RELIABILITY-BASED MAINTENANCE OPTIMIZATION OF WALKING DRAGLINES

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ABSTRACT

RELIABILITY-BASED MAINTENANCE OPTIMIZATION OF WALKING DRAGLINES

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Dragline is an earthmover extensively utilized in open cast coal mines for overburden stripping activities. Since the machinery breakdowns may induce high amount of production losses, draglines are required to be operated with high availability. In this sense, effective maintenance policies are essential to improve longevity of dragline component and sustainability of operations. In this research study, it is aimed to develop a reliability-based maintenance optimization models for two walking draglines, Page and Marion, currently operated in Tunçbilek coal mine. The study methodology consists of four main phases as: i) characterizing the machinery components via reliability models, ii) implementing a decision platform for preventive replacement of components, iii) generating risk-based maintenance importance models for the machinery components, and iv) developing an optimization algorithm for inspection intervals of the draglines. Component and system characterization was achieved generating deductive reliability models. Preventive component replacement models were created considering preventive and corrective cost factors and investigating applicability of preventive replacements for components. Risk model was developed regarding indirect and direct maintenance costs and maintenance criticality scores were estimated for system elements. Optimization algorithm on inspection intervals was implemented including random lifetime and repair behaviors of components, functional effect of each other during failures, scheduled halts in shifts and regular inspections, and direct and indirect costs of maintenance activities.

The results of reliability models revealed that dragging and bucket units were expected to fail most frequently. On the other hand, boom unit was detected to sustain its functionality for the longest time compared to the other units. Moreover, machinery house components generally lead to the longest repairing time and the highest production loss. Considering individual components and their associated structural and functional dependencies, Marion and Page draglines are expected to keep operation going for 34.04 and 35.62 hours without any breakdown, respectively. In addition, optimization algorithm for inspection intervals showed that interval lengths of 184 and 232 hours are economically optimal for Page and Marion, respectively. Maintenance costs of the draglines using these intervals are expected to decrease with 5.9% for Page and 6.2% for Marion. Moreover, risk-based reliability allocation models showed that reliability improvement in motor, generator, rotation, and walking had the greatest impact on overall system reliability considering failure frequencies and their consequences. It was revealed from the risk model that maintenance for these components should be carried out in more controlled and planned manner. This research study provides a new perspective on dragline maintenance. The main novelty and expected industrial contribution of this study is to provide a new inspection optimization model and implementation of risk factors to identify draglines' component maintenance criticality considering reliability allocation which has not been considered previously in literature.

Keywords: Dragline, reliability, maintenance optimization, age-replacement policy, risk model, inspection interval optimization.

ÖZ

YÜRÜYEN ÇEKME KEPÇELİ YERKAZARLARIN GÜVENİLİRLİK TABANLI BAKIM-ONARIM OPTİMİZASYONU

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Çekme kepçeli yerkazarlar, açık kömür ocaklarında örtü kazı dekapajı için sıklıkla kullanılan yerkazarlardır. Makine duraksamaları yüksek miktarda üretim kaybına neden olacağından, çekme kepçeli yerkazarların yüksek kullanılabilirlik oranıyla çalıştırılmaları gerekmektedir. Bu bakımdan, etkili bakım onarım politikaları, çekme kepçe parçalarının uzun ömürlü olarak kullanılması ve operasyonların sürdürülebilirliği için gereklidir. Bu çalışmada, Tunçbilek açık kömür işletmesinde kullanılan Page ve Marion marka iki farklı yerkazar için güvenilirlik tabanlı bakım onarım optimizasyonunun yapılması amaçlamaktadır. Çalışma metodolojisi dört ana aşamadan oluşmaktadır. Bunlar: i) Makine parçalarının güvenilirlik modelleriyle yaşam özelliklerinin belirlenmesi, ii) Önleyici parça değişimleri için bir karar platformunun oluşturulması, iii) Makine parçaları için risk tabanlı bakım onarım önemi modelinin kurulması ve iv) Çekme kepçeli yerkazarların düzenli denetim aralıkları için bir optimizasyon algoritması geliştirilmesidir. Bileşen ve sistem karakterizasyonu, tümdengelimli güvenilirlik modelleri oluşturularak elde edilmiştir. Önleyici parça değişim modelleri, önleyici ve düzeltici bakım masraflarını hesaba katılarak ve parçaların önleyici değişim uygulanabilirliğini incelenerek oluşturulmuştur. Risk modeli, arıza neticesinde oluşan doğrudan ve dolaylı maliyetler hesaba katılarak geliştirilmiş ve sistem elemanları için bakım-onarım öncelik sıralaması tahmin edilmiştir. Denetim aralığına dair optimizasyon algoritması,

bileşenlerin rasgele yaşam ve onarım davranışları, arızalar sırasında her bir parçanın birbirine fonksiyonel etkisi, vardiya değişimleri ve düzenli denetimlerden kaynaklı zorunlu duraksamalar ve bakım onarım aktivitelerinin neden olduğu doğrudan ve dolaylı tüm maliyetler hesaba katılarak gerçekleştirilmiştir.

Güvenilirlik modellerinin sonuçları, kepçe ve çekiş ünitelerinin en sık arızalanan üniteler olduğunu göstermiştir. Diğer yandan, bum ünitesinin diğer ünitelerle karşılaştırıldığında en uzun süre işlevselliğini devam ettirdiği tespit edilmiştir. Ek olarak, makina dairesi bileşenleri genellikle en uzun süreli onarım sürelerine ve en yüksek üretim kaybına neden olmaktadır. Bireysel bileşenler, onlar arasındaki yapısal ve fonksiyonel bağımlılıklar düşünüldüğünde, Marion ve Page çekme kepçelerinin sırasıyla 34,04 ve 35,62 saat boyunca herhangi bir bozulma yaşamadan operasyonlarına devam etmeleri beklenmektedir. Ayrıca, denetim aralıkları için oluşturulan optimizasyon algoritması, Page ve Marion için 184 ve 232 saatlik denetim aralıklarının ekonomik olarak optimal olacağını göstermektedir. Bu aralıklar kullanılarak, çekme kepçelerin bakım-onarım masraflarında Page için %6,2, Marion için %5,9 oranında bir düşüş olması beklenilebilir. Bunlara ek olarak, risk-tabanlı güvenilirlik paylaştırma modelleri, arıza aralıkları ve arıza sonuçlarına göre, motor, jeneratör, dönme ve yürüme mekanizmalarındaki güvenilirlik artışının sistem güvenilirliğine en yüksek katkıyı sağlayacağını göstermektedir. Bu parçalara yönelik bakımın, daha planlı ve kontrollü yapılması gerektiği anlaşılmıştır. Bu araştırma, çekme kepçeli yerkazarların bakım onarımına yeni bir bakış açısı sağlamaktadır. Çalışmanın literatüre ve endüstriye kazandıracağı en önemli yenilik, güvenilirlik dağılımı yolu ile çekme kepçeli yer kazarların bileşenlerinin bakım onarım öncelik sıralamasının tahmin edilmesi için risk faktörlerinin belirlenerek yeni bir bakım-denetim optimizasyonu modelinin geliştirilmesidir.

Anahtar Kelimeler: Çekme kepçeli yerkazar, bakım-onarım optimizasyonu, yaş-tabanlı parça değişim politikaları, risk modeli, denetim aralıklarının optimizasyonu.

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ARP	Alternating Renewal Process
CDF	Cumulative Density Function
CFN	Cumulative Failure Number
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes Effects and Criticality Analysis
FTA	Fault Tree Analysis
GRP	General Renewal Process
HPP	Homogenous Poisson Process
IQR	Inter-quartile Range
MTBF	Mean Time between Failures
MTTF	Mean Time to Failure
MTTFF	Mean Time to First Failure
MTTR	Mean Time to Repair
NHPP	Non-Homogenous Poisson Process
ORP	Ordinary Renewal Process
PDF	Failure Probability Density Function
RBD	Reliability Block Diagram
RPN	Risk Priority Number
TBF	Time between Failures
TTR	Time to Repair

LIST OF SYMBOLS

$R(t), \bar{F}(t)$	Reliability (Survival) Function
$F(t)$	Failure (Unreliability) Function
$f(t)$	Failure Probability Density Function
$P(x)$	Probability for the Occurrence of Event x
$P(\bar{x})$	Probability for the Occurrence of Complementary Event x
$E(t), \mu$	Mathematical Expectation
s, σ	Standard Deviation
t_{median}, T_{50}	Median Time
t_{modal}	Modal Time (Mode)
$\lambda(t), r(t)$	Failure Rate
$\mu(t)$	Repair Rate
B_q	Certain Time Period with Failure Probability of q
$N(t)$	Number of Failures at Time t
S_n	Cumulative Time between Failures
$M(t)$	Renewal Function
EX	Expected Uptime
EY	Expected Downtime
$G(t)$	Distribution Function of Downtimes
$H(t)$	Convolution of Uptime $(F(t))$ and Downtime $G(t)$ Functions
C_f	Cost of Failure Maintenance
C_p	Cost of Preventive Maintenance
C_i	Cost of Inspection
q	Probability of Perfect Repair
p	Probability of Minimal Repair

CHAPTER 1

INTRODUCTION

1.1 Background

All functional systems fail over time due faulty design of parts, errors in product manufacturing period, human-based fallacies, lack of proper maintenance and testing, and deficiencies in protection (Ebeling, 2010). These failures may cause unexpected breakdowns of system, time losses, excessive economical costs, and health and safety issues. Draglines are massive machines extensively utilized in overburden stripping operations in open-cast mines. These earthmovers have more than 4,000 tonnes overall weights and buckets with commonly 90-120 m^3 volume; and their market price may extend up to 100 million US dollars (Townson *et al.*, 2003). Draglines should continuously be operated under suitable conditions with minimized breakdowns since indirect cost due to production loss is incontrovertibly high. This situation raises the importance of maintenance strategies applied for draglines.

In recent decades, philosophy behind maintenance has varied consistently due to the changes in complexity of designs, advances in automation and mechanization, adaptation to the fast growing market demand, commercial computation in the sectors, and environmental issues (Figure 1.1). In mid-forties, simplicity of the designs, limited maintenance opportunities, and immaturity of the trade culture made enough to perform only *fix it when it broke* approach, i.e. corrective maintenance, after failures. Following World War II, competition between countries and excessive demand led application of preventive measures in maintenance programs as consequence of more complex system designs, requirements to control mechanism availability and maintenance cost. The last quarter of the 21th century made essential to develop more conservative and preventive maintenance policies in order to ensure safety, reliability, and availability of systems with longer lifetime and cost effectiveness.

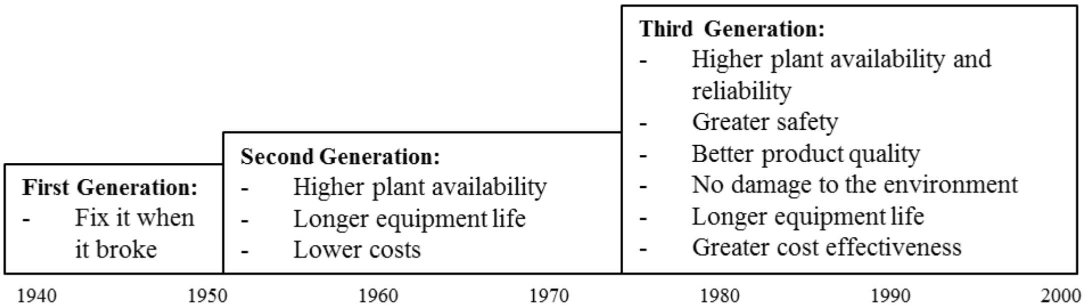


Figure 1.1 Development of Maintenance Philosophy (Moubray, 1997)

A machinery system is exposed to maintenance actions serving for either preventive or corrective purposes. Corrective maintenance, i.e. run-to-failure maintenance, is carried out after failure to recover system back to the functional state. On the other hand, preventive maintenance intends for predicting failures and taking precautions against breakdowns by repairing or replacing broken elements in system within the pre-estimated intervals. Preventive maintenance provides the longevity of systems via eliminating potential failure risks and reducing direct and indirect costs due to production losses. Draglines are maintained preventively only in weekly inspections without validating its effectiveness and optimizing inspection intervals. Adaptation of the innovations to dragline maintenance activities are rarely observed in mine sites; and portion of corrective maintenance in dragline maintenance budget still keeps its priority. Enhancement of preventive insight in maintenance plans is vitally important for the continuity of delay-free operations. In this sense, reliability-based stochastic approaches can be beneficial to detect the weakest links in a system and to build up preventive models by estimating time-dependent failure behaviors of system elements.

In recent years, there is an increasing trend in studies on reliability and maintenance engineering which concern about the characterization, measurement, and analyses of system failures to eliminate unplanned obstructions and to raise availability of systems. The term *reliability* basically answers the question “how reliable is the system in the elapsed time”. It is the indicator of failure intensity of system in operation. In this regard, reliability-based maintenance program can be used as a tool to enhance the availabilities of draglines by building proper preventive maintenance policies for critical components in the system. In addition, deductive algorithm of reliability methods may assist to realize root-causes of dragline breakdowns.

