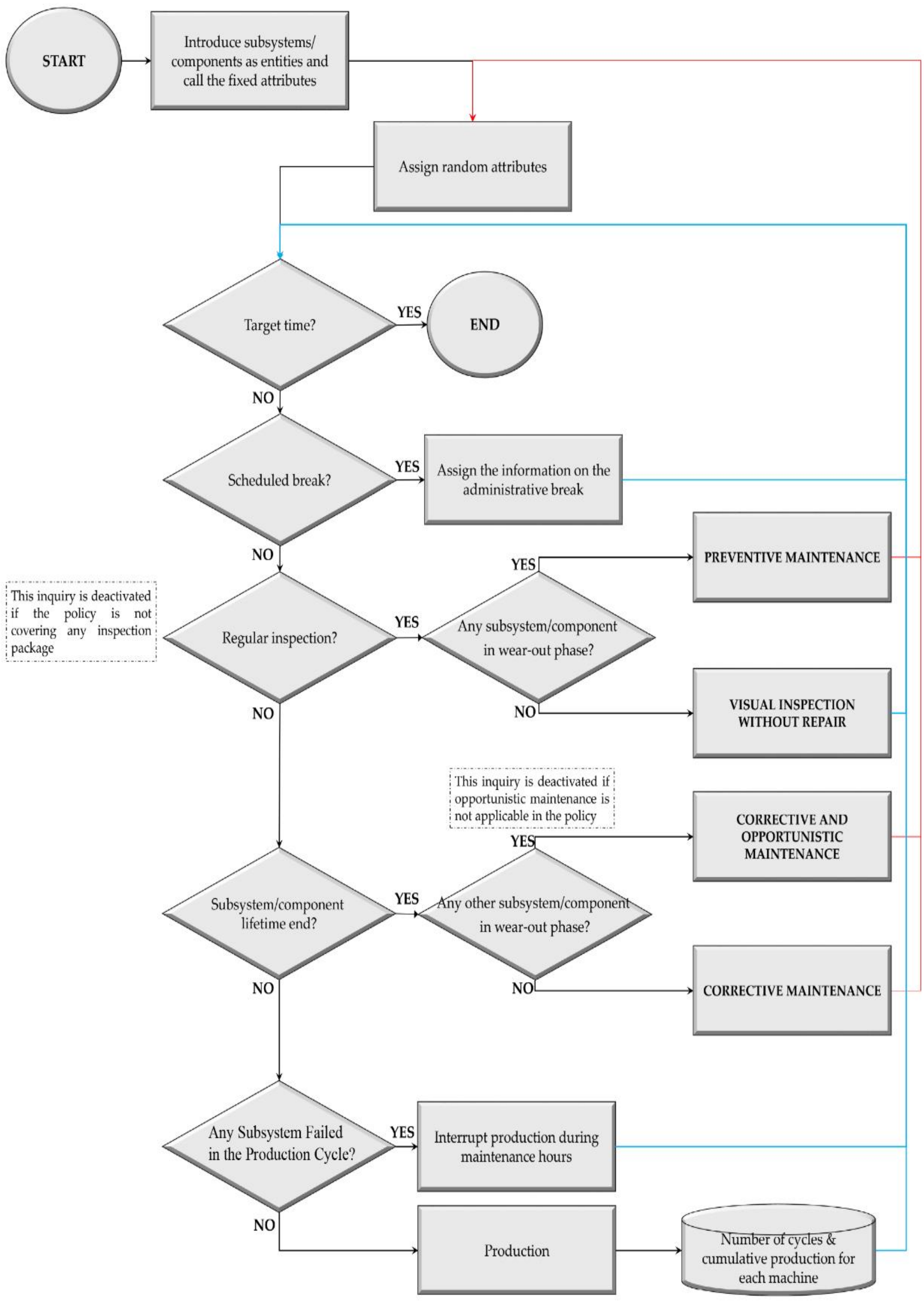


Figure 3.3. Flowchart of the Algorithm

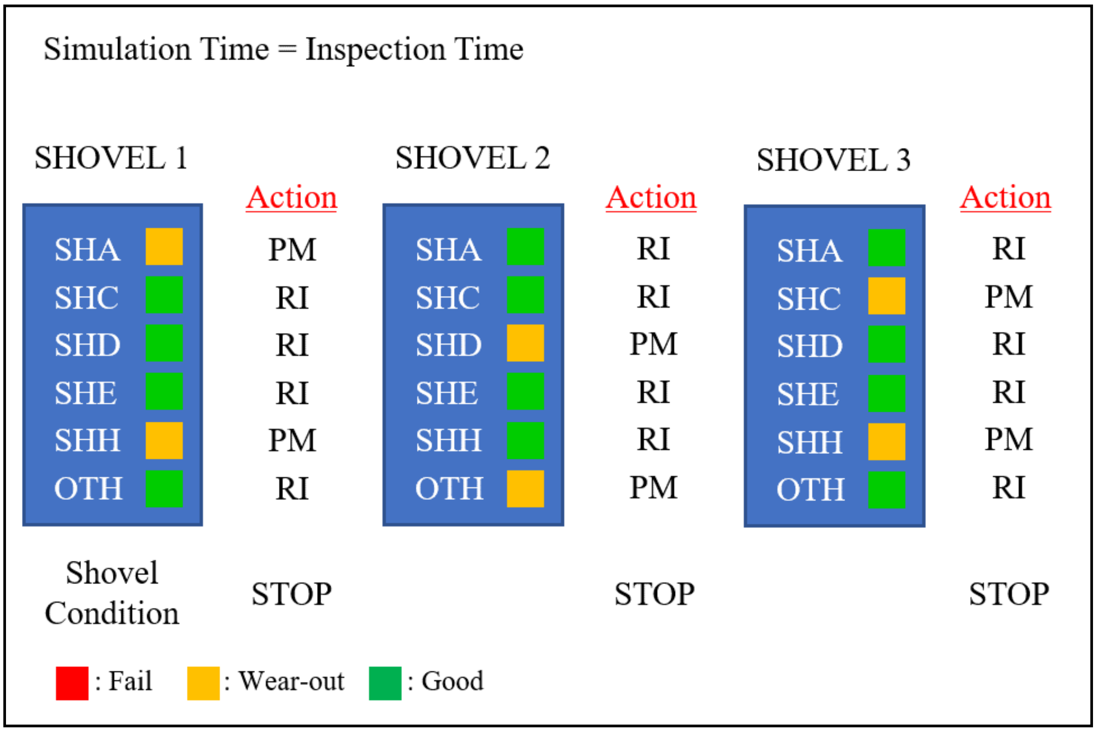


Figure 3.4. Conditions of Subsystems at Inspection Hours in the Algorithm

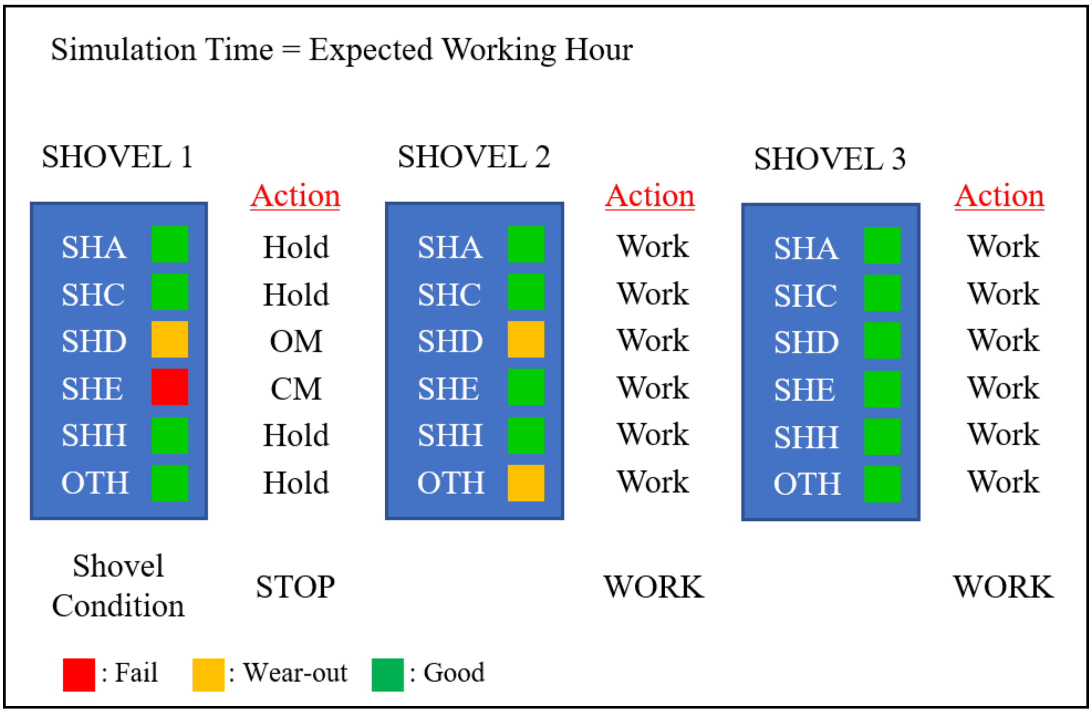


Figure 3.5. Conditions of Subsystems at Working Hours in the Algorithm

3.3. Arena® Implementation

Arena®, which is a discrete-event simulation software, has been used widely in various sectors to develop simulation models with a graphical illustration. Arena® uses SIMAN simulation languages and it gives the user a chance to build up simulations by using the graphical model or coding alternatively. For implementing the algorithm in Arena® by graphical model, two basic process panels can be used as data modules and flowchart modules. Firstly, data modules are employed to create and edit the database of the algorithm. The standard data modules are entity, attributes, resource, queue, variable, schedule, and set. In Table 3.1, each data module's functions are explained briefly. For a clear understanding of the model, the algorithm flow in Arena® will be discussed and explained with the shovel and dragline cases where the shovel case covers three shovels with six subsystems each without any component classification and the dragline case includes one dragline with twenty-seven components with six subsystems.

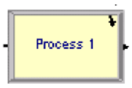
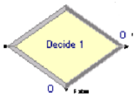
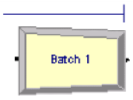
In the algorithm, shovels' subsystems are accepted as an entity for the first case where the dragline's components are introduced as an entity in the second case. Therefore, the first model covers 6 entities for each shovel and 18 entities in total and the second model covers 27 entities which belongs to 6 subsystems. Each entity has own deterministic and stochastic attributes. The deterministic attributes are defined at the beginning of the simulation. These attributes are the expected percentage of the subsystem's lifetime just before defect arises (Ths) and index of the shovel (Shov) for the first model and preventive and corrective maintenance costs, preventive repair time and index of the subsystem for the second model. Stochastic attributes, which are defined after each maintenance action, are TBF, TTR and TSW for both models. Moreover, variables of the system are time between inspection (TBI), inspection time (IT), production amount of each cycle of i^{th} equipment (Pro_cycle), a cycle time of i^{th} equipment (Cycle_shov), break schedule, and signal of each entity which profiles the condition of subsystems. The signal variable takes the value of 0 for working state, 1 for a scheduled break state, 2 for regular inspection state, 3 for preventive maintenance state, and 4 for corrective maintenance state. In addition, there is also a permanently active system that determines the subsystems with priority due to their lifetimes coming to an end in the timeline.

Table 3.1. *Data Modules in Arena®*

Data Module	General Function	Definition in Current Model
Entity	Defined players in the simulation	The subsystems of shovels The components of dragline
Attribute	Specific properties of each entity	TBF, TTR, Shov, Ths, TSW, CM cost, PM cost
Variable	Overall model dynamics	TBI, IT, Cycle_shov, Pro_cycle, Break Schedule and Signal of Each Entity
Resource	Requirements for processing	-
Schedule	Working time for resource	-
Queue	The order of processing or releasing	The entity which has minimum TBF value goes first
Set	A cluster of some data modules	-

In addition to data modules, the set of actions of entities in a timeline is defined by using flowchart modules. Although Arena® has some other modules for simulating complex systems, basic and transportation flowchart modules were utilized in the simulation chart for more flexibility. In Figure 3.6, the functions used in flowchart module are explained with their symbols and general application. In Table 3.2, the functions used in flowchart module are explained with their symbols and general application.

Table 3.2. *Flowchart Modules in Arena®*

Flowchart Module		**General Function**
Create		Starting node of entity
Dispose		Ending node of entity
Process		An activity that can require some resource with a specific time
Decide		Determining node for entity's way
Batch		Package of a specific number of entities
Separation		Duplication of entities, or separating a previous batch of entities
Assign		Assigning new values to variables, entity attributes, entity types, entity pictures, or other system variables
Record		Data collection node
Enter		Exit station of rout or conveyor
Leave		Entrance station of rout or conveyor

The general view of model is shown in Figure 3.6.In 'Create' module that is the starting point of model, all entities are created and all deterministic attributes are assigned. Then, all entities are transferred to 'Assign_attribute', which is shown in Figure 3.7 The introduction of entities is not just provided from 'Create' but also from 'Come_from_station' that connects the routes from each maintenance process.

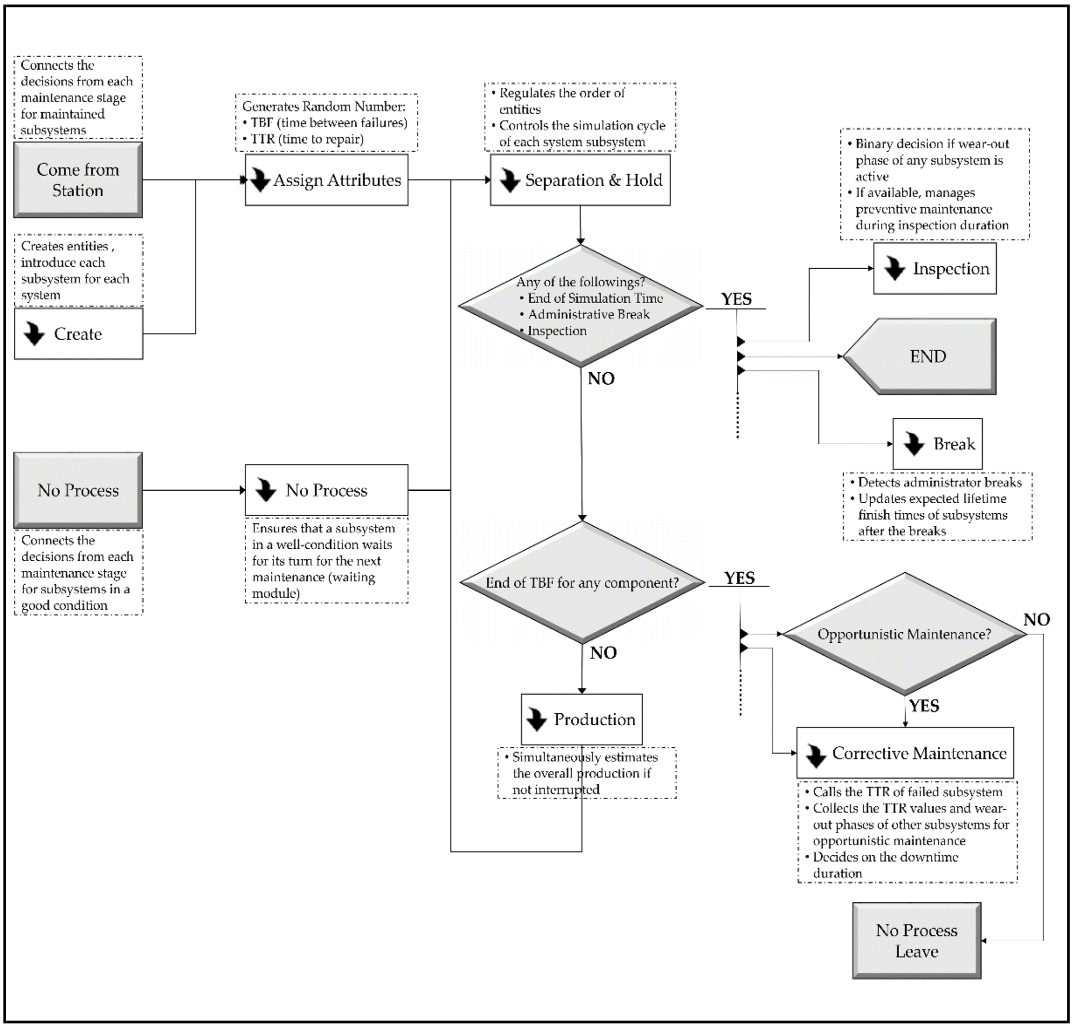


Figure 3.6. Overall view of Arena® simulation

In Assign_attribute Module, which is illustrated in Figure 3.7, each entity has its own flowchart modules for recording the number of regeneration and assigning the random attributes. Here, two modules were assigned to each entity because TSW is directly computed by using TBF. In the first assign modules, TBF and TTR attributes are randomly defined and, in second assign modules, TSW is defined as the multiplication of TBF and Ths.

The Arena® simulation behavior where each entity is simulated one by one in a specific order at the same simulation time cannot ensure the model assumptions. For that reason, occurrence order of the events needs to be regulated for each cycle. For example, let's suppose that the first entity failed where the second entity is in a wear out phase at a specific simulation time. Therefore, corrective maintenance should be applied on the first entity where opportunistic maintenance should be applied on the second entity. If the second entity is simulated before the first entity, then opportunistic maintenance is not applied on the second entity because the first subsystem is not in "Corrective Maintenance" submodule when second entity is active. Therefore, the order plays an important role in the decision of opportunistic maintenance. For that reason, before the junction of actions, a control submodule, called as 'Separation & Hold', is employed to regulate the occurrence order of entities. Moreover, the second function of 'Separation & Hold' is to hold the entities of equipment until all of them complete their simulation cycles. This ensures the series dependency between the subsystems in shovels and between components in dragline case. As shown in Figure 3.8, for the shovel model, after the separation of the subsystem with respect to their shovel code, the hold module releases subsystem by considering the ascending order of TBF values.

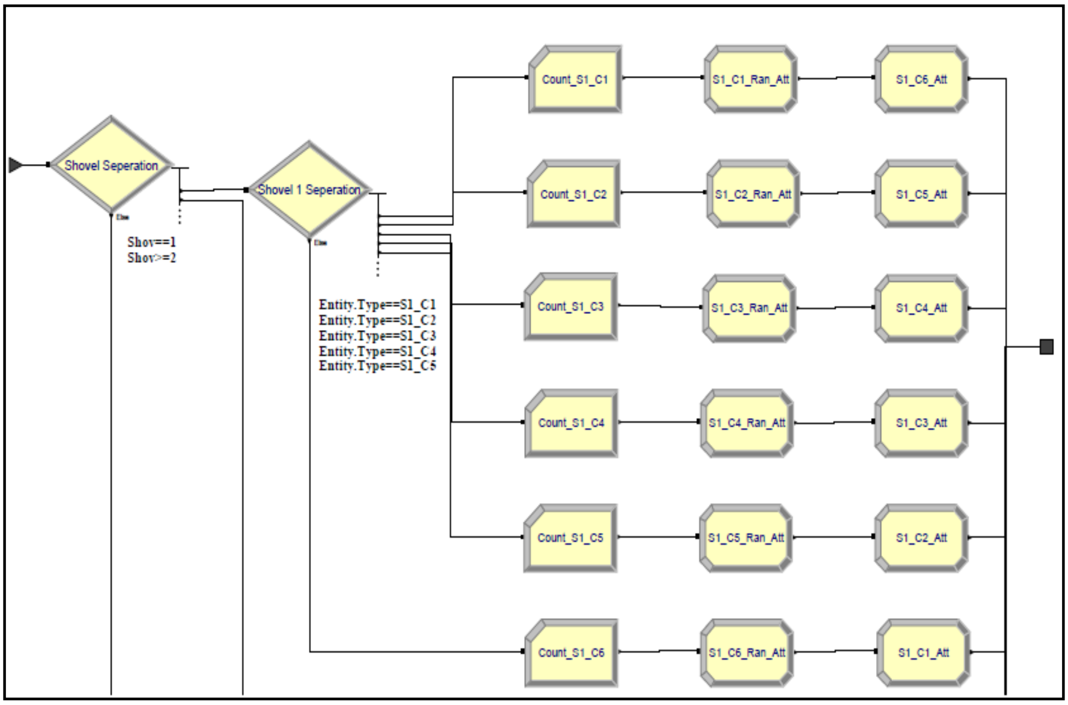


Figure 3.7. 'Assign_Attributes' Submodule to Randomize the Uptime/Downtime Behavior of System

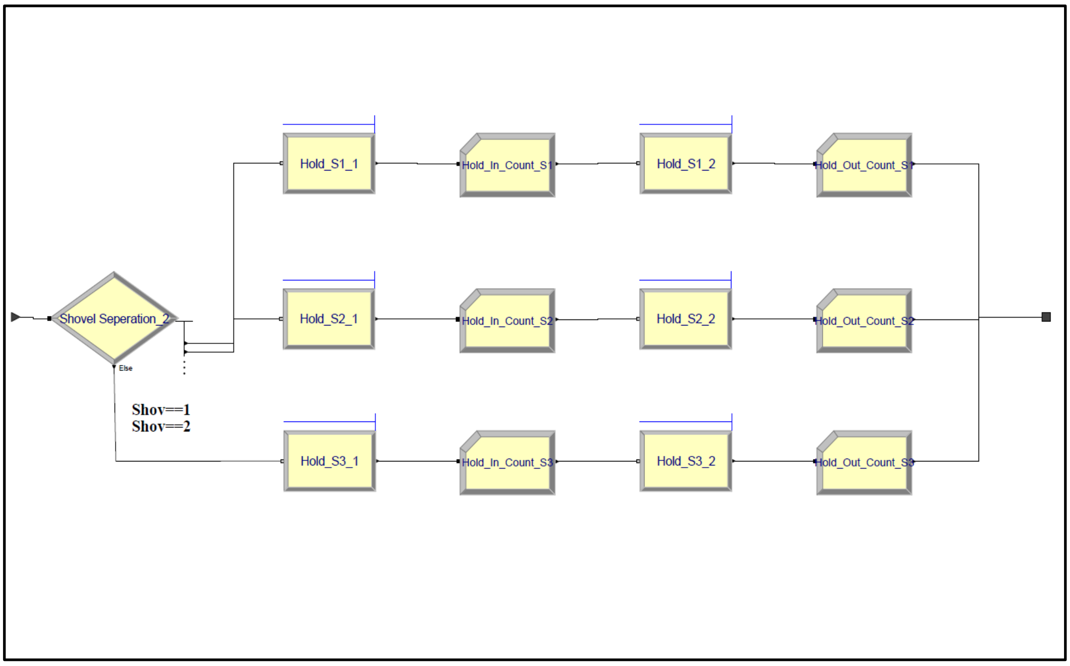


Figure 3.8. ‘Separation & Hold’ Submodule

As shown in Figure 3.6, ‘Separation & Hold’ submodule is connected to a decision module where the simulation can select either of three pathways. Firstly, the entities can only be out of the cycle when the simulation time is higher or equal to the target simulation time. In that case, the entities go to the dispose modules that is called ‘End’ and simulation is completed. Secondly, scheduled break time cause a halt for all entities that are operated in 3 shifts. When the time comes to a scheduled break, ‘Break’ submodule is introduced to all entities. As also illustrated in Figure 3.9, signal values of each entity turn to 1 and they are halted for 15 minutes at the beginning and at the end of each shift. In addition to shift break, one-hour lunch break is given at midday only for shovel case. After the scheduled break, the signals turn to 0 and entities enter the cycle in the ‘No_process’ station. Until the target simulation time, this process is repeated for every given TBI value.

As stated in the general illustration of the algorithm in Figure 3.6, if an entity is not detected to have a defect in any inspection, then that entity may fail at the end of its assigned lifetime (CM is applied) or an OM can be applied during the corrective repairing of another entity. Any corrective maintenance (CM) cause production interruption. Here, time between failures for the entity and 'Corrective Maintenance' submodule is activated. Moreover, when one of the entities is in 'Corrective Maintenance', the decision module checks whether any other operable entity in the same equipment is in a wear-out period. 'Opportunistic Maintenance' module is activated for the entity in wear-out if i) the entity's TSW value is less than or equal to zero and ii) its preventive maintenance time is less than or equal to the corrective repairing time of the failed entity. Otherwise, the operable entities that cannot satisfy the requirements of opportunistic maintenance are sent to the cycle in 'No_process' station.

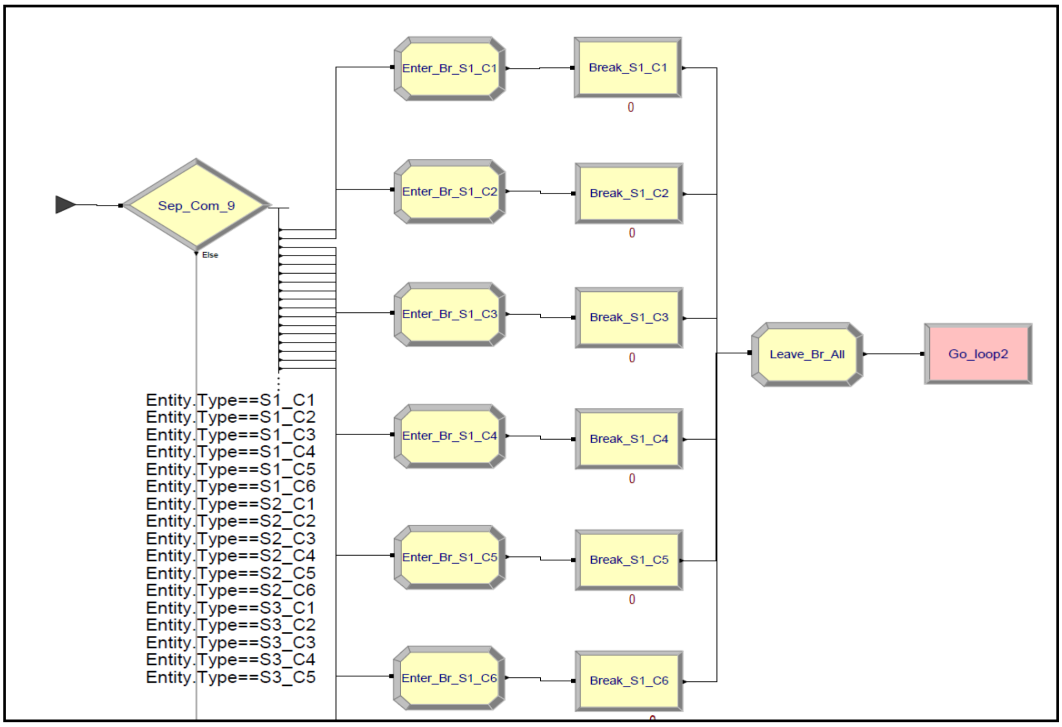


Figure 3.9. 'Break' Submodule

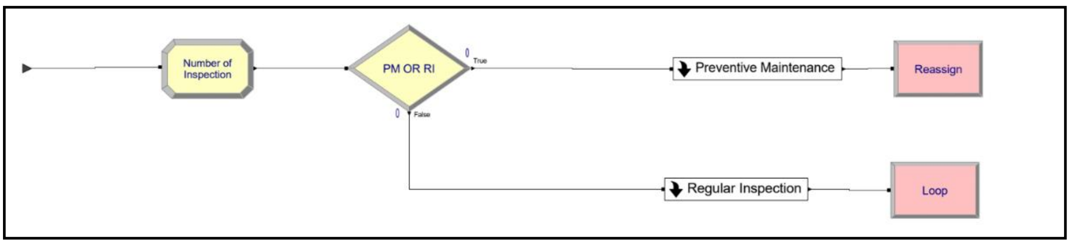


Figure 3.10. 'Inspection' Submodule

'Corrective Maintenance', which is shown in Figure 3.11, considers whether the CM duration is overlapped with a scheduled break to a certain extent. When starting time of scheduled break is between the end of lifetime and the end of corrective maintenance action, the entity goes to 'Corrective Maintenance with Break', or else 'Corrective Maintenance without Break'. In both submodules, signal of entities is set as 4 until the corrective maintenance process is completed. As expected, the process time of 'Corrective Maintenance without Break' is TTR of the entity. However, the process time of 'Corrective Maintenance with Break' is the summation of repairing time of subsystem and scheduled break time. Since any scheduled break pushes the ending of CM forward in the timeline. Then, the entity returns to the cycle by using the route, from 'Reassign 2' to 'Come_From_Application'.