1.2 Problem Statement

The design of a qualified system motives engineers to manufacture product with high reliability, longevity, and minimal maintenance cost in addition to satisfying its functional requirements. Increase in the complexity of a system boosts the severity of the time-dependent availability since many components may lead to breakdown of system in short to long-term. In mining industry, demanding working conditions and high rate of machine utilization generally cause frequent failures of machinery components and compulsory pause of production in the sequel. Commercial pressure on mining sector for continual production forces maintenance staff to recover the failed machine back to functional state in short periods. Frequency of corrective maintenance increases operating cost and also negatively affects production scheduling. Researches showed that 40 to 50% of the equipment operating cost is spent on only maintenance expenses (Forsmann and Kumar, 1992) which is approximately equal to 20-35% of the total operating cost in a mine (Unger and Conway, 1994). In addition to direct cost of maintenance, length of downtime induces indirect costs due to production losses, delays in scheduling, and even deterioration of company image in industry. For Australian coal mines, it was realized that production loss based on unplanned maintenance may reach to 10% (Clark, 1990). Moreover, there is another hidden cost due to the aging and early death of machines due to improper maintenance works. Rapid progressive of aging problem leads to replacement of machines prior to their expected mean lifetimes. In addition to the cost factors, high frequency of the failures and unorganized structure of maintenance may lead to rise in occupational injuries. The USA Mine Safety and Health Administration (MSHA) data between 2001 and 2003 pointed out that 15% of the recorded mining injuries in the United States appears to happen during maintenance activities (Smith *et al.*, 2004). Most of the negative issues mentioned above are generally due to unplanned work-flow of maintenance programs and *fix it when it broke* approach in maintenance policies. In this sense, planned preventive maintenance policy can assist to reduce unexpected cost and maintenance injuries and to keep the production as scheduled. Figure 1.2 shows that how preventive maintenance can contribute to the reduction of total maintenance cost by lowering corrective cost item.

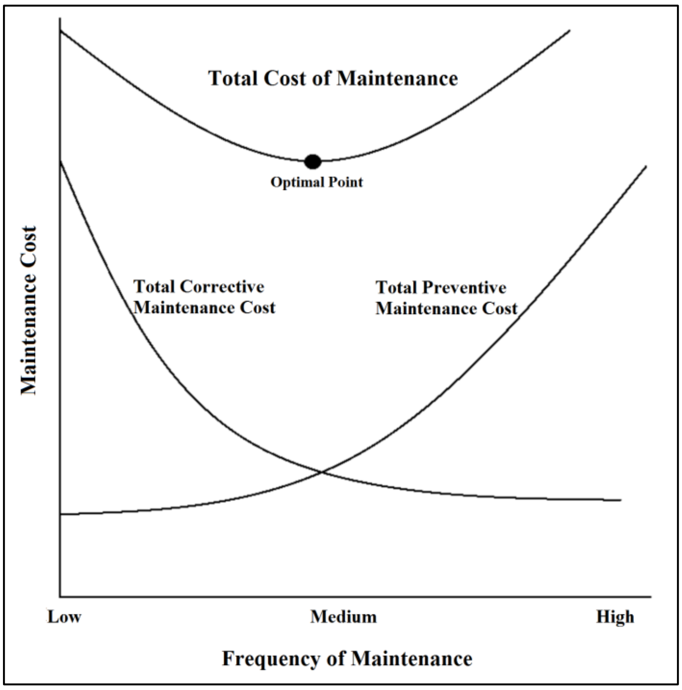


Figure 1.2 Effect of Preventive Maintenance on the Total Maintenance Cost

Draglines serve as single-unit stripping machines in open-cast coal mines to remove overburden covering top layer of orebody. They are massive and complex systems which embody different combinations of motor and generators, structural elements, and numerous components enabling to perform the earthmoving operation. These electrical and mechanical parts operate in various lifetime periods; and failure of any parts can eventuate in halting of whole machinery. Estimation of lifetime characteristics for working parts during operational period of system is important to forecast failures inducing breakdowns. Detailed and analyzed reliability study using failure behavior of machinery components may help to examine appropriateness of currently adopted maintenance program and to generate preventive maintenance policy regarding functional importance of each component in the machinery.

1.3 Objectives and Scopes of the Study

The main objective of research study is to develop reliability-based maintenance optimization model for Page and Marion draglines utilized in Tunçbilek Coal Mine. Constituents of this objective cover: (i) development of a system reliability model which identifies all structural dependencies between sub-units and components, (ii) simulation of currently utilized maintenance policy for the draglines considering cost and availability measures, (iv) optimization of the maintenance policy using stochastic replacement and inspection models, (v) detection of maintenance-critical components using risk-based reliability allocation models, and (vi) demonstration of cost-effectiveness for the optimized maintenance policy.

The scope of this study covers only two draglines currently operating in Tunçbilek coal mine and the maintenance data utilized for the study is for 1998-2011 period. Details of maintenance activities and cost values used in the thesis were specified considering opinions of dragline maintenance experts in Tunçbilek coal mine. The cost values are up-to-date values of year 2015.

1.4 Research Methodology

This research study utilizes statistical and probabilistic approaches to investigate the time-dependent reliability of draglines and to develop an optimization platform for maintenance of these earthmovers. Graphical illustration of the research methodology is given in Figure 1.3. Main stages of the research methodology is as follows:

i. Preprocessing of data: (a) Data in between 1998 and 2011 was acquired. It covers the breakdown information of two draglines, Page 736 and Marion 7820, which are still utilized in Tunçbilek coal mine owned by Turkish Coal Enterprises. (b) Dragline was divided into seven subsystems regarding their functional states in system; and individual components were distributed to subsystems. (c) Time between failures and time to repair data were assigned to individual components. (d) Grouped data was statistically tested to detect possible trend, independency, autocorrelation, and outlier occurrences.

ii. System Reliability Analysis: (a) Reliability of individual components were evaluated using general renewal process or best-fit distributions according to data trend behavior. Lifetime characteristics of components were identified using Reliasoft Weibull++7 software. Parameters of each model were analyzed to comprehend failure behaviors and expected lifetimes of components. (b) Structural dependency in the system was identified using Reliasoft Blocksim++7 to build up system reliability model. (c) Failure rate, reliability, availability, and reliability importance were utilized to designate failure intensities (functional criticality) of components in the system.

iii. Maintenance Policy Modelling: (a) Current maintenance policy of draglines applied in the mine was simulated in Reliasoft Blocksim++7 to evaluate expected downtimes of draglines due to failures and compulsory breaks in shifts and inspections. (b) In optimization stage, age-replacement policies were developed to examine the feasibility of preventive replacement for the components in wear-out period. (c) An algorithm was generated to find out the optimal inspection intervals for draglines. This algorithm considered the scheduled halts during shifts and inspections, random lifetime and repair behaviors of system components, and their effects on system in case of failures. It aimed to minimize overall maintenance cost via investigating effect of inspection intervals on the cost. (d) A risk-based reliability allocation model was developed to reveal the most critical components.

iv. Result Interpretation: (a) Cost effectiveness of the improved model was interpreted compare to the previous policy (b) Sensitivity of corrective and preventive maintenance costs to a maintenance policy were evaluated. (c) Contributions of optimization study to the current maintenance policy were assessed.

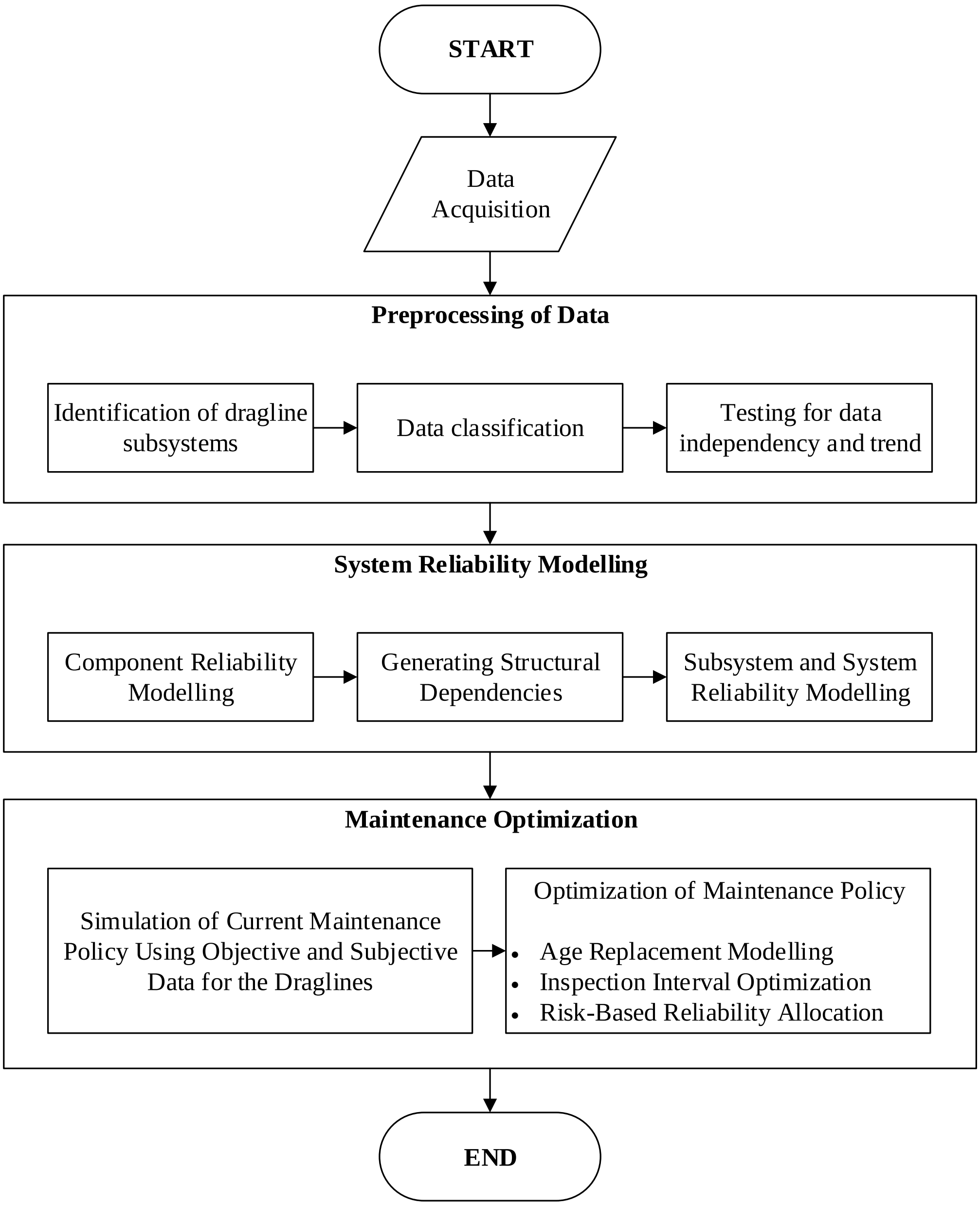


Figure 1.3 Research Methodology of the Thesis Study

1.5 Significance and Expected Contributions of This Thesis

Researches to examine maintenance of mining machines are rarely observed in the literature. They are generally lack of combining reliability and stochastic preventive maintenance models. In addition, there is no observed thesis or dissertation about the maintenance policy of earthmovers utilized in mining. This thesis study fairly contributes dragline maintenance by developing generic preventive models for critical components using retroactive failure data. The dissertation implement a generic cost-effective inspection optimization algorithm, considering corrective and preventive maintenance costs, random component lifetimes, and random repair durations. Therefore, the research gives opportunity to investigate the contributions of corrective and preventive maintenance on total maintenance cost for changing inspection intervals. The developed methodologies in the thesis can be applied for reliability assessment and maintenance optimization of any machinery system. Therefore, decision makers in machinery maintenance can apply these methodologies to their own systems in order to investigate feasibility of their current maintenance strategy or to develop new cost- and availability- effective maintenance policies.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

An extensive literature survey was carried out to comprehend the underlying theories and methodologies regarding reliability and maintenance of systems. The literature survey covers the issues on system effectiveness factors, reliability and maintenance concepts, system reliability models, stochastic modelling of maintenance policies, and recent studies on maintenance and reliability of mining systems.

2.2 Performability Factors of Engineering Systems

The origin of the word *system* comes from Greek word of *systema* which denotes leaguing together and it basically signifies the union of interoperable components holding individual restricted capacities and operating together to manage a mutual mission in a prescribed working condition with a desired success (Wasson, 2006). Performance of a system may be influenced by various factors originated from manufacturing process, utilization conditions and environment considerations. In this sense, Misra (2008) discussed the effectiveness factors under the terms of performability, dependability, sustainability, survivability, safety, reliability, maintainability, and quality as illustrated in Figure 2.1. These terms are called as 3S-parameters (Survivability-Safety-Sustainability).

Performability was firstly introduced by Meyer (1980) to interpret the effectiveness of monitoring systems for NASA aircrafts. In early times, performability only covered the topics of reliability, maintainability, and availability. Later on, accessional requirement on the definition of system effectiveness forced engineers to think about different attributes of system performance. In addition to the economy and safety aspects, unfavorable effects of the systems to the environment were analyzed within the context of progressive perspective of the 21st century. Eventually, the considerations were gathered under the issues of dependability and sustainability to advance the meaning of performability and to provide a broad scanning on the subject as shown in Figure 2.1. Hereby, systems improved to satisfy the necessities of society in various categories may run in safe conditions for both systems itself and the environment via considering the performability factors.