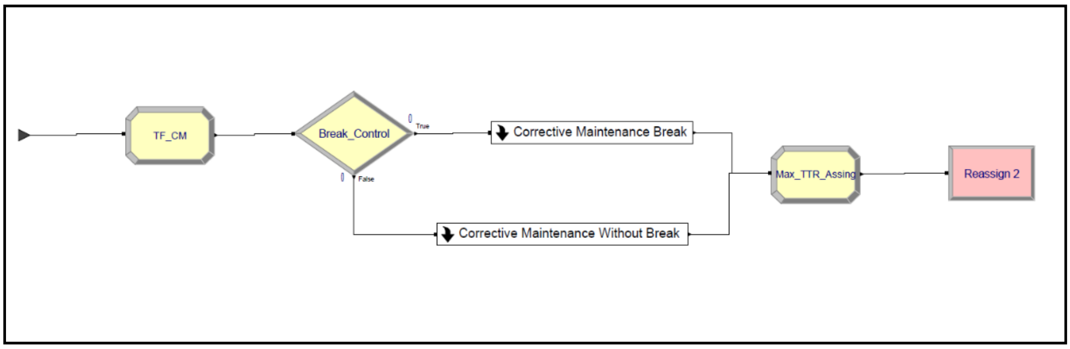


Figure 3.11.'Corrective Maintenance' Submodule

After all junction points, all entities enter 'Production' as shown in Figure 3.12. In this submodule, firstly, entities are grouped based on their equipment codes and they come together to form a whole equipment entity. Assumption in the simulation is that a failure of any entity can interrupt the production cycle of system. According to this assumption, the pathways are followed by the entity. Firstly, when remaining lifetimes of equipment's all entities are more than cycle time, a new group of entities follows to its production process module. Then, the new equipment's total production amount is increased by a cycle production amount. Secondly, if production cycle is interrupted by any entity failure, the equipment entity waits for remaining lifetimes of failed entities and the equipment's total production amount does not change. After both procedures, each equipment is again divided into its own subsystems or components and their remaining lifetimes are decreased by a production cycle time. At the end of two ways, entity go back to ‘Separation_Hold’.

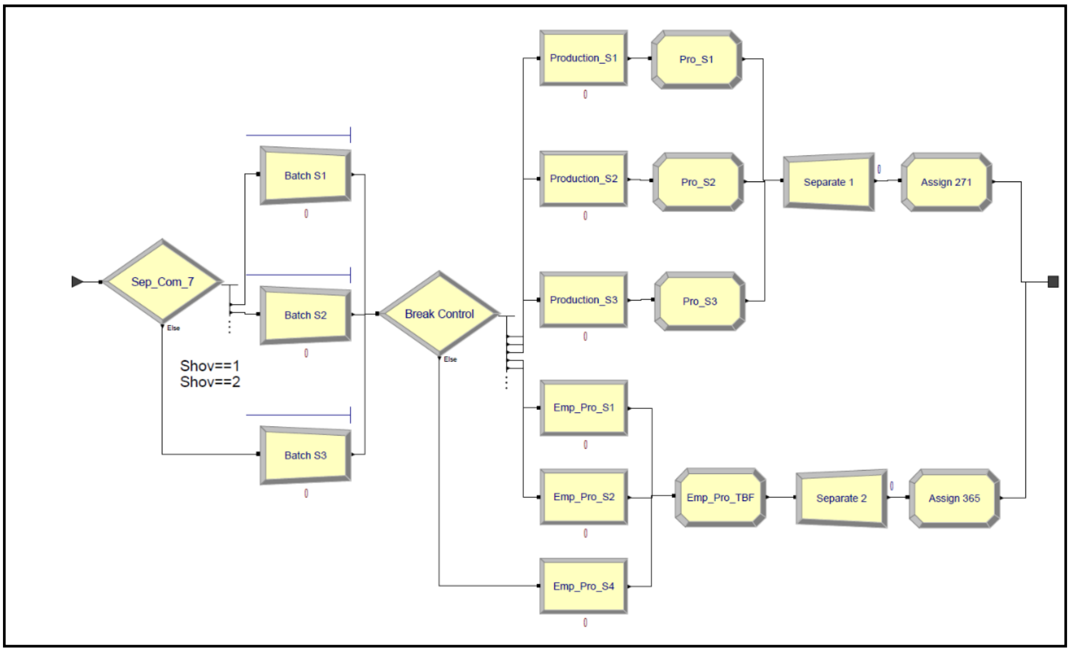


Figure 3.12. Production Submodule for Shovel Model

After evaluating and deciding decision in all submodules, data flows of the dynamic and static variables are satisfied by using two separate routes called ‘Assign_Attribute’ and ‘No_process’. ‘Assign_Attribute’ is used for reassigning the random attribute value when connecting the maintenance activities to each other. The other one connects ineffective processes that are scheduled break, regular inspection and ‘No_process’. In addition, when the one entity in an equipment fails, the operable entities use this route for going back to cycle. In ‘No_process’, equipment’s entities are held until all entities are in an operable condition.

To sum up, downtime and uptime characteristic of three shovels and a dragline were modeled in a discrete-event environment by using Arena® simulation software. In the equipment’s life cycles, three main actions are regarded in the model: Production, maintenance and scheduled breaks. Maintenance actions consist of corrective, preventive, and opportunistic maintenance activities. The inputs of the simulation model are assigned deterministically or randomly. Some attributes such as production cycle time and number of shovels are assumed fixed during the simulation time. In addition, some variables such as inspection time or time between inspections are also taken as constant values. These deterministic attributes and variables are assigned at the beginning of simulation. On the other hand, some attributes such as TBF and TTR are assigned randomly to mimic the system behavior more realistically. Finally, the simulation model can reveal the total production amount, system/subsystem availability, and total direct and indirect costs of maintenance for the examined period. In the next chapter, two cases in which one of them is on a shovel fleet and the other is on a dragline will be simulated by the developed model to highlight the outcomes and the benefits of the model more apparently.

CHAPTER 4

NUMERICAL EXAMPLES FOR THE ALGORITHM

4.1. Introduction

In this chapter, the proposed algorithm is implemented for two realistic examples taken from some research studies in the literature. In the first implementation, the algorithm was applied to three shovels working together for a joint production. In this case, fleet availability was aimed to be maximized. In the second implementation, the model was applied for a dragline case. In this application, the total cost of maintenance including direct and indirect losses was intended to be minimized. The first and second implementations will be explained in Chapter 4.2 and Chapter 4.3, respectively.

4.2. Case Study-1: An Application for Multiple Shovels

The proposed model is implemented for multiple cable shovels operating in an Rajarappa opencast mine in India. The dataset that includes reliability and maintenance probability distribution functions of the subsystems of three shovels in the same mine and was retrieved from a study by Roy *et al.* (2001). The dataset that explained under Chapter 4.2.1is used as an input of the proposed algorithm. Finally, the results of the algorithm will be discussed in Chapter 4.3.

4.2.1. Input Dataset of the Algorithm

The shovels are assumed to be stopped half an hour every shift end for shift changes and they are operated in three shifts. Other than shift changes, the shovels are assumed to be inactive for one hour during lunch break at midday. TBF and TTR are unknown parameters specific to the system itself. TTR and TBF functions of three electrical cable shovels with six subsystems are taken from Roy *et al*. (2001). The parameters of TTR and TBF distribution functions are given in Table 4.1 and Table 4.2. In addition, the contribution of each subsystem to failure numbers can be investigated with Pareto Charts in Figure 4.1. Total number of failures for a 2-years period are 224, 200, and 154 for Shovel 1, Shovel 2 and Shovel 3, respectively. According to the Pareto charts, the subsystem exposing to the failures most frequently is the dipper system (SHD) for the all shovels.

Table 4.1. *TTR and TBF Parameters of Shovel 1 and Shovel 2 (Roy et al., 2001)*

Shovel 1				
Code	**Time Between Failure (TBF)**		**Time to Repair (TTR)**	
	Best-fit Distribution	**Parameters**	**Best-fit Distribution**	**Parameters**
SHA	Weibull	β=1.169; η=522.9	Lognormal	μ=10.14; σ=8.26
SHC	Exponential	λ=880.3	Exponential	λ=32.5
SHD	Exponential	λ=60.16	Lognormal	μ=11.12; σ=17.36
SHE	Weibull	β=0.871; η=111.1	Lognormal	μ=28,.73; σ=62.76
SHH	Weibull	β=1.684; η=485	Lognormal	μ=13.3; σ=15.91
OTH	Weibull	β=0.856; η=191.3	Lognormal	μ=26.09; σ=45.08
Shovel 2				
Code	**Time Between Failure (TBF)**		**Time to Repair (TTR)**	
	Best-fit Distribution	**Parameters**	**Best-fit Distribution**	**Parameters**
SHA	Exponential	λ=384.3	Exponential	λ=16
SHC	Weibull	β=1.562; η=146.83	Lognormal	μ=26.92; σ=47.8
SHD	Weibull	β=1.115; η=57.17	Lognormal	μ=10.93; σ=13.58
SHE	Weibull	β=1.119; η=87.64	Lognormal	μ=17.25; σ=19.34
SHH	Weibull	β=1.226; η=130.44	Exponential	λ=12.36
OTH	Exponential	λ=116.3	Lognormal	μ= 20.71; σ=38.23

Table 4.2. *TTR and TBF Parameters of Shovel 3 (Roy et al., 2001)*

Shovel 3				
Code	**Time Between Failure (TBF)**		**Time to Repair (TTR)**	
	Best-fit Distribution	**Parameters**	**Best-fit Distribution**	**Parameters**
SHA	Weibull	β=1.177; η=506.14	Lognormal	μ=18.54; σ=46.45
SHC	Exponential	λ=220.6	Lognormal	μ=46.79; σ=102.6
SHD	Weibull	β=1.108; η=79.23	Lognormal	μ=15.79; σ=25.28
SHE	Exponential	λ=96.5	Lognormal	μ=35.33; σ=82.94
SHH	Weibull	β=1.029; η=206.43	Lognormal	μ=17.76; σ=23.75
OTH	Weibull	β=1.361; η=301.16	Exponential	λ=76.5

According to the statistics in Tables 4.1 and 4.2, the Weibull and exponential distributions were observed to be best-fit distributions for the TBF data. On the other hand, lognormal and exponential distribution provide the best-fit for the TTR data. According to exponential distribution behavior, the subsystem can be characterized as a constant failure/repair rate. On the other hand, if the Weibull parameter of β is more than 1, it points to an increasing failure rate, i.e. potential wear-out, for the subsystem. Four out of six subsystems for Shovel 2 and Shovel 3 are detected to be in this condition. Each subsystem reliability curve is examined based on best-fit probability function, and drawn in Figure 4.2, Figure 4.3, and Figure 4.4. According to this analysis, after 24 working hours, the levels of shovels' reliability are decreasing to 0.4, 0.35, and 0.45, respectively.

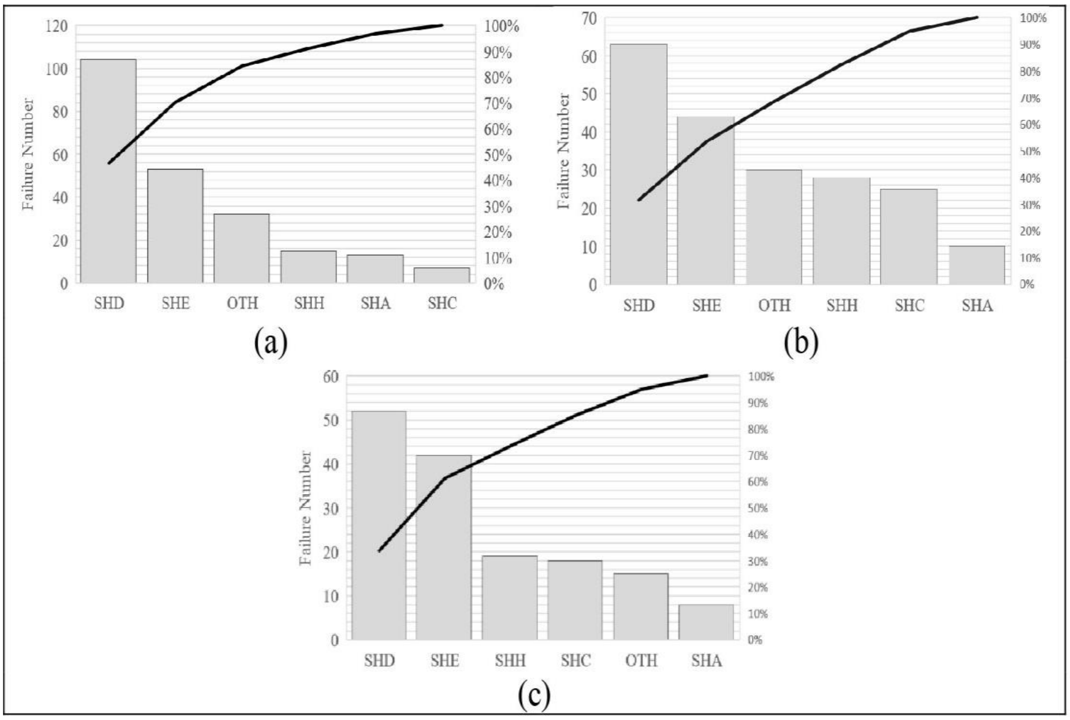


Figure 4.1. Pareto Charts of the Failure Statistics for Shovel 1 (a), Shovel 2 (b), Shovel 3 (c) (Roy et al., 2001)

As mentioned in Chapter 3.2, the other input parameter in the algorithm is the starting time of wear-out phase (TSW) that is used to detect deterioration periods of subsystems/components. Gölbaşı and Demirel (2017) determined Ths values for two draglines by using subjective data coming from the maintenance crew in the field. Although dragline and shovel have different production capacities and working principles, they have some similarity in terms of subsystem functionalities.Therefore, Ths values for shovel subsystems were assumed regarding the dragline values (Table 4.3). For instance, the wear-out phase of SHA subsystem of the shovel starts after completing 75% of its random lifetime. During that wear-out phase, the subsystem can be maintained preventively in inspections or opportunistic maintenance if it can be detected. For a more precise information, a survey may be conducted with the experts of shovel maintenance.

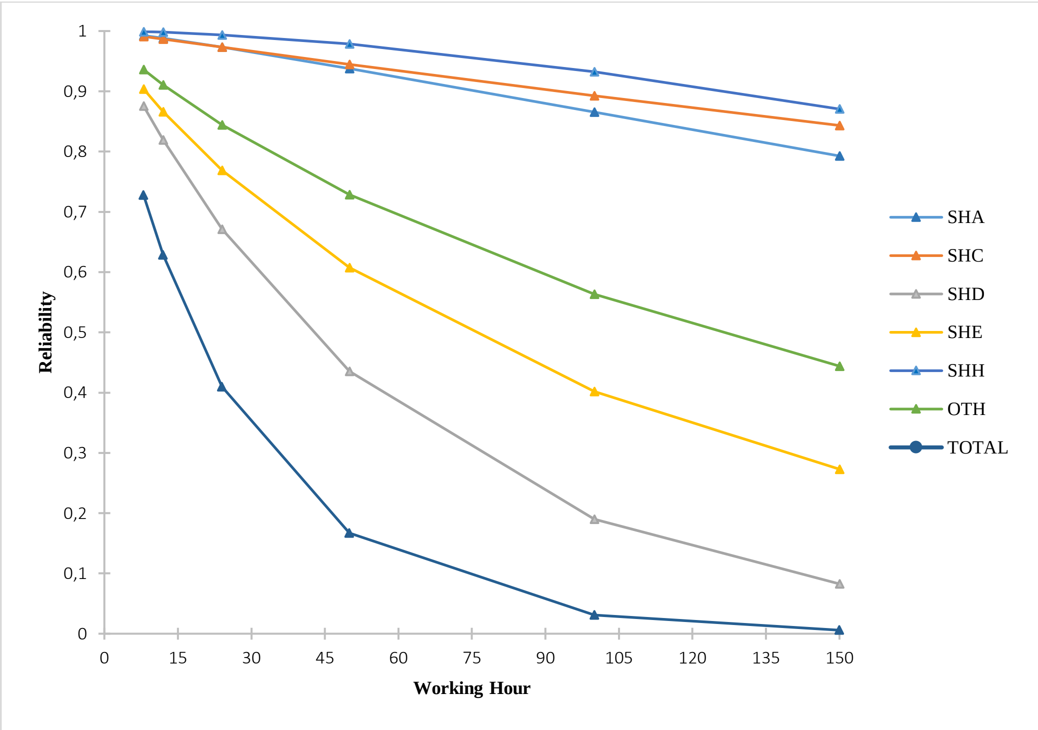


Figure 4.2. System and Subsystems Reliability Curves of Shovel 1

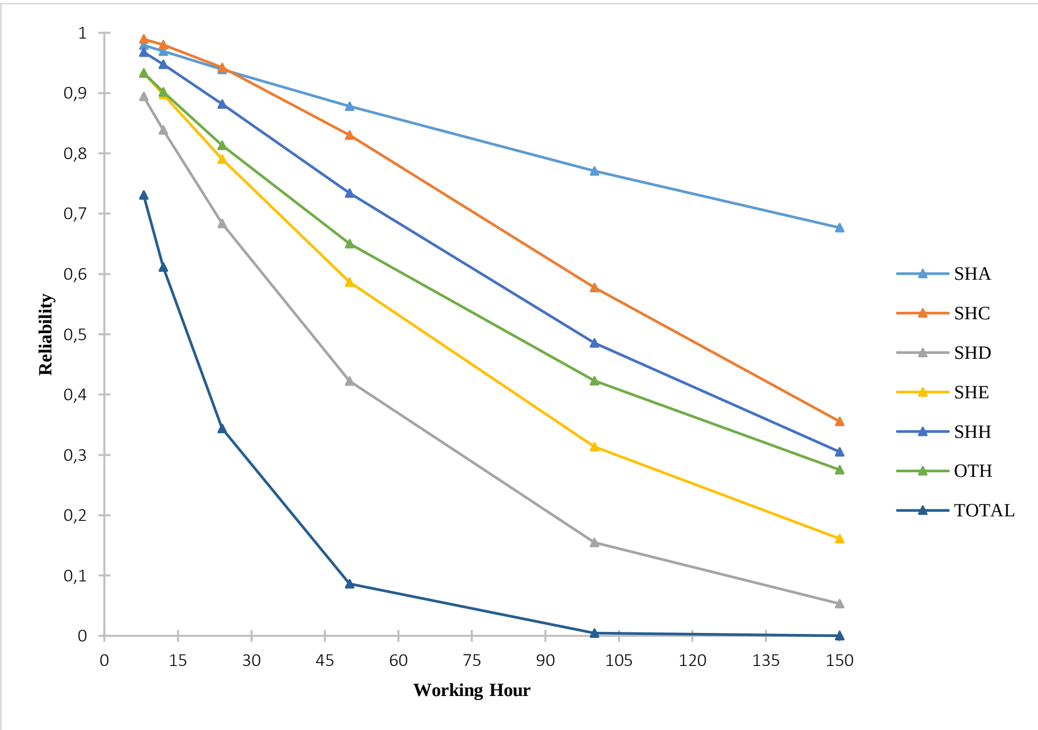


Figure 4.3. System and Subsystems Reliability Curves of Shovel 2

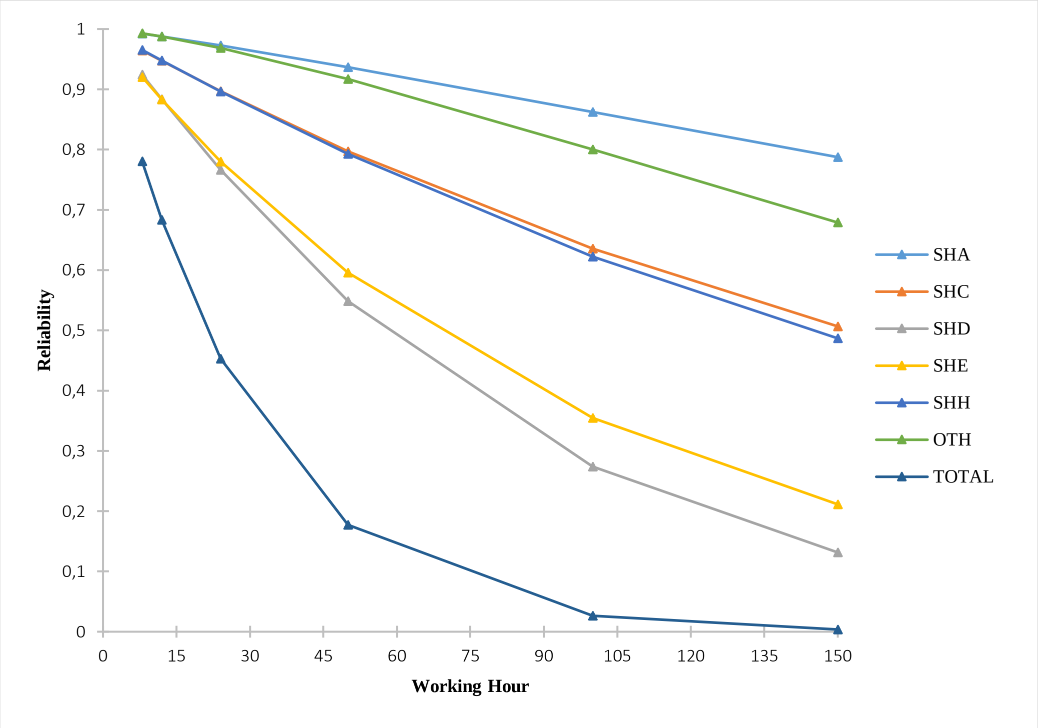


Figure 4.4. System and Subsystems Reliability Curves of Shovel 3

Finally, shovel production is directly related with not only the failure behavior but also the production capacities and production cycles. In this study, shovels' bucket capacity is equal to 10 m^3. The assumptions for fill and swell factors, expected cycle time, and operation efficiency are shown in Table 4.4. Chapter 4.2.2 will discuss the results that are obtained from the algorithm by using the available dataset.

Table 4.3. *Dragline Maximum and Minimum Ths (Gölbaşı & Demirel, 2017) and the Assumed Ths for the Shovels*

Subsystem	**Dragline Ths (%)**		**Shovel Ths (%)**
	Maximum	**Minimum**	
SHA	75	75	75
SHC	95	85	90
SHD	95	90	90
SHE	95	98	95
SHH	100	80	90
OTH	-	-	90

Table 4.4. *Assumed Production Parameters*

Factors	Shovel 1	Shovel 2	Shovel 3
Bucket Capacity (m^3)	10	10	10
Fill Factor	0.85	0.85	0.85
Swell Factor	1.45	1.45	1.45
Production volume per cycle (m^3)	4.3965	4.3965	4.3965
Cycle Time (min)	0.6	0.55	0.5

4.2.2. Results of the Algorithm

After determining the input dataset, the algorithm is used to analyze the shovel availability, statistics of maintenance actions for each subsystem, and their application times in a year. Due to the stochastic approach, the algorithm was simulated 500 times. As shown in Figure 4.5, the average availability of shovel that is around 73% becomes stable after 300th simulation.

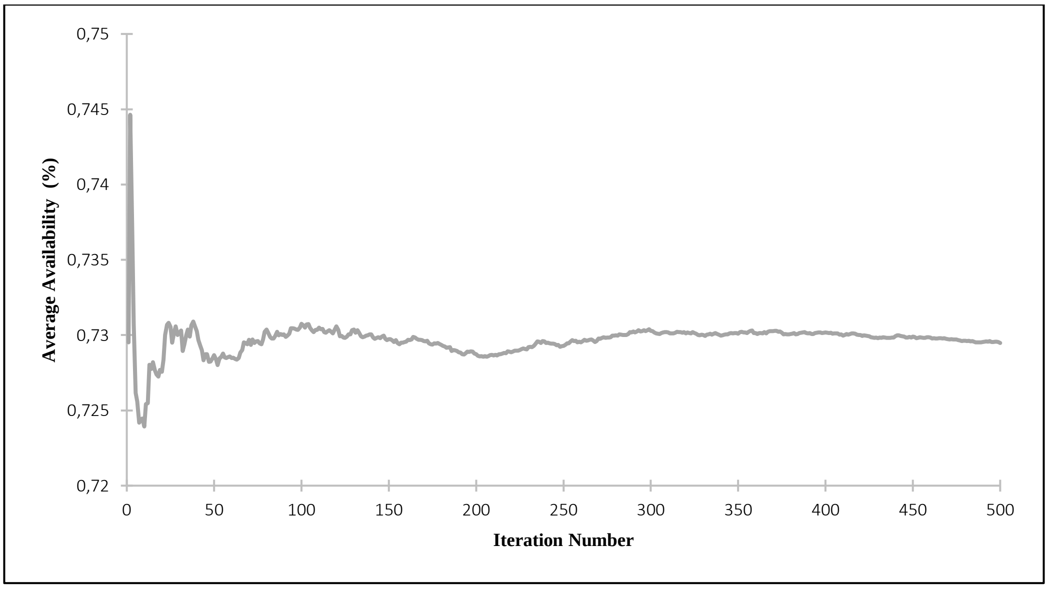


Figure 4.5. Shovel 1 Average Availability Results by Increased Iteration Number When TBI Value is 80.

The process is done for five different TBI (time between inspections) values. The overall results give a chance to understand the effect of inspection decisions on productivity and corrective maintenance statistics. As shown in Table 4.5, the availability of three shovels does not vary when the inspection interval is over 160-hours. Moreover, the maximum annual production of three shovels is nearly 7,266,714 m3. Correlation between time between inspections and corrective maintenance statistics for the subsystems can be investigated in Table 4.6 where effect of inspection interval on the shovel availabilities can be seen in Figure 4.6.