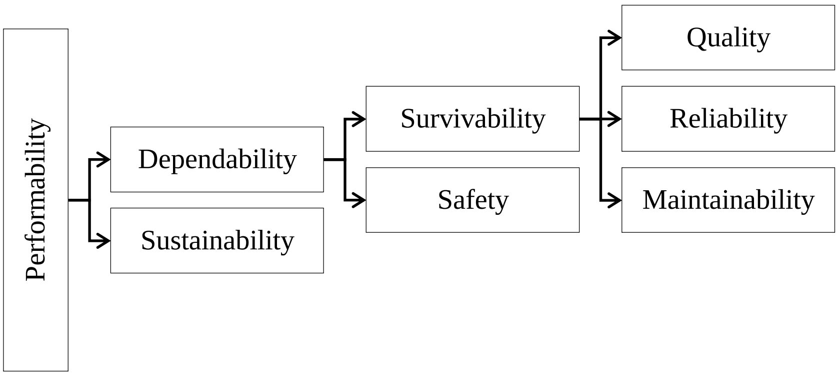


Figure 2.1 Performability Factors of Engineering Systems (Misra, 2008)

Sustainability issue arises as a requirement of 21th century where interaction between human, environment, and technology dramatically increases. On the other hand, performance factors for design and utilization of the system are accumulated under *dependability* topic as survivability and safety. The term *survivability* may be to quality, reliability, and maintainability issues as seen in Figure 2.1.

Quality is a qualitative measure to identify *goodness* of the system. Definition of the term passes in ISO 3534 as "the totality of features and characteristics of a product or service that bear on its ability to satisfy stated and implied needs". This partially intangible concept refers the requirements or specifications of the system that can be measured between very well to very bad (Verma *et al.*, 2010). Quality of any electronic or mechanic system is directly related to raw material, fabrication process, and technology utilized in production steps.

In addition to quality, *reliability* issue includes qualitative and/or quantitative analysis of a system to measure the success to keep system functionality without failure in a specified time interval and environment using interdisciplinary approaches of engineering, probability, and statistics. Reliability holds four main parameters as probability, adequate performance, time, and operating and environment conditions (Aggarwal, 1993). Reliability analyses reveal substantive results about operating performance of systems if boundaries of systems to be analyzed are determined precisely. A reliability analysis gives opportunity for (i) investigation of the functional continuity in working systems, (ii) forecasting possible interruptions and their consequences, and (iii) developing a conservative and optimal maintenance policy.

Maintainability concerns about the probability of an inoperative system to be restored to functional state in certain downtime (Xie *et al*., 2004). Maintainability can be improved in both designing stage of a system to measure reparability and serviceability of systems against breakdowns and operation stage of systems to explore efficiency of ongoing maintenance program. Maintainability is a kind of downtime management investigating system halts due to administrative, logistic, and active repairing processes (Figure 2.2).

Differently from survivability issue, *safety* is another parameter to be considered for dependability assessment. Safety identifies possible hazards and their risks that can arise during the operation of a system and related precautions to diminish potential adverse consequences of resultant hazards. To eliminate or minimize potential risks for engineering systems, safety requirements are implemented based on both national and international standards regulated by official organizations such as, European CE Mark Directive and US FDA (O'Connor, 2008).

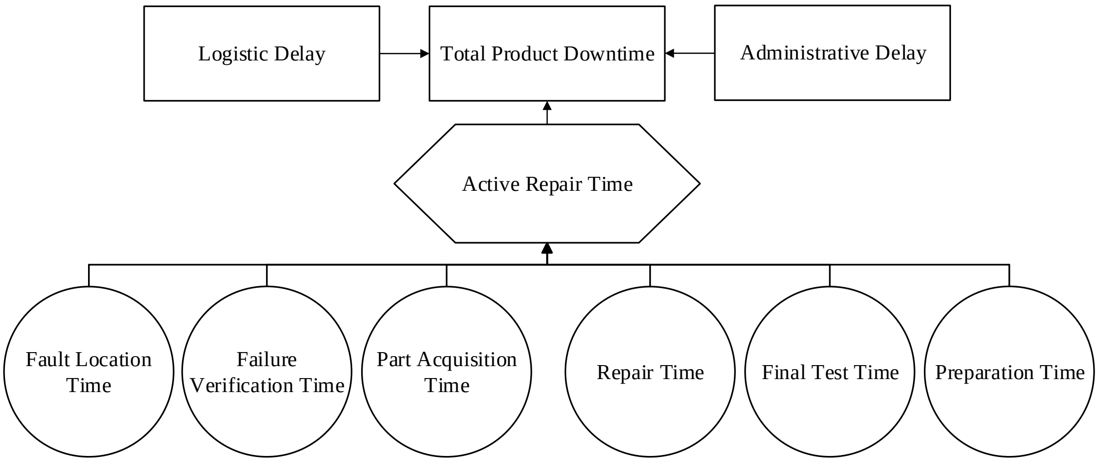


Figure 2.2 Operational Downtimes of Systems (Modified after Dhillon, 1999)

This thesis study focused on reliability and maintainability concepts of dragline using available failure and repair data. Other effectiveness factors as quality, safety, and sustainability can be investigated in future studies by acquiring data during design, manufacturing, and operation periods. Researches on the quality of dragline can focus on the design and manufacturing stages of the machine while safety and sustainability issues can be investigated regarding human-machinery and/or machinery-environment interactions in both manufacturing and operation periods.

2.3 Reliability Concept

According to Elsayed (2012), reliability can be defined as probability of a system to operate properly without any halt in a certain time period under specified operating conditions. Reliability assessment requires consideration of three main issues: intended function, determined time zone, and stated conditions. Intended function delimitates boundary of reliability analysis. According to Yang (2007), a system function can be classified due to the failure criteria as binary state, multistate, hard failure, and soft failure. If the function forced to be in either success or failure, i.e. 1 or 0, the criterion can be called as binary state. Conditions of the binary failure are obvious and objective. In case that the operating ability of the system is in either success or partial success or failure, level of the reliability is frequently subjective and called as multistate. If function of a system fails catastrophically, this condition is called as hard failures. Lastly, soft failure is the partial loss of operating ability that results in multistate products. In addition to intended function type, period of time is the main consideration to quantify the reliability since the reliability is a function of time. Time period to be assessed can be about warranty time, scheduled operation time or another intended period of time. Besides the time factor, operation condition is also critical to evaluate system model realistically. The reliability conditions can describe with system behaviors covering mechanical, electrical, thermal or another level of product property.

2.3.1 Common Mathematical Expressions in Reliability

Reliability concept utilizes probabilistic approaches to quantify the operational stability of systems. Probabilistic definition of reliability function, i.e. survival function R(t), and unreliability function, i.e. failure function F(t), can be expressed mathematically as in Equations 2.1-2.6. Failure probability density function (PDF), i.e. f(t), is basically time-dependent probability of a system to fail (Equation 2.1). It is actually a frequency curve of failure occurrences. In an infinite period of time, PDF is equal to 1 since it ensures a certain failure condition as shown in Equation 2.2 (Lazzorini *et al.*, 2011).

$$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \tag{2.1}$$

$$\int_0^\infty f(t)dt = 1 \tag{2.2}$$

For time t, probability of the system not to fail in a random failure time t_f is stated in Equation 2.3 (Lazzorini *et al.*, 2011). This situation refers survival probability of system, i.e. reliability, at time t. It can be also expressed as the area under the failure probability density function at right-hand side of the time, t, as in Equation 2.4 (Lazzorini *et al.*, 2011).

$$R(t) = P\{t_f > t\} \tag{2.3}$$

$$R(t) = \bar{F}(t) = \int_t^{\infty} f(t)dt \tag{2.4}$$

Since sum of probabilities to survive and to fail is equal to 1, failure function can be defined as in the Equation 2.5 (Lazzorini *et al.*, 2011). It is also the area under the failure probability function between time 0 and time t as given in Equation 2.6 (Lazzorini *et al.*, 2011). Exponential, Weibull and lognormal distributions are commonly utilized distribution to identify f(t).

$$F(t) = 1 - R(t) = P\{t_f < t\} \tag{2.5}$$

$$F(t) = \int_0^t f(t)dt \tag{2.6}$$

In the reliability studies, some statistical measures are extensively utilized to characterize failure behaviors. Statistical values help to realize central tendency of the distribution and spread of the data in the density function. The most frequently utilized statistical measures are mean, empirical variance, empirical standard deviation, median, and mode. In addition to general statistical terms, mean time to failure (MTTF), mean time to first failure (MTTFF), mean time between failures (MTBF), failure rate (λ), and B_q lifetime are commonly utilized in reliability.

As Levin and Kalal (2003) mentioned, MTTF is used to define the reliability of non-repairable systems. On the other hand, MTBF is a term used to describe the reliability of reparable systems and refers the average time period between the failures. However, it should be noticed that a repairable system can consist of non-repairable sub-components. Therefore, lifetime of a repairable system may also be evaluated in terms of MTTF values of non-repairable system elements. MTTF is expressed mathematically as in Equation 2.7 (Ebeling, 2010). It is sometimes notated as $E(t)$ which means mathematical expectation.

$$MTTF = E(T) = \int_0^{\infty} t\, f(t)dt = \int_0^{\infty} R(t)dt \tag{2.7}$$

According to the reliability and maintainability standards such as, DEF-STAN-00-40 and MIL-HDBK-217, MTBF can be defined as in Equation 2.8 (Kumar *et al.,* 2006). In Equation 2.8, T refers the total operating time and n is the number of failure during the period covering the stated operating time. MTBF is equal to MTTF if the maintenance after failure recovers the system to as good as new condition.

$$MTBF = T/n \tag{2.8}$$

On the other hand, MTTFF estimates mean time to the first failure. For new reparable systems, it can take a long time to face with first failure. Therefore, it is beneficial to consider failure behavior after the first failure when establishing a maintenance schedule. Differences between the mean time terms can be examined in Figure 2.3.

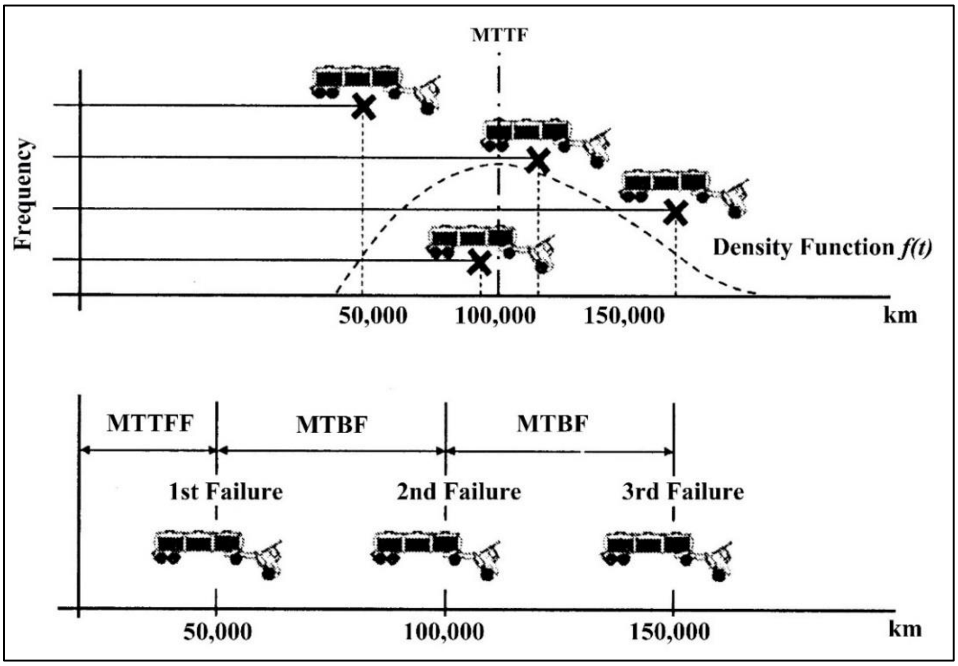


Figure 2.3 Mean Time Parameters (Modified after Bertsche, 2008)

In addition to the mean time parameters, B_q lifetime estimates the time point where the failure probability is $\% \, q$. B_{50}, B_{10}, and B_1 are the frequently utilized $B_q$lifetime measures in reliability studies. Lastly, one of the common parameters to express reliability and failure behavior of systems is failure rate (λ). This parameter gives expected number of failure at time t, it is calculated by ratio between failure and survival probabilities, $f(t)/R(t)$. Cumulative failure (hazard) rate, i.e. $H(t)$, in an interval can be obtained using Equation 2.9 (Kumar *et al.*, 2006).

$$H(t) = \int_0^t \lambda(x)\, dx \tag{2.9}$$

2.3.2 System Reliability Analysis

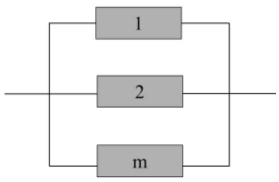
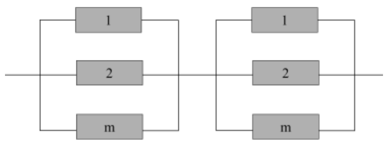
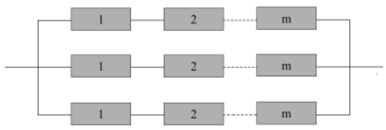
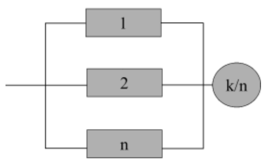
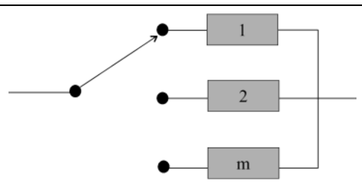
System is a combination of subsystems which carry out separate tasks under a common-target working structure. Reliability analysis can be performed to examine failure behavior of whole system or only specified subsystems. Each subsystem can be regarded as an individual system by itself.