Table 4.5. *Annual Production Amounts (m^3) of Shovels Regarding to TBI Value*

TBI	Shovel 1	Shovel 2	Shovel 3	Total
40	2,205,394	2,184,099	2,515,932	6,905,425
80	2,282,711	2,271,006	2,579,780	7,133,496
120	2,294,421	2,302,556	2,597,571	7,194,549
160	2,305,440	2,319,851	2,607,453	7,232,744
200	2,308,879	2,327,013	2,606,259	7,242,151

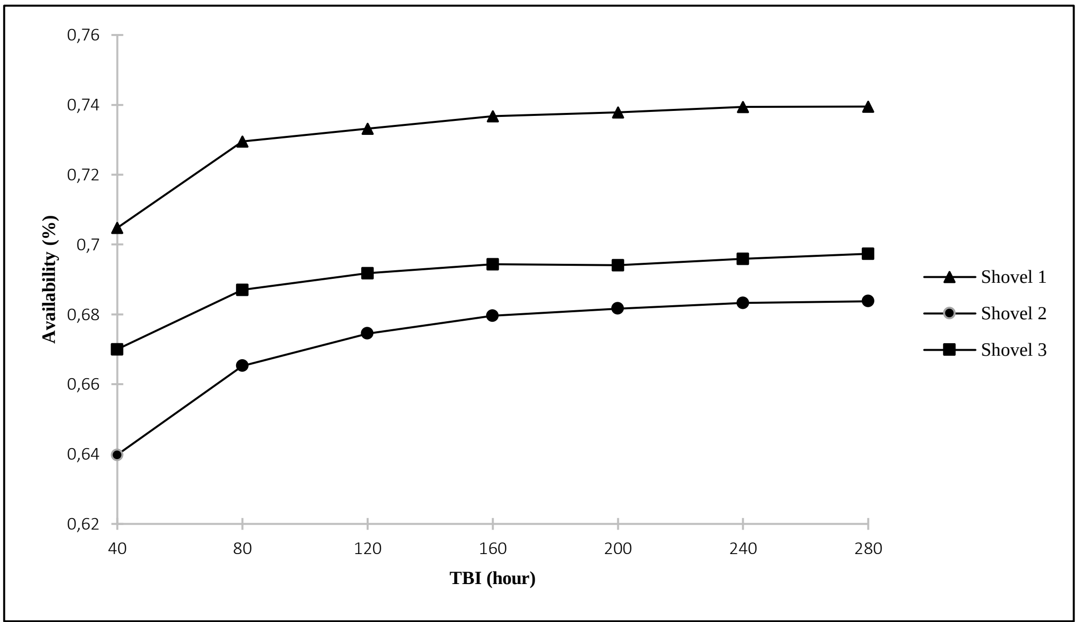


Figure 4.6. Availability Values for Three Shovels Regarding to Changing TBI Values

Increasing TBI will lead to a less number of inspection a year so that there is less inspection downtime. This can improve shovel availability. However, the shift from preventive to corrective maintenance applications will cause a remarkable jump in the deterioration and failure rates of subsystems. Therefore, decisions considering just availability should be given very carefully depending on the risk appetite of company.

Variations in corrective maintenance statistics in terms of repair time and repair number can be viewed in Tables 4.6.

Table 4.6. *Corrective Maintenance Statistics Regarding to TBI Values*

TBI (hour)			**40**	**80**	**120**	**160**	**200**
Shovel 1	Repair Time (h)	SHA	2.57	5.40	6.78	7.59	9.21
		SHC	38.04	64.88	88.96	100.57	107.03
		SHD	201.63	239.14	248.32	258.46	258.39
		SHE	264.44	308.12	327.01	334.67	347.97
		SHH	19.66	40.73	63.04	70.08	71.29
		OTH	132.53	172.18	187.86	190.70	193.74
	Repair Number	SHA	0.71	1.44	1.79	2.01	2.41
		SHC	2.30	3.78	5.00	5.63	6.00
		SHD	43.77	51.62	53.37	55.30	55.39
		SHE	24.79	29.00	30.21	30.71	31.26
		SHH	1.77	3.77	5.24	5.91	6.15
		OTH	23.50	29.94	32.42	32.98	33.57
Shovel 2	Repair Time (h)	SHA	23.08	39.50	48.47	58.46	62.82
		SHC	96.79	130.82	146.54	150.95	156.13
		SHD	269.23	298.06	309.77	314.18	319.07
		SHE	250.63	276.12	282.07	283.82	284.97
		SHH	123.68	151.54	163.52	167.72	170.92
		OTH	213.49	240.23	248.81	257.05	256.88
	Repair Number	SHA	3.08	4.96	5.89	6.98	7.41
		SHC	16.47	21.67	24.01	24.66	25.43
		SHD	65.46	72.48	75.31	76.41	77.11
		SHE	57.67	63.65	65.04	65.27	65.68
		SHH	27.11	32.80	34.88	35.82	36.33
		OTH	54.92	61.77	63.67	65.39	65.84

Table 4.6. *Corrective Maintenance Statistics Regarding to TBI Values(cont'd)*

TBI (hour)			**40**	**80**	**120**	**160**	**200**
Shovel 3	Repair Time (h)	SHA	14.75	27.10	32.83	38.56	41.82
		SHC	110.46	133.06	142.45	147.74	146.13
		SHD	278.99	317.54	332.20	338.01	346.62
		SHE	219.59	236.83	244.10	245.66	246.01
		SHH	24.67	38.91	43.11	45.57	46.36
		OTH	191.10	292.51	334.08	359.42	376.51
	Repair Number	SHA	2.95	5.02	5.80	6.64	7.08
		SHC	24.74	29.49	31.49	32.73	32.28
		SHD	47.16	52.88	55.25	56.06	57.05
		SHE	43.92	47.27	48.75	48.88	48.87
		SHH	5.82	8.99	9.92	10.30	10.49
		OTH	11.74	17.90	20.15	21.45	22.30

The nonlinear relationship between inspection intervals and the corrective maintenance profiles of shovels were shown in Table 4.7 and plotted in Figure 4.7 and Figure 4.8. In the equations, the dependent variable which is the time between inspections (TBI) is symbolized as and the independent variables which are and refer to total corrective repairing times of the shovel, and total corrective repairing numbers, respectively. For these equations, the mean sum of squared errors (MSE) and the standard error (S) that are used to measure the deviation and the upper and lower boundaries were calculated with 95% confidence interval were also given in Table 4.7. Instead of a single point in the line, these ranges help to identify influence areas as given in Figure 4.7 and Figure 4.8 with the dashed lines. The analysis shows that the length of inspection interval has a remarkable effect on the failure behaviors of subsystems. Excessive failure occurrences cause a frequent interruption in production and deterioration of system components before their expected useful lifetimes. The simulation was performed up to an inspection interval of 200 h. The generated equations can be used to make a forecasting for higher inspection intervals

Table 4.7. *Nonlinear Regression Equation*

	Equation	Model Accuracy	Parameters in 95% CI
Shovel 1	$y = 1170.97x^{-6.22/x}$	MSE:35.4792 S:5.9564	Pr1: (1144.49, 1198.07) Pr2: (-6.70, -5.74)
	$z = 146.85\, e^{-16.60\,/\,x}$	MSE:0.08 S:0.29	Pr1: (145.93, 147.78) Pr2: (-17.13, -16.06)
Shovel 2	$y = \frac{1348.27x}{(x + 15.12)}$	MSE:6.11 S:2.47	Pr1: (1339.47, 1357.18) Pr2: (14.44, 15.81)
	$z = \frac{304.51x^2 - 3.231}{x}$	MSE:3.67 S:1.92	Pr1: (297.22, 311.97) Pr2: (-3.71, -2.76)
Shovel 3	$y = \frac{1353.16x}{(x + 24.14)}$	MSE:27.26 S:5.22	Pr1: (1331.52, 1375.48) Pr2: (22.23, 26.15)
	$z = \frac{194.27x}{x + 16.72}$	MSE:1.14 S:1.07	Pr1: (190.41, 198.28) Pr2: (14.61, 18.96)

According to the simulation results, the sensitivity of subsystems to the changing inspection intervals can be analyzed. Figure 4.9, Figure 4.10, and Figure 4.11 presents a representative graph for the subsystems of Shovel 1, Shovel 2 and Shovel 3, respectively. Inspection interval of 120 h was taken as a reference point; and increase or decrease in the total corrective maintenance times for different inspection intervals were shown comparatively in the figure. It is concluded from the graph that SHA and SHE are the subsystems with the most sensitivity to the changes in inspection intervals. Also, OTH and SHH respond slowest to inspection intervals.

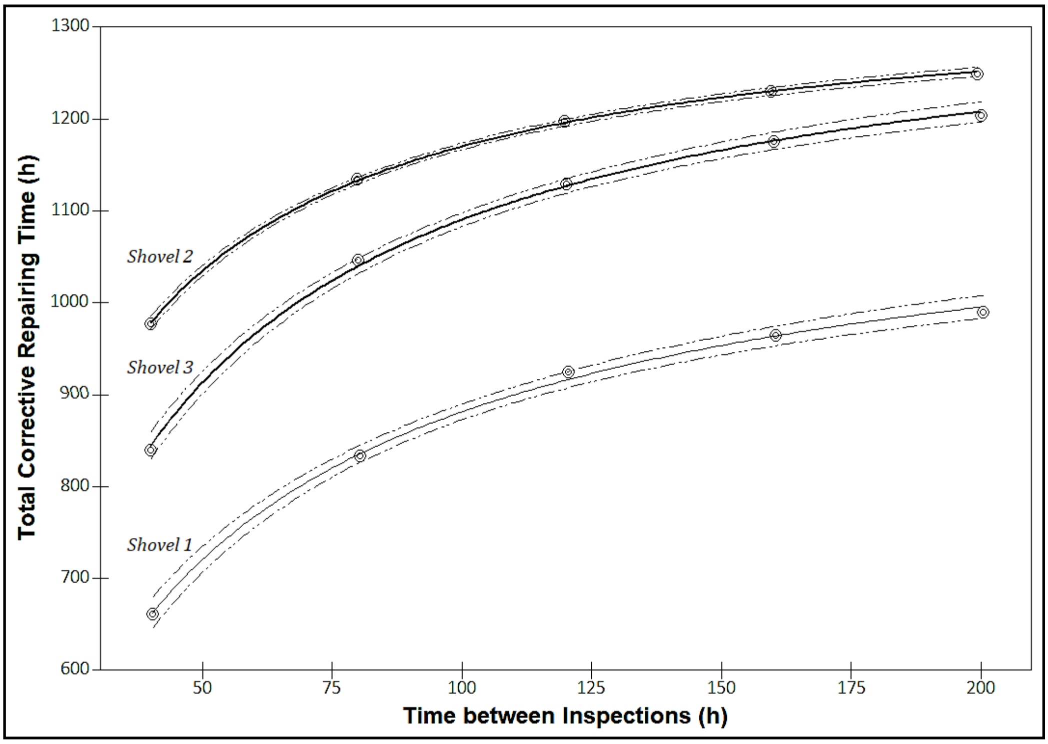


Figure 4.7. Effect of Time between Inspections to Corrective Maintenance Time

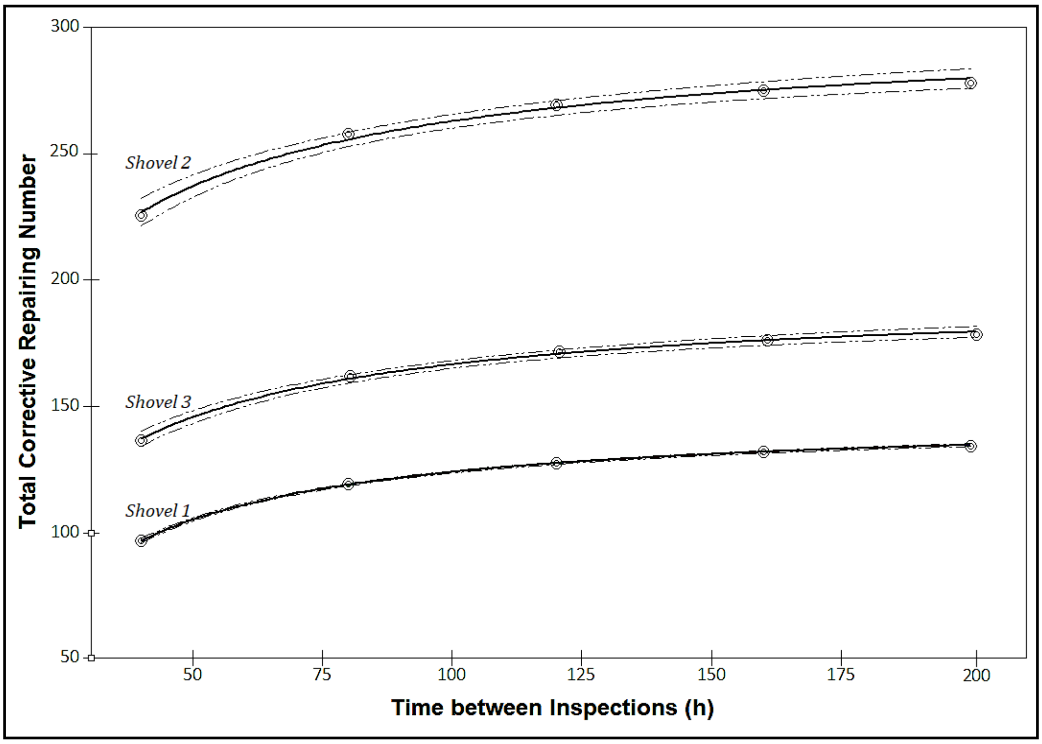


Figure 4.8. Effect of Time between Inspections to Corrective Maintenance Number

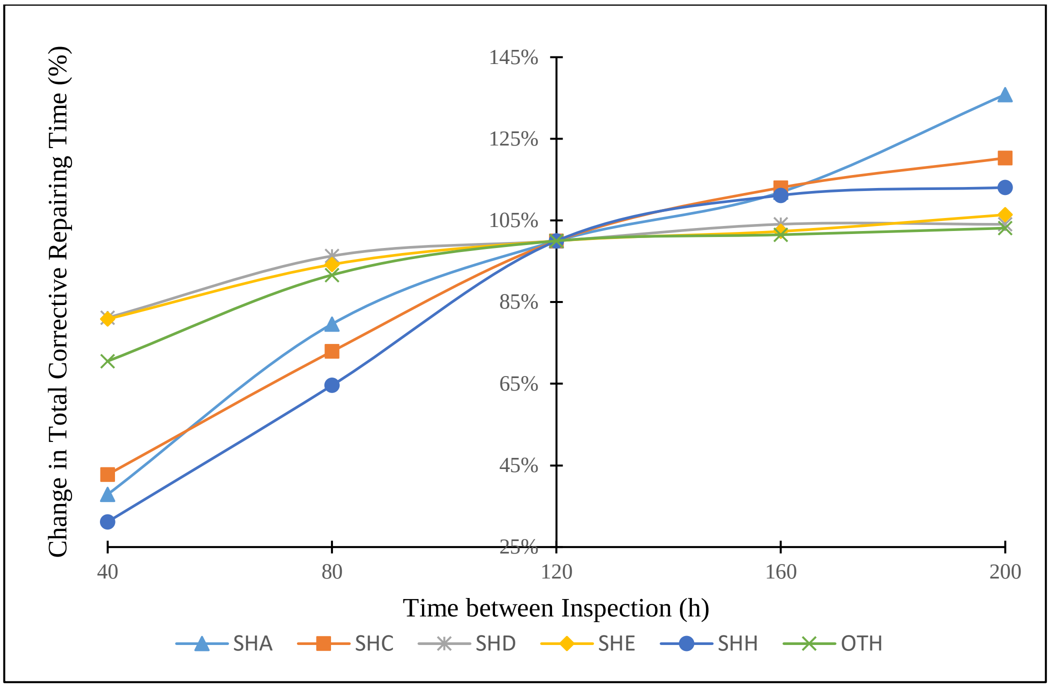


Figure 4.9. Sensitivity of Total Corrective Maintenance Time of Shovel 1 Subsystems to Inspection Interval

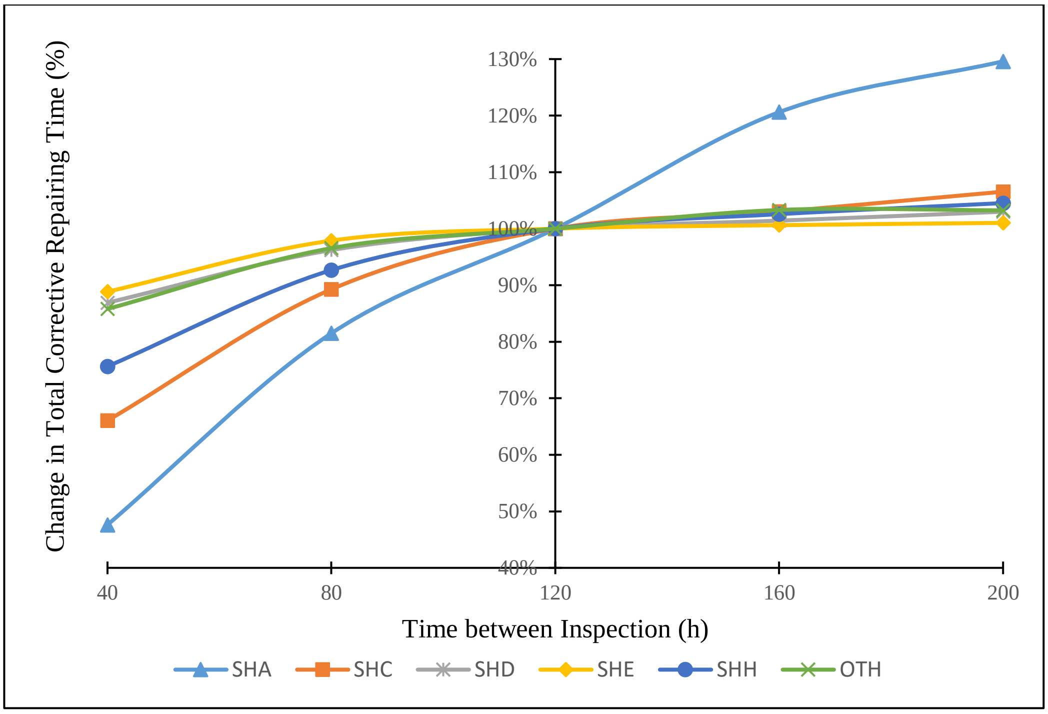


Figure 4.10. Sensitivity of Total Corrective Maintenance Time of Shovel 2 Subsystems to Inspection Interval

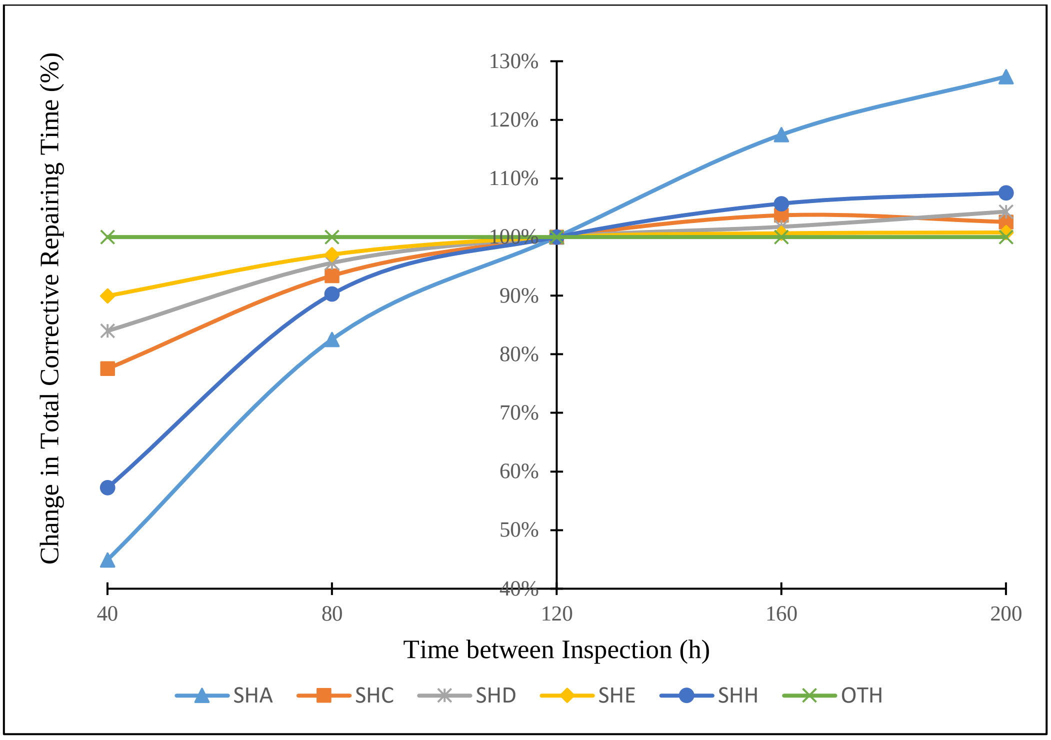


Figure 4.11. Sensitivity of Total Corrective Maintenance Time of Shovel 3 Subsystems to Inspection Interval

4.3. Case Study-2: An Application for a Dragline

The second implementation of the proposed model is done for a dragline which operates in an opencast mine in Turkey. The dataset was retrieved from a study by Gölbaşı and Demirel (2017); and it includes reliability and maintenance probability distribution functions for the components of a dragline. The available dataset and the results of the algorithm will be discussed in Chapters 4.3.1 and 4.3.2, respectively.

4.3.1. Input Dataset of the Algorithm

TTR and TBF functions of the dragline with 6 subsystems and 27 components were taken from Gölbaşı and Demirel (2017). It was stated in that study that the dragline is halted 903 times from 1998 to 2011. In this study, these halts are classified as correspondent components and components were arranged under subsystems. While estimated TBF distribution functions show a variation for components, the best estimation function for TTR is a lognormal distribution for the all components. The system components and their TBF function parameters are shown in Table 4.8. In order to prevent the assignment of outlier values above the upper bound and below the lower bound during the simulation, random TBF values will be generated in a 90% confidence interval. The limit values of the confidence interval can also be examined in the tables.

Table 4.8. *TBF Parameters of the Dragline Components (Gölbaşı and Demirel, 2017)*

	Components			**TBF**	
	Code	**Name**	**Model**	**Parameter**	**Limits(h)**
Dragging	DR1	Chain assembly	GRP	$\beta = 0.9$ $\eta = 626.7$	Max: 2121 Min: 23
	DR2	Ringbolt	Lognormal-2P	$\mu' = 6.34$ $\sigma' = 1.03$	Max: 2398 Min: 100
	DR3	Rope-mode01	Weibull-2P	$\beta = 1.45$ $\eta = 1358.5$	Max: 2667 Min: 85
	DR4	Rope-mode02	Weibull-2P	$\beta = 1.0$ $\eta = 2439.8$	Max: 7777 Min: 122
	DR5	Control	Lognormal-2P	$\mu' = 5.66$ $\sigma' = 1.2$	Max: 1664 Min: 29
	DR6	Socket	Lognormal-2P	$\mu' = 8.4$ $\sigma' = 1.45$	Max: 48139 Min: 410
Hoisting	HO1	Brake	GRP	$\beta = 0.65$ $\eta = 1443.7$	Max: 7808 Min: 15
	HO2	Rope-mode01	Normal-2P	$\mu = 2851.6$ $\sigma = 1640.6$	Max: 5550 Min: 153
	HO3	Rope-mode02	Lognormal-2P	$\mu' = 8.17$ $\sigma' = 1.3$	Max: 29628 Min: 419
	HO5	Control	Weibull-2P	$\beta = 0.71$ $\eta = 1042.1$	Max: 4843 Min: 16
Bucket	BU1	Bucket Body	Weibull-2P	$\beta = 0.95$ $\eta = 1013$	Max: 3331 Min: 54
	BU2	Chain Assembly	Lognormal-2P	$\mu' = 9.0$ $\sigma' = 0.43$	Max: 19507 Min: 4784
	BU3	Digging Teeth	Weibull-2P	$\beta = 0.88$ $\eta = 740.8$	Max: 2561 Min: 26
	BU4	Pins	Weibull-2P	$\beta = 0.92$ $\eta = 675.7$	Max: 2320 Min: 33
	BU5	Ringbolt	Exponential	$\lambda = 0.0009$	Max: 3388 Min: 85

Table 4.8. *TBF Parameters of the Dragline Components (Gölbaşı and Demirel, 2017) (cont'd)*

	Components		**TBF**		
	Code	**Name**	**Model**	**Parameter**	**Limits(h)**
Rigging	RI1	Socket	GRP	$\beta = 0.81$ $\eta = 6790.1$	Max: 26312 Min: 174
	RI2	Ringbolt	Weibull-2P	$\beta = 0.92$ $\eta = 3608.0$	Max: 11894 Min: 143
	RI3	Rope-Mode01	Loglogistic-2P	$\mu' = 5.78$ $\sigma' = 0.48$	Max: 1336 Min: 78
	RI4	Rope-Mode02	Weibull-2P	$\beta = 0.79$ $\eta = 2494.6$	Max: 10086 Min: 57
	RI5	Pulley-Mode01	Normal-2P	$\mu = 3765.2$ $\sigma = 2954.0$	Max: 8624 Min: 101
	RI6	Pulley-Mode02	Lognormal-2P	$\mu' = 7.17$ $\sigma' = 0.88$	Max: 4578 Min: 220
Machinery House	MH1	Generators	Weibull-2P	$\beta = 0.83$ $\eta = 871.7$	Max: 3415 Min: 30
	MH2	Motors	Exponential	$\lambda = 0.0008$	Max: 3847 Min: 86
	MH3	Lubrication	Lognormal-2P	$\mu' = 5.81$ $\sigma' = 1.27$	Max: 2674 Min: 42
Movement	MO1	Rotation	GRP	$\beta = 0.78$ $\eta = 782.4$	Max: 3194 Min: 17
	MO2	Walking	Weibull-2P	$\beta = 0.8$ $\eta = 704.3$	Max: 2959 Min: 25
	MO3	Warning	Lognormal-2P	$\mu' = 7.83$ $\sigma' = 1.0$	Max: 10757 Min: 511

In Tables 4.8, components in dragging, bucket, and machinery house subsystems seems to have smaller operating lifetimes. On the other hand, repair time values in Table 4.9 show that although the majority of components can be repaired in less than 5 hours; this can be extremely high for the machinery house components when failed.

Table 4.9. *Estimated TTR Parameters (Gölbaşı and Demirel., 2017)*

Components			TTR			
	Code	Name	Lognormal Mean	Lognormal Standard Deviation	Limits(h) Max	Limits(h) Min
Dragging	DR1	Chain assembly	0.96	0.53	6.3	1.1
	DR2	Ringbolt	0.48	0.49	3.6	0.7
	DR3	Rope-mode01	1.64	0.8	19.2	1.4
	DR4	Rope-mode02	0.35	0.59	3.7	0.5
	DR5	Control	1.16	1.17	22.1	0.5
	DR6	Socket	0.16	0.37	2.2	0.6
Hoisting	HO1	Brake	0.59	1.07	10.4	0.3
	HO2	Rope-mode01	2.4	0.69	34.3	3.5
	HO3	Rope-mode02	0.49	0.35	2.9	0.9
	HO5	Control	0.85	1.32	20.5	0.3
Bucket	BU1	Bucket Body	1	1.21	20.0	0.4
	BU2	Chain Assembly	1.22	1.03	18.4	0.6
	BU3	Digging Teeth	-0.02	0.64	2.8	0.3
	BU4	Pins	0.08	0.61	2.9	0.4
	BU5	Ringbolt	0.43	0.63	4.3	0.5
Rigging	RI1	Socket	0.16	0.7	3.7	0.4
	RI2	Ringbolt	0.51	0.64	4.8	0.6
	RI3	Rope-Mode01	0.44	0.58	4.0	0.6
	RI4	Rope-Mode02	0.48	0.59	4.2	0.6
	RI5	Pulley-Mode01	0.72	0.69	6.4	0.7
	RI6	Pulley-Mode02	0.31	0.78	4.9	0.4
Machinery House	MH1	Generators	2.63	1.95	342.6	0.6
	MH2	Motors	2.76	1.73	270.1	0.9
	MH3	Lubrication	0.76	1.04	11.7	0.4
Movement	MO1	Rotation	0.55	1.09	10.4	0.3
	MO2	Walking	1.46	1.56	56.4	0.3
	MO3	Warning	1.23	1.27	27.8	0.4

Like the probability distribution functions, cycle time, production loss, components Ths and cost parameters have a critical role in the model. As mentioned in Chapter 3, Ths value is a percentage that points to healthy portion of component lifetime without any wear-out. Once this threshold is exceeded, the component starts to a signal for deterioration and approaching failure. In Gölbaşı and Demirel (2017), Ths percentage, and preventive and corrective maintenance costs were determined from maintenance experts (Table 4.10). In addition, the cycle time of dragline and unit production loss were stated as 0.87 min and 9.03 $/min, respectively.