Reliability studies are handled in two groups as repairable and non-repairable ones. Non-repairable systems cannot be restored after failures and they are placed with the new ones. Best-fit distributions are utilized to investigate the time-dependent reliabilities of these systems. On the other hand, repairable systems are the systems that can be returned into functional states after failures via repairing activities. Repairable systems can include non-repairable components or subsystems. For instance, an individual light bulb is non-repairable system. However, a traffic light mechanism is a repairable system which holds three non-repairable signal lights. In this sense, mining equipment and machines can be considered as repairable systems.

In recent decades, various methods have been improved and modified for investigation of repairable system reliability. These methods intend to evaluate reliability in both qualitative and quantitative measures. Reliability block diagrams, fault tree analysis, Markov process, and renewal process can be utilized to evaluate system reliability quantitatively where failure modes and effects analysis, result process analysis, design reviews, check list, and fault tree analysis are common in qualitative reliability analysis (Bertsche, 2008). This section only focuses on reliability block diagrams, failure modes and effects analysis, fault tree analysis, and Markov process. Renewal process will be discussed in Section 2.5.

In practice, a system is generally identified with a network illustration where subsystems are linked to each other in various configurations. In this sense, reliability block diagrams (RBD) offer a conventional way to investigate functional and structural correlations between components. RBD introduces schematic and logical illustration of blocks in various connections such as, series, parallel, series-parallel combinations, k-out-of-n, and standby. Block configurations and their reliability equations can be viewed in Table 2.1.

Table 2.1 Configurations of Reliability Block Diagrams (Kumar *et al.*, 2006)

Type	**Configuration**	**Equation**
Series		$R_s(t) = R_1(t)\ x\ R_2\ (t)\ x \dots x\ R_m(t)$
Parallel		$R_s = 1 - \prod_{i=1}^{m}(1 - R_i)$
Series-parallel		$R_s = \prod_{i=1}^{m} 1 - \prod_{j=1}^{n}(1 - R_{ij})$
Parallel-series		$R_s = 1 - \prod_{i=1}^{m}(1 - \prod_{j=1}^{n} R_{ij})$
K out of n		$R_s = \sum_{i=k}^{n}\binom{n}{i} R^i(1-R)^{n-i}$
Standby		$R_s(t) = \sum_{i=0}^{m}\frac{[\int_0^1 \lambda(t)dt]^i \exp(-\int_0^1 \lambda(t)dt)}{i!}$

Series and parallel network are the most frequently utilized configurations in RBD. Series network points to high functional dependency between the elements, means that operational continuity of a system can be achieved only with survival of all components. In parallel configuration of a system, the functionality succeeds until one component remains to operate. Parallel network indicates that interruptions due to failure of any component can be compensated with another working component. In addition, system can be configured in combination of series and parallel networks as series-parallel and parallel-series as given in Table 2.1.

Moreover, one special configuration is k-out-of-n network utilized for the system where at least k out of n units should work for operability of the system. This working condition means that functionality of n-k failed components can be tolerated by k surviving components. K-out-of-n system can be identified as in Table 2.1 if all components are identical and functionally independent.

Another configuration in RBD is standby network, also called as redundant systems. In this system, one unit works while other units are hold in standby condition. In case of failure, standby unit starts to operate instead of the failed unit. If no delay is assumed during transition from the failed unit to the standby one and all units are identical, equation in Table 2.1 can be utilized.

In addition to RBD, Failure modes and effects analysis (FMEA) is another common qualitative methods in system reliability investigation. It is utilized to describe, analyze, and document the potential failure modes that can occur within a system and the effects of those failures on the system efficiency (Murthy *et al.,* 2008). If FMEA also includes criticality analysis for failure modes, the method is called as Failure Modes, Effects, and Criticality Analysis (FMECA). Differently from FMEA, FMECA allows to examine system reliability quantitatively. This criticality analysis uses two methods, (i) Risk Priority Number (RPN) utilized in industrial areas commonly. It uses ranking values for failure occurrence, severity, and detection and (ii) military standard technique with code of MIL-STD-1629 which is performed in high-security areas such as, military defense, aerospace, and nuclear plants with ranking the criticality of failure modes (Stapelberg, 2009).

FMEA aims to form a perspective to comprehend all causes of failure modes and resultant effects on operability of components and systems. Qualitative evaluation using FMEA is generally achieved answering the following questions (Murthy *et al.,* 2008): (i) What is the probability of component failure modes to occur? (ii) Which interactions might cause failure modes? (iii) What are the resultant effects of the probable failures? (iv) How might the failures be detected? (v) What are the ways to prevent these failures at early stages?

FMEA is an informative process covering definition of the functions, definition of the functional failure, determination and assignment of the failure modes for the failures, and effects of the failure modes on the mechanism (Marquez, 2007). Before initiating the process, symptom, mode, cause, and effect should be well-defined (Smith, 2007). Failure symptom is an early indicator of approaching failure. However, some failures may suddenly appear without revealing any symptom in many cases. Secondly, failure mode answers the question “what is wrong?”. Failure modes can be described in various ways, e.g. bent, ruptured, sheared, cracked, and frayed. In addition, failure cause investigates the underlying reasons of failures. Lastly, failure effect describes the potential consequences of the failure.

FMEA might be classified into three groups due to application area as design-level FMEA, system-level FMEA, and process-level FMEA (Ireson *et al.*, 1995). Design-level analysis concerns about the parametric validity of product design by identifying failure modes for components in subsystems and evaluating via alternative design ways to improve the reliability of system design. System-level FMEA interests in hierarchical system assessment in the preliminary product design to minimize failure risk. Lastly, process-level analysis deals with the prevention and description of potential failures in fabrication and assembly stages.

Another reliability assessment method, fault tree analysis (FTA) presents deductive and systematical system reliability assessment using graphical illustrations to symbolize internal and external reliability considerations of system elements. It gives opportunity to evaluate system reliability both qualitatively and quantitatively. This structured method was first developed by Bell Laboratories in corporation with Boing and American Air Force to identify all potential risks of an unintentional launch of ballistic missile between 1950 and 1960 (Berk, 2009). Then, it was started to be utilized extensively for critical and complex systems especially in aerospace and nuclear industries.

This analysis method covers logical, systematic, and effective attitude to realize the weaknesses of pre-defined top event with employing *top-to-down* definition structure (Kumar *et al.*, 2006). Fault tree does not evaluate all failure modes in the system if they are irrelevant of the top event. Deductive nature of the process conveniently reveals the effectiveness of sub-events on the top event. Developing a FTA starts with identification of top event and proceeds with assignment of down-events using interaction symbols.

Symbols used in FTA can be grouped as events, gates, and transfer symbols (Berk, 2009). Events symbolize the incidents themselves that occur and cause the failures. They can be classified as command event, basic failure event, normal event, human error or undeveloped event, and condition event. Command event is in rectangle shape and it refers the incident originated from its down-events, i.e. basic failure events. These basic failure events are illustrated with circle and they present how the command event can fail. Normal events are house shape and they indicate the events normally expected to occur. Their probabilities are fixed and take the binary values, i.e. 1 or 0. Human error or undeveloped event is diamond shape. Human error is a failure event due to the operational or technical errors of working staff. On the other hand, undeveloped events are considered as basic failure events that don not require further solution. Condition event is in ellipsoid shape and it shows the restriction or inhibiting condition that can be applied to any gate.

In addition to the events, gates point to the relationships between the events. AND gate and OR gate are the most frequently utilized gates to define component dependencies in systems. AND gate means that failure of one event depends on the occurrence of all sub-events. On the other hand, OR operator states that occurrence of at least one input event is enough for the occurrence of the output event. There are also some special gates such as, voting (k-out-of-n), inhibit, priority AND, and XOR. Voting gate symbolizes the cases where at least k out of n input events should take place for the occurrence of output. Inhibit gate refers a restriction case that occurrence of the output event depends on an external event as well as the input events. Priority AND is a special case of AND operator where the output event happens if the input event eventuates in a specific sequence. Besides, XOR is a special version of OR gate where the output incident occurs if exactly one input arises. Boolean and binary expression of the gates and their symbolic presentations can be viewed in Table 2.2 and Figure 2.4, respectively.

Table 2.2 Boolean Expression Fault Tree Gates (Bertsche, 2008)

Name	Synonym	Boolean Equation	Operator	Binary Description		
				x_1	x_2	y
Negation	NOT, negator, inverter	$y = \bar{x}$	$\bar{x}$	0 1	- -	1 0
Disjunction	OR	$y = x_1 \vee x_2$ $= x_1 + x_2$	$\vee$ +	0 0 1 1	0 1 0 1	0 1 1 1
Conjunction	AND	$y = x_1 \wedge x_2$ $= x_1 . x_2 = x_1 \, x_2$ $= x_1 and x_2$	$\wedge$. and	0 0 1 1	0 1 0 1	0 0 0 1

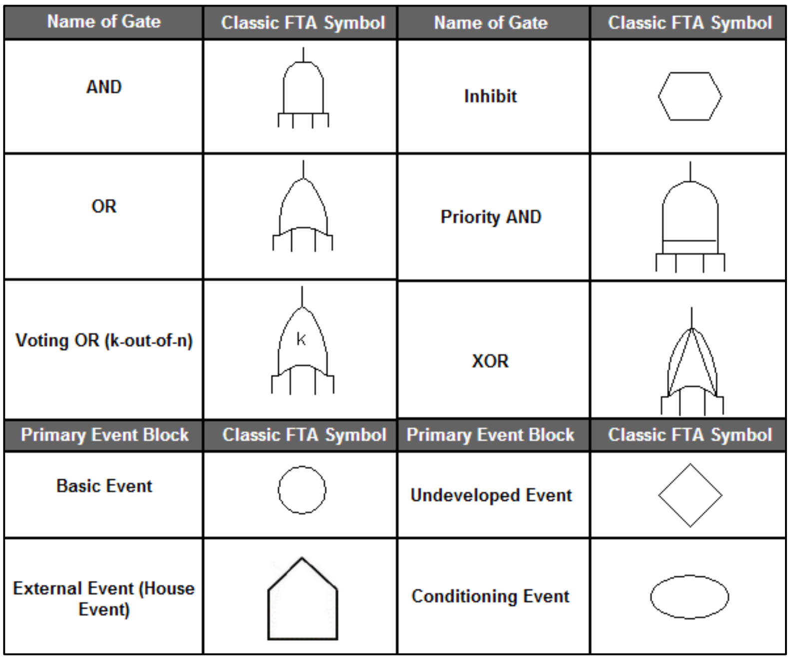


Figure 2.4 FTA Gate and Event Symbols (Reliasoft R&D Staff, 2004)

The last reliability method, Markov analysis is a *memoryless* stochastic process to determine the probabilistic behavior of the systems in future using the present working state (Marquez, 2007). This stochastic analysis is free of past behavior of system and only utilizes its present state and age (Kumar *et al.*, 2006). Assumptions in Markov analysis are (Shooman, 1990):

(i) Failure and repair rates utilized as transition rate are kept constant. It means that Markov method defines failure and repair behaviors with exponential distribution.
(ii) Components are independent of each other.
(iii) Probabilistic transition of one system state in Δt time is stated as $\lambda\Delta t$ or $\mu\Delta$, where λ and μ are failure and repair rates respectively.
(iv) Probability of more than one transition in Δt time is ignored.

Markov analysis can work with discrete or continuous space of states and time. Discrete state and discrete time-based Markov analysis is called as Markov chain while continuous state and continuous time-based Markov analysis is named as Markov process (Marquez, 2007). In addition, system state and time can be discrete and continuous or vice versa.

In Markov analysis, each system state refers different condition of the system. For instance, system state can be assumed as *fail* and *succeed*. Figure 2.5 presents a sample Markov chain which includes two identical components holding failure rate (λ) and repair rate (μ).

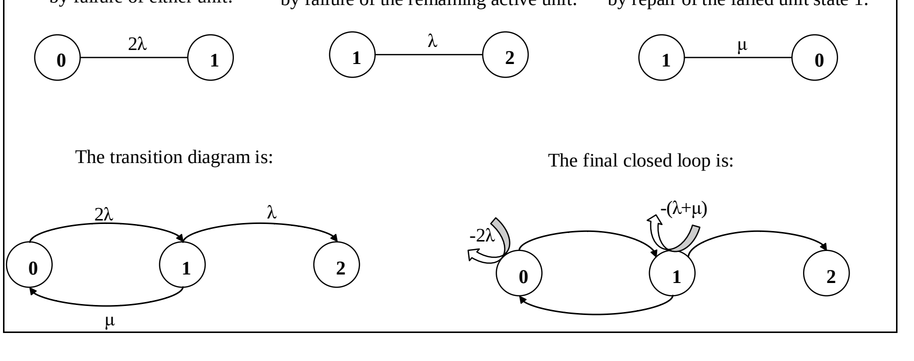


Figure 2.5 Transitions in Markov Chains (Smith, 2001)

The states of system in Figure 2.5 can be donated as (i) State-0, succeed of both components, (ii) State-1, one component operating other failed, and (iii) State-2, both components failed. Mathematical expressions of Markov analysis for simple systems and their derivative solutions can be investigated from Smith (2001).