Corrective maintenance can be applied in all components while preventive maintenance can be applied only to the components which Ths value is below 100. It means that the component gives signals for deteriorations. Moreover, preventive maintenance is applied during inspection times that takes 8 hours every 160 hours in normal conditions in the field. On the other hand, opportunistic maintenance may be applicable only in corrective maintenance downtimes. For the eligibility of a component for opportunistic maintenance: i) The component needs to be in a wear-out period with a visible signal. In the study, it is assumed that the period between the start of wear-out according to component's Ths value and its expected failure point in the timeline is the wear-out period for the component. In the timeline, components will have dynamic wear-out periods that is updated after every maintenance decision, and independent of each other. ii) Preventive maintenance duration of the component under opportunistic maintenance needs to be less than the corrective maintenance duration of the failed component. These conditions help to build up a realistic case such that a long-duration opportunistic maintenance is avoided in case of a short-duration corrective maintenance. iii) Opportunistic maintenance can be applicable only in operation time other than the inspection hours.

Table 4.10. *Ths Values and Maintenance Activity Costs (Gölbaşı & Demirel, 2017)*

	Code	Name	Ths (%)	CM Direct Cost ($)	PM Direct Cost ($)	PM Time (h)
Dragging	DR1	Chain assembly	95	1114	98	-
	DR2	Ringbolt	90	56	16	-
	DR3	Rope-mode01	100	1132	0	1
	DR4	Rope-mode02	100	0	0	-
	DR5	Control	90	500	295	4
	DR6	Socket	95	95	65	-
Hoisting	HO1	Brake	85	45	65	1.81
	HO2	Rope-mode01	100	1216	0	1.5
	HO3	Rope-mode02	100	0	0	-
	HO5	Control	95	591	164	3.19
Bucket	BU1	Bucket Body	95	309	327	1.44
	BU2	Chain Assembly	90	295	229	1.45
	BU3	Digging Teeth	95	109	65	0.31
	BU4	Pins	90	659	98	0.33
	BU5	Ringbolt	90	614	245	0.48
Rigging	RI1	Socket	95	34	16	1.35
	RI2	Ringbolt	90	164	131	1.65
	RI3	Rope-Mode01	100	98	0	-
	RI4	Rope-Mode02	100	0	0	-
	RI5	Pulley-Mode01	95	843	33	-
	RI6	Pulley-Mode02	100	655	0	-
Machinery House	MH1	Generators	90	364	295	6
	MH2	Motors	95	159	87	4
	MH3	Lubrication	80	341	49	2
Movement	MO1	Rotation	95	3977	589	-
	MO2	Walking	90	2205	785	-
	MO3	Warning	90	291	393	2

4.3.2. Results of the Algorithm

The model is used to understand the effects of TBI value and different maintenance policy on production time and total maintenance cost that includes direct and indirect financial burdens. By using the dataset, the model gives maintenance statistics and their resultant downtime and cost values for each component. By using these outputs, the total cost and production time of the dragline in a year can be obtained. As explained in Chapter 4.2.2, for increasing accuracy, the algorithm was simulated for 350 times. This process is completed for three different maintenance scenarios. First maintenance policy covers only corrective and preventive maintenance in inspections. The second scenario includes opportunistic maintenance in an addition to corrective maintenance and preventive maintenance in inspection. The third scenario also includes all three maintenance actions, but opportunistic maintenance was restricted to the subsystem level. It means that likelihood of an opportunistic maintenance can be checked for the subsystem components where one component in that subsystem is under corrective maintenance.

For each maintenance policy, 15 different TBI values are simulated. It starts at 16-hours and increases 24-hours for 14 analysis. Finally, TBI value is assigned 8760-hours for inactivated preventive maintenance module in simulation. The production time and costs results of the simulations are shown in Table 4.11, Table 4.12, and Table 4.13 for 3 different maintenance policies. Moreover, Figure 4.12 is illustrated TBI, production time and total cost in a three-dimensional plane for each maintenance. In the figure, 350 h TBI represents the maintenance policy without PM for better illustration. The minimum cost values for the three maintenance policies are 981,738 $, 913,480 $ and 974,674 $, respectively. The result shows that there is no significant cost change when OM is applied with subsystem constraint. The third model just increase the annual production by 24 hours. On the other hand, the second model reduced the cost by 68,000 $ annually. It reaches a minimum point when only OM and CM is applied. By this way, the production time can be increased by 130 hours without inspection.

Table 4.11. *1st maintenance policy annual uptime and cost value with TBI*

TBI	Direct Cost ($)	Indirect Cost ($)	Total Cost ($)	Production Time (h)
16	47,839	1,840,040	1,887,880	5,364
40	71,296	1,192,143	1,263,438	6,560
64	82,718	1,018,202	1,100,920	6,884
88	91,967	946,616	1,038,583	7,014
112	99,674	913,383	1,013,057	7,077
136	102,278	893,087	995,364	7,115
160	105,291	885,918	991,209	7,127
184	108,571	875,617	984,188	7,146
208	112,088	869,650	981,738	7,157
232	112,837	883,302	996,139	7,132
256	114,621	880,265	994,886	7,138
280	115,918	871,653	987,570	7,154
304	116,995	870,747	987,742	7,154
320	117,040	886,402	1,003,442	7,130
8760	126,080	886,197	1,012,277	7,127

Table 4.12. *2nd maintenance policy annual uptime and cost value with TBI*

TBI	Direct Cost ($)	Indirect Cost ($)	Total Cost ($)	Production Time (h)
16	46,953	1,838,694	1,885,647	5,366
40	70,521	1,193,208	1,263,729	6,558
64	82,599	1,011,743	1,094,342	6,894
88	91,117	936,294	1,027,411	7,034
112	95,801	900,886	996,687	7,099
136	105,334	841,872	947,206	7,209
160	103,189	853,689	956,878	7,185
184	105,334	841,872	947,206	7,209
208	106,568	854,335	960,903	7,186
232	108,539	842,437	950,976	7,209
256	109,582	833,707	943,289	7,224
280	108,786	831,302	940,088	7,228
304	111,115	826,567	937,683	7,238
320	112,480	819,169	931,649	7,251
8760	121,272	792,209	913,481	7,304

Table 4.13. *3rd maintenance policy annual uptime and cost value with TBI*

TBI	Direct Cost ($)	Indirect Cost ($)	Total Cost ($)	Production Time (h)
16	47,204	1,839,156	1,886,360	5,366
40	70,949	1,195,537	1,266,486	6,554
64	82,804	1,013,599	1,093,507	6,890
88	92,212	947,067	1,039,279	7,013
112	97,875	911,539	1,009,414	7,079
136	101,197	892,060	993,257	7,116
160	104,329	879,381	983,709	7,140
184	106,419	880,893	987,311	7,138
208	108,404	876,974	985,378	7,146
232	110,010	873,884	983,894	7,151
256	112,893	862,546	975,440	7,170
280	112,554	869,202	981,756	7,157
304	113,516	861,159	974,675	7,174
320	113,726	862,441	976,167	7,173
8760	125,123	858,675	983,798	7,180

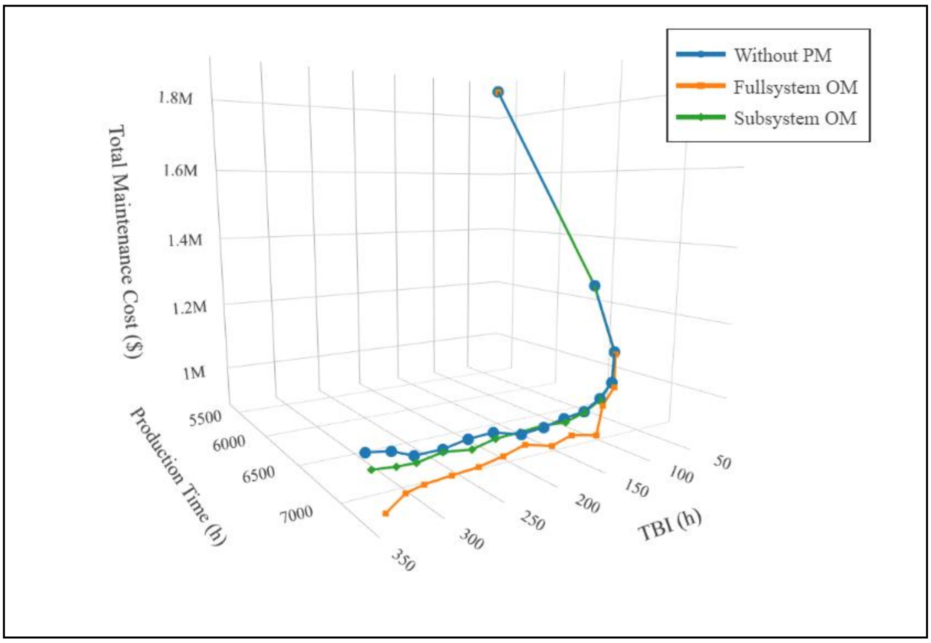


Figure 4.12. Production time and total cost results with TBI

As mentioned in Chapter 4.1.3, the production time and total maintenance cost results may not be enough to decide on equipment condition. Therefore, corrective maintenance statistics explained in Table 4.14 are analyzed for each subsystem regarding to TBI values. As expected, for all maintenance policies, when the inspection interval increases, corrective maintenance time and its application number also increase. The comparison between the corrective maintenance profiles of each maintenance that the increase rate of repairing time and number decrease from first maintenance policy to third maintenance policy.

Table 4.14. *Corrective Maintenance Statistics Regarding to TBI Values for Each Maintenance Policy*

<table>
<tr><th colspan="3">TBI (h)</th><th>16</th><th>64</th><th>112</th><th>160</th><th>208</th><th>256</th><th>304</th><th>8760</th></tr>
<tr><td rowspan="12">1st Maintenance Policy</td><td rowspan="6">Repair Time (h)</td><td>DR</td><td>47.6</td><td>112.6</td><td>136.3</td><td>150.5</td><td>159.3</td><td>165.4</td><td>166.7</td><td>184.0</td></tr>
<tr><td>HO</td><td>26.6</td><td>44.1</td><td>52.1</td><td>56.0</td><td>57.3</td><td>60.5</td><td>61.6</td><td>68.7</td></tr>
<tr><td>BU</td><td>5.4</td><td>27.2</td><td>39.1</td><td>46.9</td><td>51.2</td><td>52.7</td><td>56.7</td><td>69.3</td></tr>
<tr><td>RI</td><td>34.1</td><td>45.2</td><td>46.8</td><td>48.3</td><td>49.3</td><td>49.3</td><td>49.7</td><td>54.7</td></tr>
<tr><td>MH</td><td>33.3</td><td>206.9</td><td>300.8</td><td>364.8</td><td>391.5</td><td>446.1</td><td>449.5</td><td>596.6</td></tr>
<tr><td>MO</td><td>12.2</td><td>43.0</td><td>63.5</td><td>73.0</td><td>85.0</td><td>89.2</td><td>95.6</td><td>123.5</td></tr>
<tr><td rowspan="6">Repair Number</td><td>DR</td><td>8.74</td><td>25.29</td><td>32.34</td><td>36.32</td><td>39.48</td><td>40.74</td><td>42.00</td><td>48.05</td></tr>
<tr><td>HO</td><td>2.87</td><td>6.49</td><td>8.40</td><td>9.55</td><td>9.86</td><td>10.60</td><td>11.17</td><td>8.83</td></tr>
<tr><td>BU</td><td>3.09</td><td>14.23</td><td>20.34</td><td>24.50</td><td>26.49</td><td>27.86</td><td>29.32</td><td>36.88</td></tr>
<tr><td>RI</td><td>17.78</td><td>23.70</td><td>24.41</td><td>25.12</td><td>25.23</td><td>25.52</td><td>26.11</td><td>28.31</td></tr>
<tr><td>MH</td><td>0.94</td><td>8.32</td><td>13.31</td><td>16.02</td><td>18.18</td><td>19.95</td><td>20.96</td><td>27.71</td></tr>
<tr><td>MO</td><td>2.49</td><td>8.49</td><td>12.27</td><td>13.79</td><td>15.63</td><td>16.42</td><td>17.29</td><td>21.78</td></tr>
<tr><td rowspan="6">2nd Maintenance Policy</td><td rowspan="6">Repair Time (h)</td><td>DR</td><td>47.5</td><td>112.6</td><td>138.5</td><td>149.7</td><td>159.0</td><td>160.9</td><td>164.0</td><td>184.8</td></tr>
<tr><td>HO</td><td>26.4</td><td>45.8</td><td>51.3</td><td>55.2</td><td>57.1</td><td>60.8</td><td>60.3</td><td>68.3</td></tr>
<tr><td>BU</td><td>5.4</td><td>26.4</td><td>38.4</td><td>44.4</td><td>46.9</td><td>50.6</td><td>52.5</td><td>61.2</td></tr>
<tr><td>RI</td><td>34.1</td><td>45.1</td><td>47.2</td><td>48.5</td><td>49.0</td><td>49.3</td><td>50.0</td><td>54.4</td></tr>
<tr><td>MH</td><td>31.1</td><td>197.5</td><td>297.3</td><td>351.8</td><td>412.8</td><td>415.5</td><td>440.8</td><td>563.0</td></tr>
<tr><td>MO</td><td>12.1</td><td>42.3</td><td>62.7</td><td>77.2</td><td>83.4</td><td>93.6</td><td>95.0</td><td>119.4</td></tr>
</table>

Table 4.14. Corrective Maintenance Statistics Regarding to TBI Values for Each Maintenance Policy (cont'd)

TBI(h)			**16**	**64**	**112**	**160**	**208**	**256**	**304**	**8760**
2nd Maintenance Policy	Repair Number	DR	8.68	25.07	32.70	36.05	38.90	40.11	41.45	47.65
		HO	2.85	6.75	8.42	9.34	9.85	10.56	10.99	13.31
		BU	3.10	13.98	19.69	22.78	24.39	25.85	26.69	31.37
		RI	17.82	23.41	24.51	25.08	25.25	25.55	25.88	28.20
		MH	0.93	8.21	12.76	15.66	17.73	19.30	19.83	26.00
		MO	2.49	8.64	12.30	14.22	15.50	16.89	17.26	21.47
3rd Maintenance Policy	Repair Time (h)	DR	47.8	109.5	131.8	145.4	151.6	156.1	158.2	178.9
		HO	26.4	45.0	50.8	52.4	52.4	55.2	56.3	59.9
		BU	5.7	22.7	30.3	32.1	33.0	35.1	34.3	36.0
		RI	34.2	44.8	47.3	48.8	48.6	50.1	50.3	55.1
		MH	29.7	199.1	290.8	320.6	392.0	387.0	405.8	485.8
		MO	11.9	44.7	62.8	77.3	86.1	91.0	92.0	112.6
	Repair Number	DR	8.82	24.46	31.17	35.18	37.67	39.24	39.91	46.69
		HO	2.95	6.47	7.86	8.10	8.43	8.86	8.98	10.14
		BU	2.98	11.95	15.12	16.17	16.76	17.15	17.20	18.53
		RI	17.77	23.27	24.49	25.28	25.14	25.85	25.90	28.21
		MH	0.94	7.89	11.62	13.42	15.15	15.87	16.71	19.49
		MO	2.42	8.79	12.31	14.41	15.60	16.54	16.89	20.30

According to the corrective maintenance statistics, the sensitivity of subsystems to the changing inspection intervals can be analyzed for each maintenance policy. Figure 4.13, Figure 4.14, and Figure 4.15 present a representative graph for the first, second and third maintenance policy, respectively. Inspection interval of 160 h was taken as a reference point. In these figures, the percentage of change in the total corrective maintenance times for different inspection intervals were shown comparatively. It is concluded from the graph that MH and MO subsystems are the most sensitive to the changes in inspection intervals. Besides, RI and HO are the subsystems with the least sensitivity to the changes in inspection intervals.

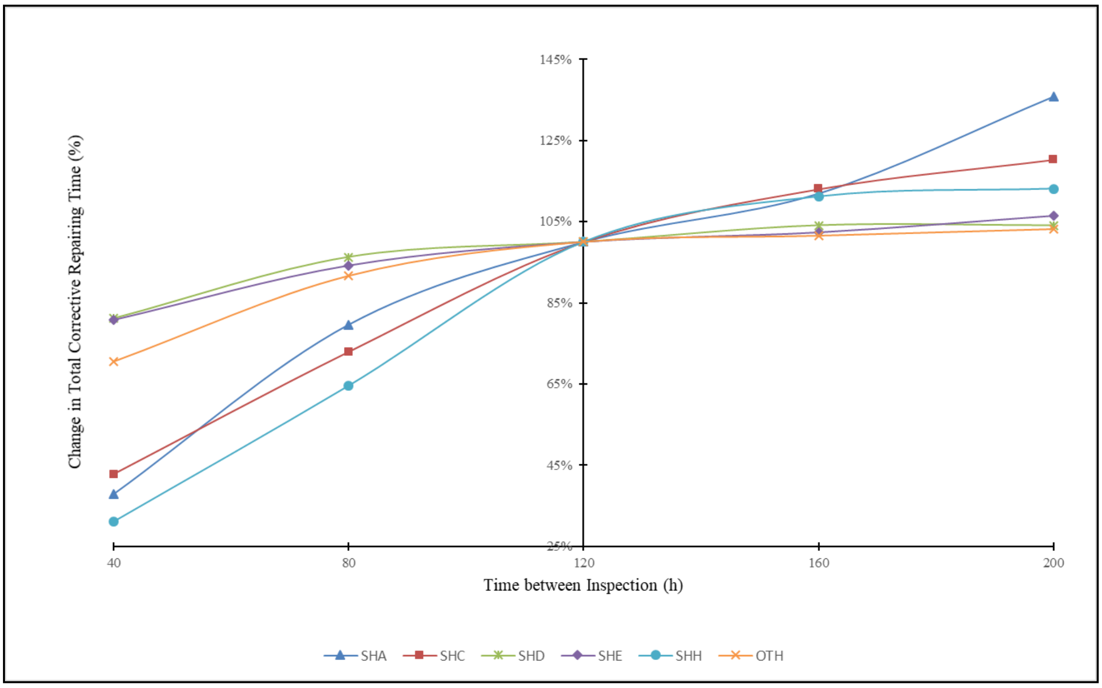


Figure 4.13. Sensitivity of Total Corrective Maintenance Time to Inspection Interval for 1st Maintenance Policy

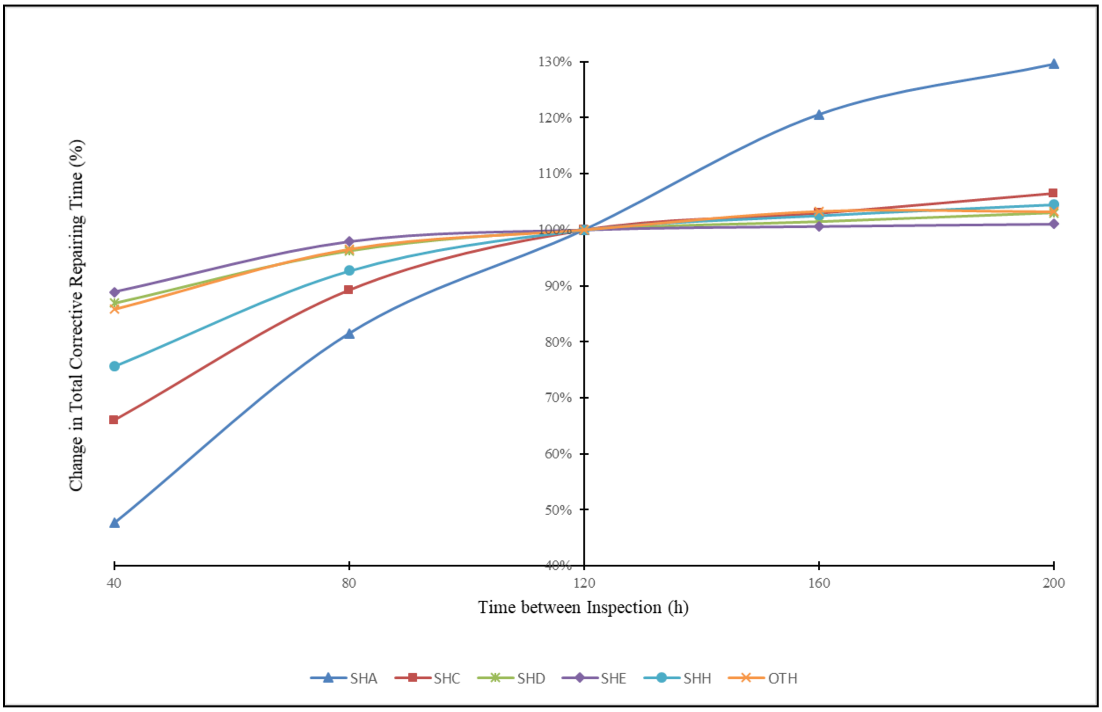


Figure 4.14. Sensitivity of Total Corrective Maintenance Time to Inspection Interval for 2nd Maintenance Policy

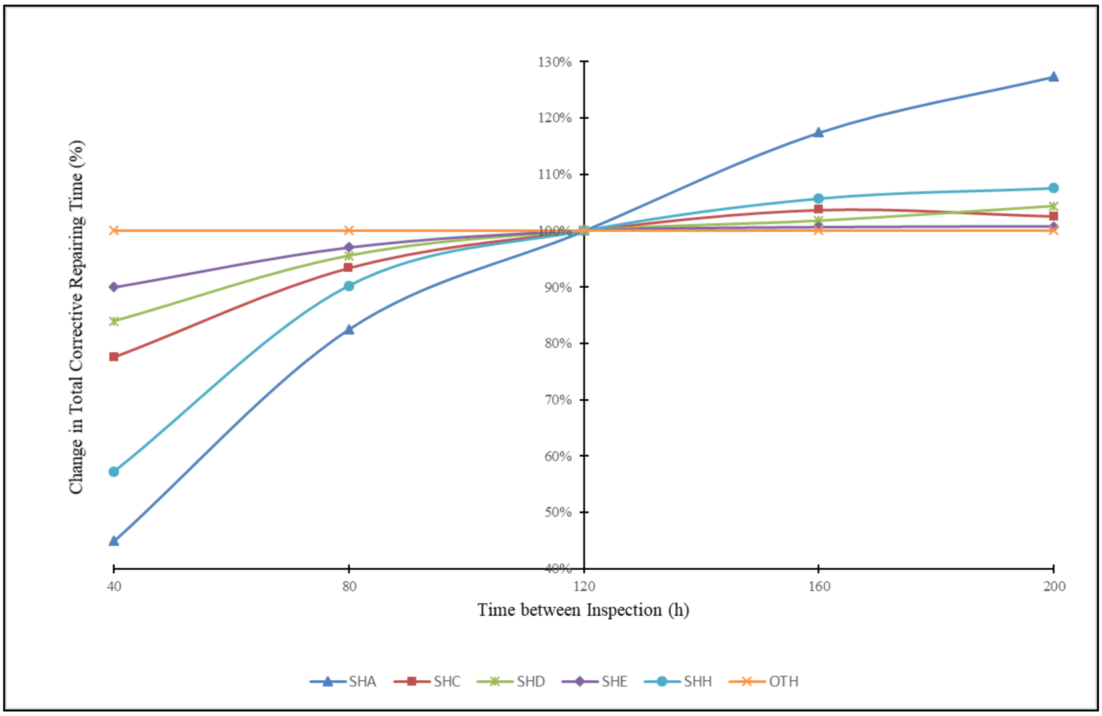


Figure 4.15. Sensitivity of Total Corrective Maintenance Time to Inspection Interval for 3rd Maintenance Policy

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

Effectiveness of a maintenance policy reserves a high uncertainty coming from the stochastic behavior of component and subsystem lifetimes in the maintained systems. In addition, what to implement in planned and unplanned activities may change the financial and operational benefits of a maintenance policy. This study intends to develop a simulation algorithm that integrates corrective, preventive, and opportunistic maintenance to the stochastic repairing and operating behaviors of a working system. Once the stated integration was achieved, the model was tested for different inspection intervals since inspections, as a part of maintenance policy, is critical in mines especially for operationally important loading and hauling machines. The study methodology required (i) allocation of components in the system and characterization of component uptime and downtime profiles, (ii) mathematical correlation of production cycles, administrative breaks, regular inspections and maintenance work packages, which include corrective, preventive and opportunistic maintenance actions, (iii) introducing the model in a discrete-event software called Arena®, and (iv) computing and analyzing the sensitivity of production rates and maintenance cost to the different maintenance policies.

The developed model was applied in two different case studies. First, the model was performed for three shovels operating in the same mine. Random characteristics of repairing and lifetime durations of the shovel subsystems were adapted in the model for a better understanding of downtime behavior of the systems. The results showed that the maximum total production amount for the shovel fleet can be achieved as 7,242,151 m^3 when the inspection intervals is 280 hours. It was realized that production amount was decreased drastically after 80 hours of inspection interval.

Although increasing inspection intervals raises the total productivity, it may accelerate the deterioration rates of components. Therefore, there should be a balance between corrective maintenance activities and annual production amount. Moreover, the outputs of the simulation were used to reveal the sensitivity of shovel subsystems to the changeable inspection intervals. In the sensitivity graphs, it was seen that SHA subsystem is the most sensitive to the changing inspection interval where it is the least for OTH.

Second, the model was applied to a dragline case. The dragline components and subsystems were introduced with random repair times and lifetimes as an input of the model. Six different maintenance scenarios which are combination of CM, PM, and OM with different constraints were examined by using the algorithm. In addition, PM application was tested for 14 different inspection intervals between 16 and 320 hours with 24 hours increments. The results showed that the scenario where only CM and OM (for full system) is applied without any regular inspection minimizes the total maintenance cost which is equal to 913,481 $. Moreover, according to corrective maintenance statistics, MH and RI subsystems are the most and the least sensitive to the variations in inspection intervals, respectively.

5.2. Recommendations

Contribution of the research study can be extended regarding the following recommendations in the future studies:

- In this study, the shovels are taken functionally independent of each other where the dragline performs a self-operation. Therefore, it is assumed that individual productivities are not affected from the failures in the other machines. The current model can be improved more for k-out-of-n systems where stand-by machines are available. Haul truck fleets can be given as an example to this kind of systems.

- In addition to production rate and maintenance cost estimation, component deterioration rate can also be included to the model to see the long-term effect of the maintenance policy.
- Some other operational and environmental constraints or variables, and driver skills can be introduced to the model in for a more comprehensive characterization of the machines.
- Crew capacity and competency may be added to the maintenance policy for a better evaluation of maintenance effectiveness.
- An inventory policy may be adapted to reveal the additional production loss due to lack of enough spare part in case of maintenance.
- Interaction of different machines working together can be considered to develop a more holistic maintenance policy since resources, i.e. crew capacity and spare part numbers, are limited in the production area.

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