2.4 Definition and Classification of Maintenance Activities

Maintenance can be identified as activities required to hold a system and its subsystems in operational state and to keep sustainability of production while minimizing operational cost (Stephens, 2010). Maintenance cost can be classified as direct costs including physical expenses and indirect cost which is nonphysical consequences of system halts due to maintenance. Amount of cost may reach to substantial levels if downtime management of system fails and unplanned breakdowns induce successive negative effects on system functionality. In addition, increasing demand in industries and high-rate production cycle may raise failure frequency and resultant costs. This condition forces sectors to develop more conservative and preventive maintenance programs.

Portion of maintenance cost in operating cost of systems has raised dramatically in recent decades. Only in 1981, $ 600 billion was spent for maintenance of substantial plant systems in the USA and the amount was doubled in early 2000 (Mobley, 2004). One third of the maintenance expenses were observed to be wasted due to insufficient maintenance policies and/or techniques. In this sense, issues covering determination, testing and confirmation of proper maintenance program particular to systems hold vital importance for the longevity of the system operations. *Maintainability*, which is a phenomenon to control planned and unplanned failures, basically aims to satisfy system requirements to decrease factors such as, working hours, equipment, logistic expenses, skill level, and service area (Dhillon, 1999). In this basis, the maintainability defines a probabilistic approach considering spare part condition and maintenance crew capacity, and also optimal time intervals for repairing and inspection (Bertsche, 2008). On the other hand, a maintenance policy defines how to implement corrective and preventive activities with including also when and who questions.

Maintenance types can be categorized according to occurrence types of failures as planned and unplanned. Figure 2.6 visualizes branches of system restoration activities under planned and unplanned maintenance. Unplanned maintenance is performed in emergency cases when unpredictable failures occur. All effort in unplanned maintenance is given to only repairing and recovering the system without exploring causes of the resultant failure modes. In an unplanned maintenance, production schedule can suffer from holding inadequate amount of spare part and delays in breakdown management. Therefore, it is important to prevent unplanned maintenance as much as possible with conservative maintenance policies.

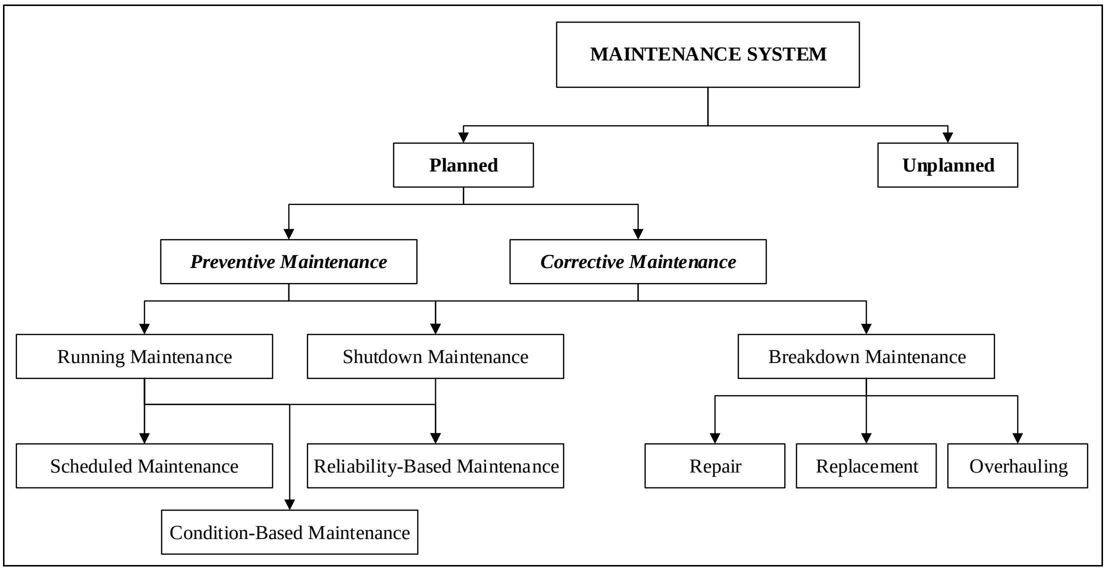


Figure 2.6 Types of Maintenance (Mishra and Pathak, 2004)

Planned maintenance operations can be aggregated under two major topics as preventive and corrective maintenance. Preventive maintenance forecasts possible failures via inspections, monitoring activities, and statistical analyzes while corrective maintenance is carried out only when a failure takes place. Percentage of maintenance activities according to their types in the United States are illustrated in Figure 2.7. It is realized from the figure that majority of maintenance activities is performed correctively with reactive action in case of failure.

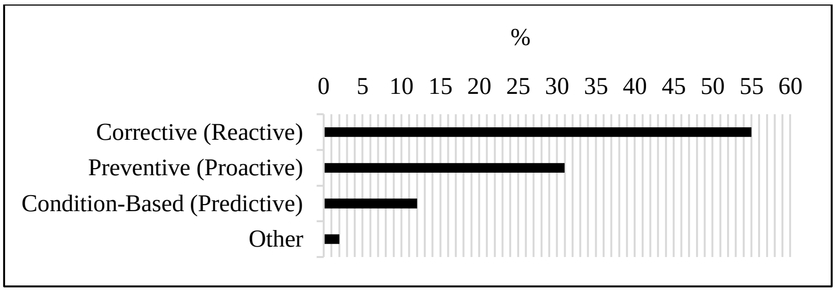


Figure 2.7 Percentage Distributions of Maintenance Activities (The USA Department of Energy, 2010)

Preventive maintenance can be described as “actions performed on a time- or machine-run-based schedule that detect, preclude, or mitigate degradation of a component or system with the aim of sustaining or extending its useful life through controlling degradation to an acceptable level”; and it can provide an economic saving more than 18% of the operating cost (The USA Department of Energy, 2010). Preventive maintenance aims to detect impairments that causes weakness in reliability and safety of systems using (i) lubrication and servicing, (ii) operational, visual or automated checking, (iii) inspection, functional test or condition monitoring, (iv) restoration, and (v) discard (Smith, 2007). Major mission of preventive maintenance is to protect system functionality by avoiding potential failures and resultant damages induced by aging, wear-and-tear, and other structural incompatibilities.

Corrective maintenance is a reactive action, also called as run-to-failure maintenance, which is carried out after the failure to restore failed components to functional state. It involves repairing or replacing of failed component and the related overhauling processes. Since the failures appear in random failure intervals, it is hard to forecast breakdown occurrence times. However, a planned corrective maintenance policy should be still available to organize maintenance activities in case of possible failures. Corrective maintenance program is performed via three steps as, (i) identification of failure zones by locating and evaluating non-operational regions, (ii) repairing or replacing the damaged parts to remove negative consequences of failures, and (iii) verification stage to ensure that replacing and repairing process bring system to a desired working level (Misra, 2008). Corrective maintenance follows the logic *if it is* *not failed, do not fix it*. It can be reasonable for new systems since maintenance does not emerge as a major problem. However, a long-time application of corrective maintenance policy alone can lead to inextricable and overpriced conditions since system suffers from aging and wear-and-tear problems. Since many industrial plants apply a maintenance strategy holding corrective measures by a majority and small portion of preventive activities, this condition induces additional costs for spare parts, excessive man-hours, high production loss, and low system availability (Mobley, 2004).

Condition-based maintenance, i.e. predictive maintenance, implements decision making algorithm by monitoring system condition consistently with depictive and corroborative data flow (Ben-Daya *et al.*, 2009). Since the mechanism of a system and internal components exhibit random mechanic and electronic characteristics that may lead to breakdowns, condition-based maintenance assists to collect early warning data prior to failures and it also eliminates time losses due to redundant inspections. Condition-based maintenance utilizes technologies such as, infra-red, particle discharge, corona detection, vibration, acoustical, and oil level analysis to monitor operating nature of systems (Misra, 2008). Most of the controls are carried out in a scheduled time when components are in service to reduce halts in planned operating schedule. Condition-based maintenance is not only monitoring process but also an optimization philosophy considering quality, availability, productivity, and profitability of systems. It provides actual mean-time-to-failure analyses with direct monitoring via maximizing time between corrective maintenance activities and minimizing unscheduled failures (Mobley, 2002). Besides nondestructive methods such as, operation parameter monitoring, thermography, tribology (oil analysis), and visual inspection, vibration monitoring is the most widely utilized monitoring type for mechanical systems, since the moving components can procure continuous data stream for vibration (Mobley, 2002). On the other hand, electronic system uses other techniques expect for vibration analysis to gather data.

Reliability-based maintenance program were initiated in the late 1960s since more apprehensive maintenance plans were needed to arise in the USA aviation sector. Later on, utilization area of the program was extended to nuclear power plant maintenance. Nowadays, reliability-based maintenance is adapted to the sectors where safety and reliability become a greater concern. Reliability-based maintenance gives opportunity to create an holistic view considering effects of subsystems and internal components on the whole system. To evaluate the system, following subjects are required to be answered (Dhillon, 1999): (i) Functions and performance criteria of the component in current working conditions, (ii) potential situations that the component's functionality may fail, (iii) factors effecting each failure, (iv) resultant negative conditions after failures, (v) importance of each failure, (vi) precautions against the failures, (vii) corrective action that may be applied where preventive maintenance is not proper.

Reliability-based maintenance program can be performed via combining corrective (reactive), preventive, condition-based, and predictive (proactive) actions as shown in Figure 2.8 (Afefy, 2010). Following steps can be performed for a complete reliability-based maintenance: (i) Determination of the system and data acquisition, (ii) qualifying the system boundaries, (iii) definition of functional issues of the system, (iv) failure mode and effect analysis, (v) logic tree diagram, and (vi) specifying the mission.

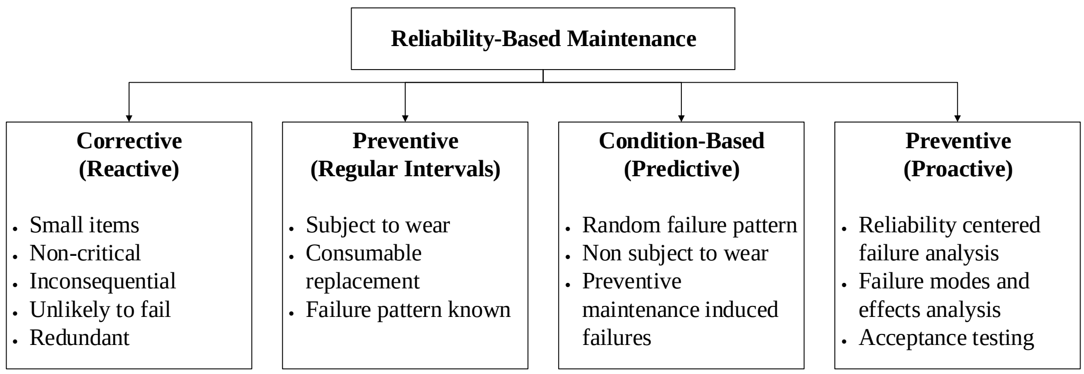


Figure 2.8 Utilization Areas of Reliability-Based Maintenance (Dhillon, 1999)

Merits and demerits of the maintenance activities according to their types can be investigated in Table 2.3. To sum up, a strategy to decrease the portion of corrective maintenance is significantly important to prevent the out-scheduled production due to the unexpected breakdowns. However, it is required to justify cost-effectiveness of preventive maintenance over corrective maintenance since redundant preventive activities may cause high amount of production loss. Therefore, maintenance plans should consist of effective and applicable preventive maintenance approaches. In this perspective, scheduled maintenance, reliability-based maintenance or real-time condition monitoring are emerging issues to be addressed to eliminate unplanned failures. Moreover, applicability and optimization of maintenance policies and effect of maintenance on system lifetimes can be examined mathematically using stochastic models. Section 2.5 will explain common stochastic approaches in maintenance modeling.

Table 2.3 Merits/Demerits of Maintenance Types (The USA Department of Energy, 2010)

Maintenance Type	Advantages	Disadvantages
Preventive Maintenance	• Cost-driven in various capital-intensive operations • Flexibility • Raised life-cycle of the equipment • Energy conversation • Decrease of the failures • Economic saving between 12% and 18% over corrective maintenance	• Possibility of catastrophic breakdowns • Labor-intensive • Some redundant maintenance activities • Negative effects of the redundant maintenance on the components
Corrective Maintenance	• Low initial cost • Less staff requirement	• Additional cost due to unplanned failure condition • Additional labor cost in case of overwork • Repairing and replacement costs of the components • Extra hazard occurrence in a secondary component or system
Condition-Based Maintenance	• Raise in the operational life of systems • Opportunity for great amount of corrective programs • Shortening in downtime periods • Decrease in the costs for components and manpower • Raise in the quality of products • Advanced health and safety conditions • Improved staff manner • Economic saving between 8% and 12% over corrective maintenance	• Additional expenses for the control devices • Additional expenses for the training of staff • Amount of saving not easily recognized by the management
Reliability-Based Maintenance	• The most productive maintenance type • Reduced costs by eliminating redundant inspections or overhauls • Optimized overhauling periods • Decrease in the possibility of instantaneous failures • Focusing on the most critical elements for maintenance • Reliability improvement • Root cause analysis	• High initial capital cost covering training, equipment, etc. • Amount of saving not easily recognized by the management

2.5 Stochastic Maintenance Models

There are various approaches for stochastic modelling of maintenance policies. Each one holds different assumptions on repair effectiveness and resultant system deterioration. These assumptions can be classified into five main categories as perfect, imperfect, minimal, worst, and worse repairs. Perfect repair assumes restoration of failed component into *as good as new* state. It is also called as *replacement*. After each repairing activity, component is assumed to be a new one. Perfect maintenance reduces the failure rate to the start rate level. On the other hand, minimal repair recovers the component to *as bad as old* state. It refers that the system is back to the condition just prior to the failure. Minimal maintenance keeps the failure rate at the same level. In addition, imperfect maintenance assumes that the recovered component gets younger but not to as good as new condition. It points to that component reaches a level between minimal and perfect repair. Failure rate with imperfect maintenance reduces after the maintenance but not to zero level. Moreover, worse maintenance implies that component is turned to a worse condition due to wrong maintenance strategy. Following a worse maintenance, failure rate after repair raises noticeably. Lastly, worst maintenance causes component to be non-functional and non-reparable, i.e. catastrophic failure state. Stochastic model generally consider that repairing is performed as perfect, minimal, or imperfect. Modelling techniques according to repairing assumptions are stated in Figure 2.9.

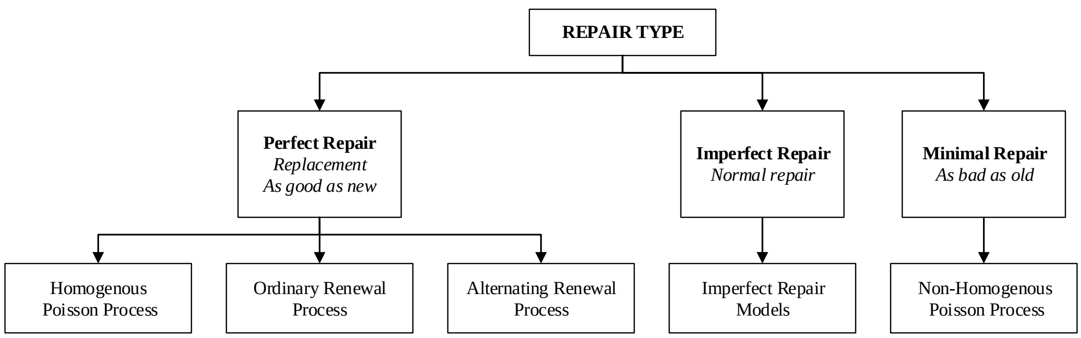


Figure 2.9 Maintenance Models according to the Repairing Assumption

Homogenous Poisson process, ordinary renewal process and alternating renewal processes can be utilized to define perfect repair. In case of minimal repair, non-homogenous Poisson process is one of the common method to model as bad as old conditions in maintenance. Various imperfect maintenance methods such as, (p, q) rule, $(p(t), q(t))$ rule, improvement factor method, virtual age method, shock model method, (α, β) rule, and multiple (p, q) rule can be used to analyze systems with normal repair.

2.5.1 Perfect Repair Models

Recovering condition of a system after maintenance can be sorted as worse than old, better than new, better than old but worse than new, as bad as old, and as good as new (Yanez *et al.*, 2002). In ordinary renewal process (ORP), failed component is replaced with an identical one or restored to original state, i.e. as good as new condition (Høyland and Rausand, 2004). Therefore, the process assumes that maintenance is carried out perfectly and it neglects aging problem of the systems.

Ordinary renewal process is basically a generalization of Poisson process where values of time between failures, i.e. survival times, are identically and independently distributed (Osaki, 1975; Natagawa, 2001). In other words, it is a counting process for non-negative and random numeric values $[N(t),\ t \geq 0]$ where $F(t) = Pr[X_k \leq t]$ (Dohi, 2002). This process is called as Homogenous Poisson Process (HPP) if distribution of survival times follows exponential distribution with constant failure rate. Formulations and related notations are illustrated in Table 2.4.

Ordinary renewal process considers only survival times between failures and neglect durations to recover the system, i.e. repair times. It is incapable of estimating the probability of system to be operable in any time, i.e. system availability. In this sense, Alternating Renewal Process (ARP) regards both uptime and downtime durations of system. Expected uptime is referred as mean time between failures (MTBF) for repairable systems or mean time to failure (MTTF) for non-repairable systems. On the other hand, expected downtime is called as mean time to repair (MTTR). Average renewal interval is estimated by the summation of MTTF (or MTBF) and MTTR (Rausand and Hoyland, 2004). Therefore, system availability can be estimated with MTTF/(MTTF+MTTR) for non-repairable systems and MTBF/(MTBF+MTTR) for repairable systems.

Table 2.4 Descriptive Equations of Renewal Functions (Dohi, 2002)

Equations	Definitions
$S_n = \sum_{1}^{n} X_n, \ \ S_0 = 0$	Cumulative time between failures
$N(t) = max[n: S_n \leq t]$	Number of failures until time t
$P[N(t) = n] = P[N(t) \geq n] - P[N(t) \geq n+1]$ $= P[S_n \leq t] - P[S_{n+1} \leq t]$ $= F^{(n)}(t) - F^{(n+1)}(t)$	The probability that the specified number of failures take place up to time t
$M(t) = E[N(t)] = \sum_{n=1}^{\infty} n\, P[N(t) = n]$ $= \sum_{k=1}^{\infty} P[N(t) \geq k] = \sum_{k=1}^{\infty} P[S_k \leq t]$ $= \sum_{k=1}^{\infty} F^{(k)}(t)$ $= F(t) + F * M(t) = \int_0^t m(x)dx$	Renewal function - Expected number of renewals for a time interval
$m(t) = \frac{dM(t)}{dt} = \sum_{k=1}^{\infty} f^{(k)}(t)$ $= f(t) + \int_0^t m(t-x)f(x)$ $= f(t) + \int_0^t f(t-x)m(x)$	Renewal density function
$\boldsymbol{X_n}$ Time between Failures for n^{th} period $\boldsymbol{f(t)}$ Probability density function of $\boldsymbol{X}$ $\boldsymbol{F(t)}$ Cumulative density function of $\boldsymbol{X}$ $\boldsymbol{f^{(k)}(t)}$ n-fold convolution of f(t) $\boldsymbol{N(t)}$ Total Number of Failure at Time t	

2.5.2 Minimal Repair Models

Perfect repair models neglects aging of system and assumes that maintenance recover the system to as good as new condition. On the other hand, non-homogenous process (NHPP), i.e. minimal repair, is a failure counting process utilized for the system where reliability degradation or growth is observed and failure data exhibits a trend behavior with monotone increasing or decreasing (Coetzee, 1997). Time between failures data where NHPP utilized holds non-identical distributions for different time intervals and exhibits ascending or descending failure rates. Since individual distribution functions fail to define this condition, power law function is extensively utilized in NHPP. Mathematical expressions for NHPP with power law can be examined in Table 2.5.

Table 2.5 Descriptive Equations of NHPP (Uzgören and Elevli, 2010)

Equations	Definitions
$\rho(t) = \lambda\beta t^{\beta-1}$	Power Law Function
$\hat{\beta} = \frac{n}{\sum_{i=1}^{n-1}\ln(\frac{t_n}{t_i})}$ $\hat{\lambda} = \frac{n}{t_n^{\hat{\beta}}}$	Best estimates of parameters for failure number-based interval
$\hat{\beta} = \frac{n}{\sum_{i=1}^{n}\ln(\frac{t}{t_i})}$ $\hat{\lambda} = \frac{n}{t^{\hat{\beta}}}$	Best estimates of parameters for time-based interval
$m(t) = \int_0^t \rho(t)dt = \int_0^t \lambda\beta t^{\beta-1}dt = \lambda t^{\beta}$	Renewal density function – Total number of failures 0-t period
$\boldsymbol{\lambda}$ Scale parameter of power law function	
$\boldsymbol{\beta}$ Shape parameter of power law function	
$\boldsymbol{n}$ Total number of failure	
$\boldsymbol{t_i}$ Observation period until i^{th} failure	
$\boldsymbol{t_n}$ Observation period until n^{th} failure	

2.5.3 Imperfect Repair

Perfect or minimal maintenance gives upper and lower extreme limits for effectiveness of maintenance. In practice, maintenance of the failed part may be in the range between minimal and perfect levels. It means that recovered component will be between as good as new and as bad as old states after maintenance. The reasons about why maintenance is performed imperfectly can be explained as follows (Brown and Proschan, 1983; Nakagawa and Yasui, 1987):

i. Maintenance of an irrelevant component,
ii. Semi-repair of a failed component,
iii. Damaging neighbor components while maintaining the relevant component,
iv. Wrong evaluation of failure mode for a component,
v. Delays in maintenance of interrupted component (waiting for the scheduled plan),
vi. Unable to identify hidden failures during inspections,
vii. Human-based errors,
viii. Faults in the replaced spare parts.

Imperfect maintenance models can be developed using seven common methods: (p, q) rule, $(p(t), q(t))$ rule, improvement factor method, virtual age method, shock model method, (α, β) rule, and multiple (p, q) rule (Pham and Wang, 1996; Wang and Pham, 2006).

Imperfect maintenance model using (p, q) rule assumes that repairing of the failed item is performed perfectly with the probability q and minimally with the probability of p. The condition $q = 1 - p$ is assumed in the model. Mathematical expression of (p, q) rule can be investigated in Figure 2.10 and Table 2.6, respectively.

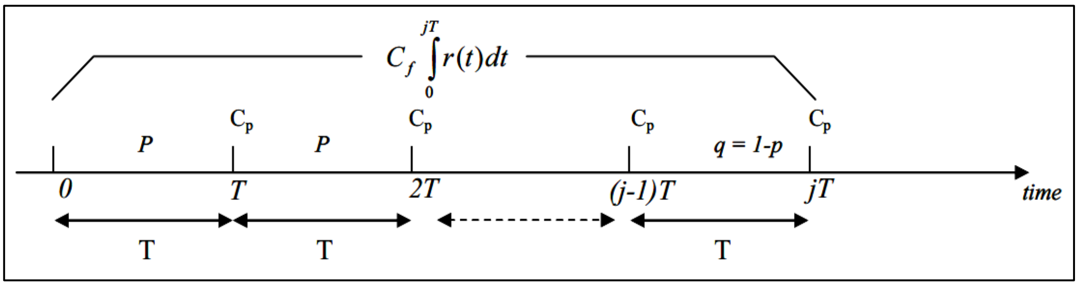


Figure 2.10 Imperfect Maintenance Using (p,q) Rule (Manzini *et al.*, 2010)

The model with (p, q) rule was extended to $(p(t), q(t))$ rule via including item age as a factor. Block *et al.* (1985) utilized this rule to demonstrate that the successive perfect repairs follow a time distribution with the related failure rate $r_p(t) = p(t)r(t)$. In addition, Block *et al.* (1988) modified the rule to find out the cost function of i^{th}

minimal maintenance and quantity of repair regarding conditions that the component will be preventively replaced (perfect repair) at age T; or perfectly (probability of $p(t)$) or minimally (probability of $q(t)$) repaired when failed prior to age T. Besides, Makis and Jardine (1992) formed a general technique to define imperfect corrective repairing at failure and imperfect preventive maintenance which keep the probabilities of $p(n,t)$ and $q(n,t)$ as perfect and minimal repair respectively. The models includes the probability of unsuccessful maintenance with probability of $s(n,t) = 1 - p(n,t) - q(n,t)$.

Table 2.6 Descriptive Equations of Imperfect Maintenance with (p, q) Rule (Manzini *et al.*, 2010)

Equations	Definitions
$EC[P,T] = \sum_{j=1}^{\infty} q\, p^{j-1} \left[jC_p + C_f \int_0^{jT} r(t)\, dt \right]$	Expected cost at the end of j^{th} period
$E[cycle] = \sum_{j=1}^{\infty} q\, p^{j-1} (jT)$	Expected time between perfect repairs (0, jT)
$UEC[P,T] = \frac{EC[P,T]}{E[cycle]} = \frac{\sum_{j=1}^{\infty} q\, p^{j-1} \left[jC_p + C_f \int_0^{jT} r(t)\, dt \right]}{\sum_{j=1}^{\infty} q p^{j-1} (jT)}$ $= \frac{C_p + C_f q^2 \sum_{j=1}^{\infty} p^{j-1} \int_0^{jT} r(t)\, dt}{T}$	Expected unit cost in (0, jT)
$\boldsymbol{q}$ Probability of perfect repair $\boldsymbol{p}$ Probability of minimal repair $\boldsymbol{C_f}$ Cost due to failure maintenance $\boldsymbol{C_p}$ Cost due to preventive maintenance $\boldsymbol{j}$ Number of periods $\boldsymbol{T}$ Length of period $\boldsymbol{r(t)}$ Failure rate	

In the third method, improvement factors were utilized by Malik (1979) to define imperfect maintenance. As stated in Figure 2.11, minimal repair does not affect the failure rate after the maintenance while perfect repair get the failure rate back to lifetime start point. Since imperfect maintenance returns the failed component a state between as good as new and as bad as old, failure rate after imperfect maintenance is expected to be between the rates due to minimal and perfect repairs.

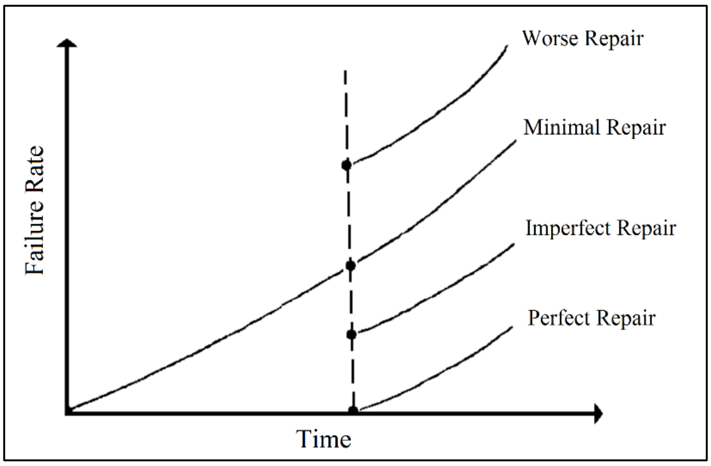


Figure 2.11 Effect of Repair Types on Failure Rate (Blischke and Murthy, 2000)

Lie and Chun (1986) developed an algorithm with improvement factors to combine imperfect, perfect and minimal repairing actions to keep reliability in the desired level and to minimize the total cost. In the algorithm, failure rate path after maintenance were defined as: 1P and 2P for imperfect and perfect preventive maintenance and 1C and 2C for minimal and perfect corrective maintenance, respectively (Figure 2.12).

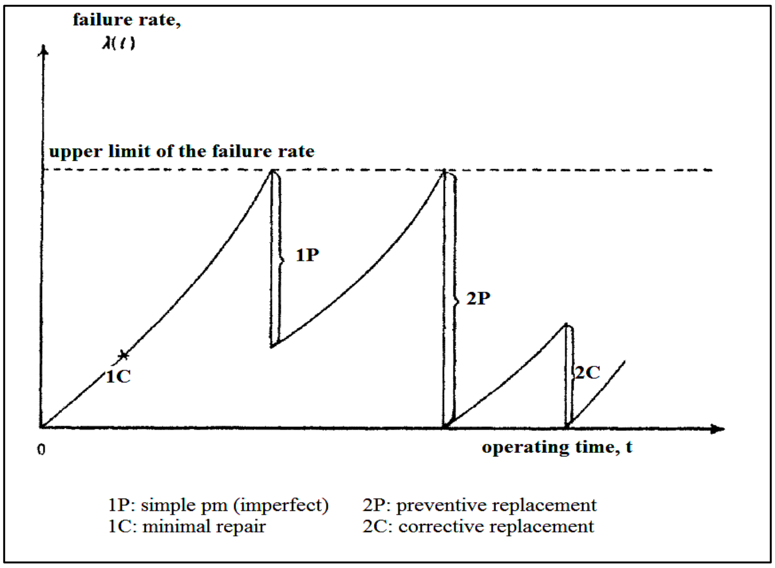


Figure 2.12 Maintenance-Based Failure Rate Variations (Lie and Chun, 1986)

The forth model for building an imperfect maintenance methodology is virtual age method by Kijima *et al.* (1988). The proposed model assumes that system age increases depending on the repair improvement factor. It means that if the repair is performed perfectly, no aging is seen between the $(n)^{th}$ and $(n-1)^{th}$ repair (Tadj *et al.*, 2011). Virtual age of a system was defined with two separate models by Kijima *et al.* (1988). In the first model, it is supposed that $(n)^{th}$ repair eliminates the damage only between $(n)^{th}$ and $(n-1)^{th}$ repairs. If the time elapsed between this time point is defined as $X_n = t_n - t_{n-1}$, virtual age for Model-I can be expressed as in Equation 2.10. In the equation, V_{n-1} is the virtual age prior to the $(n-1)^{th}$ repairs and A_n (also denoted as q or A in some studies) is the improvement factor (also referred as restoration factor, degree of repair).

$$V_n = V_{n-1} + A_n X_n \tag{2.10}$$

Equation 2.10 indicates that maintenance improvements only effect time period between maintenance activities and it does not offer a general recovery on whole lifetime. On the other hand, Kijima Model-II assumes that maintenance recovers cumulative damage loss in system instead of the damage only in an exact period. Equation 2.11 shows the formula related to Model-II.

$$V_n = A_n (V_{n-1} + X_n) \tag{2.11}$$

Equation 2.11 reveals the effect of improvement factor on increasing lifetime of system. In this sense, improvement after maintenance does not concern only a small period between two maintenance point but also effect overall cumulative lifetime.

Shock model is another common method for imperfect maintenance. The model basically considers the accumulating damages on the item that may cause failure when the limits are exceeded (Nakagawa, 2007). Successive shocks on item may cause deterioration. Even, sudden shocks may result in catastrophic failure of component. In this sense, preventive maintenance supports component health by keeping the cumulative loss under the limit values. Kijima and Nakagawa (1991) used shock model to measure the percentage of damage reduction due to the preventive maintenance. It is assumed that the preventive maintenance decreases the addictive shock (damage) by $100\ (1-b)\%$ where $b=1$ refers the minimal repair and $b=0$ means perfect repair. In addition, Finkelstein (1998) combined virtual age and shock models to examine the probabilities of shocks to induce failure. The study covered various models for minimal, perfect, and general (imperfect) maintenance.

Sixth model of imperfect maintenance modelling is quasi-renewal process, also called as (α, β) rule. Model assumes that survival times between the failures will decrease with rate of α due to system aging and repair time will rise with rate of β, proportionally. Inter-arrival times can be defined in terms of nonnegative random variables, X_n, as $\{X_1 = Z_1,\ X_2 = \alpha Z_2,\ X_3 = \alpha^2 Z_3, \ldots\}$ (Wang, 2008). It is obvious that If $\alpha = 1$, then the process is reduced to ordinary renewal process. The conditions of $\alpha < 1$ and $\alpha > 1$ points to decreasing and increasing quasi-renewal processes, respectively.

The last model used to identify imperfect maintenance is multiple (p, q) rule. This model (Shaked and Shanthikumar, 1986; Sheu and Griffith, 1992) considers functional dependencies between components. Therefore, joint distribution functions were utilized to describe the dependency regarding the (p, q) rule where p and q refer perfect and minimal repair probabilities, respectively.

2.6 Optimization of Maintenance Policies

Maintenance policies organize all maintenance activities to be applied during operational periods of systems. These policies decide the strategies for failure conditions, preventive replacements, and inspections via clarifying questions of who, how, when, and how long. Concept and complexity of a maintenance policy change due to factors such as, number of components in systems, dependencies between components, economic variables, capacity of maintenance crew, spare part conditions, and administrative decisions. Maintenance policies should be developed in cost-effective manner considering all negative and positive contributions of maintenance activities. This section will focus on two main maintenance optimization approaches as optimization of inspection intervals with delay time concept and preventive component replacements.

2.6.1 Optimization of Inspection Intervals with Delay-Time Modelling

Inspections are system-check activities performed in regular intervals to detect possible anomalies in systems and preventively maintain system elements. Regular inspections are generally carried out according to pre-specified calendar times. These activities may cover: (i) visual inspection of system components, (ii) repairing or corrective replacement of hidden failed components, (iii) lubrication, (iv) overhauling, and (v) preventive replacement of specified wear-out components. Estimation of optimum inspection interval is important to reduce unit cost of maintenance activities and to keep availability and sustainability of systems in desired levels. In this sense, delay time modelling can be utilized to find out optimum inspection intervals for single- or multi-unit systems.

Delay time modelling was firstly introduced by Christer (1976) and then its utilization area was extended in various industries (Cerone, 1991; Christer and Waller, 1984; Christer, 1987; Christer *et al.*, 1995; Christer *et al.*, 1998; Christer *et al.*, 2000). This method assumes that system components can have detectable defects prior to failures and time between defect arrivals and failure points give opportunity for maintaining these components preventively during inspections. Defect arrivals of components can be noticed via anomalies such as, vibration, noise, temperature, smell, or performance (Wang, 2008). If component fails without any defect alert, delay-time modelling cannot be applied for this component.

In delay time modelling, arrival point of the defect is called as initial point, u, and time interval between u and failure time is called as delay time of the defect, h (Christer, 1999). The inspection is fulfilled in (u, u+h) where the defect initiates and propagates the failure condition. Illustration of delay times for a single component can be viewed in Figure 2.13.

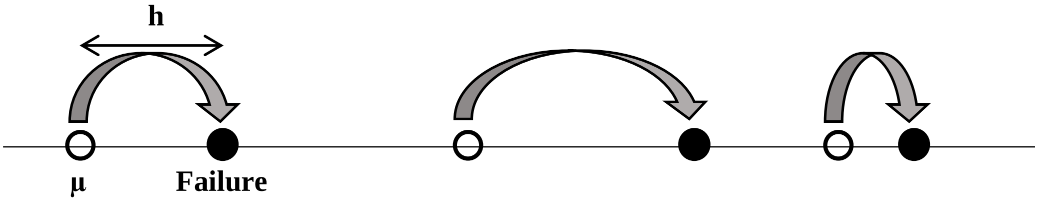


Figure 2.13 Delay Times of Single Component

According to the model, maintenance of a single component is carried out with repairing or replacement actions either upon the failure or after the detection of the defect in the inspection. An inspection is divided into two groups as perfect or imperfect according to the defect detection performance during the period. If there is a probability of not to find out any potential defect during the inspection, the situation is called as imperfect inspection. Otherwise, inspection is named as perfect inspection and it guarantees the exposal of defect during inspection. If the inspection is perfect and the distribution for defect arrivals is assumed to be exponential with a constant rate, objective function to determine the inspection period aims to minimize expected cost in each cycle as shown in Table 2.7.

The estimated cost is the sum of the costs due to possible failure maintenance prior to inspection, possible renewal of the component detected at inspection, and possible inspection cost without any detection.

Basic delay time models for multi-component system assume:

i. Inspections are performed in every T time interval, holds a cost of c_i, and leads to d_i amount of process time where $d_i \ll T$.
ii. Inspections are perfect. Therefore, the defects are not overlooked.
iii. Repairing of the defects is carried out in inspection time slot.
iv. Arrival rate of the defects (λ) is constant (Homogeneous Poisson Process).
v. There is not any correlation between PDF of the delay times, $f(h)$, and u.
vi. If a failure takes place before inspection, it leads to an expected cost of c_f and downtime of d_f.
vii. If defect is detected during an inspection, repairing cost of the component is c_d.

Table 2.7 Descriptive Equations of Delay-Time Maintenance (Christer, 1999)

Equations	Definitions
$P(x) = \int_{u=0}^{x} g(u)F(x-u)du$	Failure probability of the component
$E(CC) = c_f P(t) + (c_r + c_i)\int_0^T g(u)\big(1 - F(T-u)\big)du + c_i \int_T^{\infty} g(u)\,du = (c_f - c_r - c_i)P(T) + c_r G(T) + c_i$	Expected cost in each cycle
$E(CL) = \int_0^T t\int_0^t g(u)\ f(t-u)dudt + T(1 - \int_0^T g(u)\ F(t-u)du$	Expected inspection cycle length
$C(T) = \dfrac{E(CC)}{E(CL)}$	Unit cost
$EN_f(T) = \lambda \int_0^T F(T-u)du$	Expected number of breakdown
$b(T) = \dfrac{EN_f(T)}{\lambda T} = \dfrac{1}{T}\int_0^T F(T-u)du$	Probability of a defect inducing a failure inside the inspection period
$C(\hat{T}) = \dfrac{c_i + c_f\lambda T b(T) + c_d \lambda T(1 - b(T))}{T + d_i}$	Expected unit cost
$D(\hat{T}) = \dfrac{d_i + d_f \lambda T b(T)}{T + d_i}$	Expected unit downtime

$\boldsymbol{g(u)}$; $\boldsymbol{G(u)}$	PDF and CDF of initial point of defect, u, respectively
$\boldsymbol{f(h)}$; $\boldsymbol{F(h)}$	PDF and CDF of delay time, h, respectively
$\boldsymbol{c_f}$	Cost of each failure maintenance prior to inspection
$\boldsymbol{c_r}$	Cost of each possible renewal of the component detected at inspection
$\boldsymbol{c_i}$	Cost of each possible inspection cost without any detection
$\boldsymbol{d_f}$	Downtime due to failure
$\boldsymbol{d_i}$	Downtime due to inspection
$\boldsymbol{\lambda}$	Failure rate
$\boldsymbol{T}$	Inspection interval

For multi-component systems, i.e. complex systems, inspection period is affected from various failure modes. Failure of any component may cause the breakdown of the system (Figure 2.14).

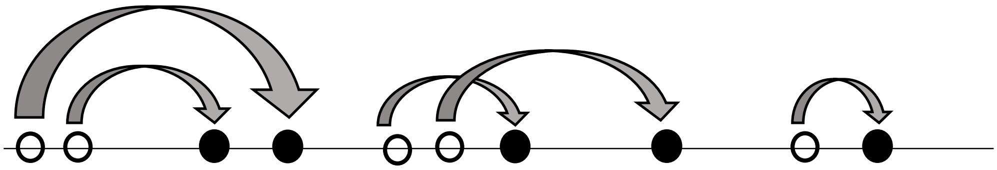


Figure 2.14 Delay Times of Multi-Component Systems

For both single component and multi-component systems, precise prediction of initial time and delay time distributions are essential for the correct computation of delay time modelling. Estimation of these parameters may be carried out using subjective and objective techniques.

Subjective estimation method was initially utilized by Christer and Waller (1984). This method is performed via applying questionnaires to maintenance staff or engineers who can give answers to two main critical questions about the breakdowns: (i) How long ago (HLA) could the defects have initially realized by the crew? (ii) How much longer (HML) could the components continue to operate if the repair was not performed? For breakdown maintenance where the component is completely failed, subjective delay time $\hat{h}$ is HLA. On the other hand, the delay time $\hat{h}$ is $HLA + HML$ for inspection maintenance since the component is still operative (Figure 2.15). This value can be given in a range instead of an exact value. This range may help to generate optimistic and pessimistic limits of the delay times. Distribution of the proposed delay time values can be fitted using maximum likelihood methods.

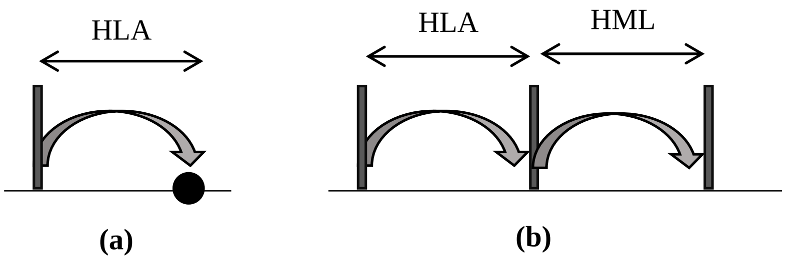


Figure 2.15 Subjective Delay Times for Breakdown (a) and Inspection (b)

On the other hand, objective method uses observational data that can be acquired during operations or inspection periods. Objective data covers information about amount of failures during operation between inspection points, number of repairing action to fix the defects, quantity of inspections, time period values for each halt point, and defect arrival periods.

2.6.2 Preventive Replacement Models for System Components

In addition to inspection intervals optimization, preventive replacement models can also be utilized in improvement of maintenance policies. Using these models, system components in wearing period are detected and replaced preventively in cost-effective intervals. Block replacement and age replacement models are two common methods in estimation of intervals for preventive component replacement. Block replacement generates a policy regarding the preventive replacements in the predetermined periods and corrective maintenance at the failure times. On the other hand, age replacement considers the age of item as the main parameter instead of the period interval. Although there are other preventive maintenance policies such as, failure limit, repair limit, repair number counting and reference time policies, this section only focuses on block and age replacement policies.

Block replacement is a preventive maintenance policy which ensures the replacement of the component periodically. Intervals can be in terms of either time condition (kt_0) or predetermined failure number (kN). The policy also assumes that if a failure takes place between the periodic replacement points, corrective maintenance is carried out. Failure condition can be defined with three different scenarios (Dohi *et al.*, 2000): (i) inoperative part is replaced immediately upon the failure, (ii) inoperative part stands in the system up to the periodic replacement point (especially in the redundant system), (iii) inoperative part is exposed to minimal repair instead of the replacement, i.e. perfect repair.

The first scenario assumes (i) implementation of perfect repair (replacement) upon the failure correctively and (ii) replacement of the operative items in the periodic replacement points preventively. Unit cost amount for this model can be estimated using Equation 2.12 (Barlow and Proschan, 1965).

$$B_c(t_0) = \frac{c_c M(t_0) + c_p}{t_o} \tag{2.12}$$

In the equation 2.12, c_c and c_p are the costs due to corrective replacement of the failed item upon the failure and preventive replacement of the item at the periodic time points, respectively. $M(t_0)$ is the renewal function which counts the number of breakdowns in time interval $(0, t]$ where $m(t_0)$ is the renewal density function. Optimal replacement time (t_0^*) can be assessed by equalizing the derivation of Equation 2.12 to zero. Numerator of the derived formulation is found out as in Equation 2.13 (Barlow and Proschan, 1965).

$$j_c(t_0) = c_c[t_0 m(t_0) - M(t_0)] - c_p \tag{2.13}$$

Following conditions should be considered when calculating t_0^*, optimal period duration:

i. If there is a continuous raise of $m(t)$ with the time and $j_c(\infty) > 0$, then t_0^* can be calculated in $(0, \infty)$ equalizing $j_c(t_0)$ function to zero.
ii. If there is a continuous raise of $m(t)$ with the time and $j_c(\infty) \leq 0$, then $t_0^* \rightarrow \infty$; and it signifies that there is no requirement of preventive replacement and corrective maintenance is enough for this case.
iii. If there is a continuous decrease of $m(t)$ with the time, then $t_0^* \rightarrow \infty$ and it again signifies that there is no requirement of preventive replacement.

In case that number of failure is chosen as a limiting parameter instead of time in the designation of optimal period duration, then the policy turns into discrete-state. Equation 2.12 is converted to Equation 2.14 to calculate the unit cost per failure (Barlow and Proschan, 1965).

$$B_d(N) = \frac{c_c M(N) + c_p}{N} \tag{2.14}$$

Numerator of the derivation to detect the optimum failure number is stated in Equation 2.15 (Barlow and Proschan, 1965).

$$j_d(N) = c_c[N\, m(N+1) - M(N)] - c_p \tag{2.15}$$

Following items should be considered in the assessment of Equation 2.15 (Barlow and Proschan, 1965):

i. If there is a continuous raise of $m(n)$ with the time and $j_d(\infty) > 0$, then N^* can be calculated in $(0, \infty)$ with equalizing $j_d(N)$ function to zero. This condition ensures that $j_d(N-1) < 0$ and $j_d(N) \geq 0$. Therefore, minimum cost will be between $(c_c m(N^*), c_c m(N^*+1))$.

ii. If there is a continuous raise of $m(n)$ with time and $j_c(\infty) \leq 0$, then $N^* \to \infty$ and it signifies that there is no requirement of preventive replacement and corrective maintenance is enough for this case.

iii. If there is a continuous decrease of $m(n)$ with the time, then $N^* \to \infty$ and it again signifies that there is no requirement of preventive replacement.

The second scenario for block replacement assumes that the inoperative item stay in the system until the periodic replacement time. This condition generally arises in standby systems where functionality of failed component is compensated with the redundant one. Resultant unit cost expectation in block replacement for this model is given in Equations 2.16-2.18 (Osaki *et al.*, 1992). Equation 2.16 gives the mathematical expectation of time interval between the failure existence and the periodic replacement point, which indicates the tolerated time after the failure.

$$E(t_0 - t) = \int_0^{t_0} (t_0 - t)\, dF(t) = \int_0^{t_0} F\,(t)\, dt \tag{2.16}$$

Unit cost can be evaluated using Equation 2.17. Optimal time interval for the periodic replacement can be found equalizing derivative of Equation 2.17 (Equation 2.18).

$$C_c(t_0) = \frac{c_c \int_0^{t_0} F(t)dt + c_p}{t_0} \tag{2.17}$$

$$k_c(t_0) = c_c \left\{ F(t_0)t_0 - \int_0^{t_0} F(t)\, dt \right\} - c_p \tag{2.18}$$

The numerator function in Equation 2.18 should be examined as follows:

i. If $k_c(\infty) > 0$, then t_0^* can be calculated in $(0, \infty)$ with equalizing $k_c(t_0)$ function to zero.
ii. If $k_c(\infty) \leq 0$, then $t_0^* \to \infty$; and it signifies that there is no requirement of preventive replacement and corrective maintenance is enough for this case.

If the unit cost equation is developed in terms of number of failure in discrete case, then the Equation 2.17 is converted to Equation 2.19. Eventually, numerator of the derived formula turns into Equation 2.20 (Osaki *et al.*, 1992).

$$C_d(N) = \frac{c_c \sum_{k=1}^{N-1} F(k) + c_p}{N} \tag{2.19}$$

$$i_d(N) = c_c[N\, F(N) - \sum_{k=1}^{N-1} F(k)] - c_p \tag{2.20}$$

The third and the last scenario in block replacement covers the minimal repair concept instead of replacement (perfect repair) in case of failure. Minimal repair mean that the failed item will be recovered to as bad as old state, not to as good as new. If the failure rate is defined as $r(t)$, the ratio between failure and survival probability, quantity of the minimal repairs in each cycle can be estimated using non-homogeneous Poisson process as stated in Equation 2.21. Parameter of $\Lambda(t)$ is called as cumulative hazard function.

$$\Lambda(t) = \int_0^t r(x)\, dx \tag{2.21}$$

Then, unit cost function and numerator of the derived unit cost function can be calculated using Equations 2.22-2.23 (Barlow and Hunter, 1960).

$$V_c(t_0) = \frac{c_m \Lambda(t_0) + c_p}{t_0} \tag{2.22}$$

$$l_c(t_0) = c_m[t_0 r(t_0) - \Lambda(t_0)] - c_p \tag{2.23}$$

In addition to block replacement models, age replacement models can be applied considering operational age of components. In this situation, the item is subjected to preventive-purpose maintenance replacements without any failure or corrective maintenance in case of failure (Ben-Daya, 2000; Wang and Pham, 2006; Nakagawa, 2005; Dohi *et al.*, 2000). Renewal-reward explanation of the basic unit cost model is assessed using Equation 2.24 (Barlow and Proschan, 1965; Osaki and Nakagawa, 1975):

$$A_c(t_0) = \frac{c_c F(t_0) + c_p R(t_0)}{\int_0^{t_0} R(t)dt} \tag{2.24}$$

If the failure rate is denoted by $r(t)$, ratio between failure and survival probability ($f(t)/R(t)$), numerator of the derived $A_c(t_0)$ function can be defined as in Equation 2.25 (Barlow and Proschan, 1965).

$$h_c(t_0) = r(t_0) \int_0^{t_0} R(t)\, dt - R(t_0) - \frac{c_p}{c_c - c_p} \tag{2.25}$$

Optimal time interval for age replacement $t_0{}^*$ can be found by equalizing Equation 2.25 to zero with regarding following items:

i. If $F(t)$ is an increasing failure rate and $r(\infty) > \lambda c_c/(c_c - c_p)$, then t_0^* can be calculated in $(0, \infty)$.
ii. If $F(t)$ is an increasing failure rate and $r(\infty) \leq \lambda c_c/(c_c - c_p)$, then it signifies that there is no requirement of age replacement ($t_0 \to \infty$).

iii. If $F(t)$ is a decreasing failure rate, then it signifies that there is no requirement of age replacement ($t_0 \rightarrow \infty$).

If the failure number is used as decision variable instead of time, then the equations are converted to discrete state. Therefore, unit cost function for discrete time age replacement model can be expressed with Equation 2.26 (Nakawaga and Osaki, 1977). Numerator of the derived unit cost function is stated in Equation 2.27. Considerations for determining the optimal age replacement interval is similar to the continuous case.

$$A_d(N) = \frac{c_c F(N) + c_p R(N)}{\sum_{i=1}^{N} R(i-1)} \tag{2.26}$$

$$h_d(N) = r(N+1)\sum_{i=1}^{N} R(i-1) - F(N) - \frac{c_p}{c_c - c_p} \tag{2.27}$$

2.6.3 Maintenance Policies for Single-Unit Systems

Maintenance policies for single-unit systems can be classified as age-dependent preventive maintenance, periodic preventive maintenance (block replacement), failure limit, sequential preventive maintenance, repair limit, and repair number counting and reference time (Wang, 2002).

Age-dependent preventive maintenance policy is one of the common models utilized in replacement decisions of single-unit systems. Initially, age replacement policy was studied assuming that replacement of a unit was carried out at its age, constant T, or failure time with perfect maintenance. Later on, age-dependent researches have been enlarged with various restoration degrees such as, perfect, minimal, and imperfect. In addition to constant age replacement policy, age T can be assumed as a random variable in which the periodical maintenance intervals are assumed to be inconstant. This kind of process is called as random age-dependent policy. On the other hand, if the maintenance after failure is carried out with minimal repair, age replacement process is named as periodic replacement with minimal repair.

There are various researches (Tahara and Nishida, 1975; Nakagawa, 1984; Sheu *et al.*, 1993; Block *et al.*, 1993; Sheu *et al.*, 1995; Wang and Pham, 1999) based on age-dependent preventive maintenance policy; each of them rearranges the replacement or repair activities for different restoration levels and time conditions (Wang, 2002). Tahara and Nishida (1975) stated a maintenance policy that replacement of a unit was carried out at the time of first failure occurred after t_0 operating hour or at the periodical time T where t_0 did not exceed T. The assumptions in the study mentioned that if a failure takes place, the unit is recovered by minimal repair activity. In addition, condition where t_0 is zero refers age replacement policy. On the other hand, equality between t_0 and T indicates the maintenance is performed using *periodic replacement with minimal repair at failure* policy.

In another research, Nakagawa (1984) combined the replacement time T and number of failure N as decision variables in the policy. The model assumes that the component may be replaced in time T or after N failures. When the number of failure is taken as 1, the policy returns to basic age replacement. Failures are assumed to be recovered minimally in the study. The maintenance policy can be also performed with imperfect preventive maintenance at time T, or imperfect corrective maintenance in N^{th} failure.

In another study (Sheu *et al.*, 1993; Sheu *et al.*, 1995), it was aimed to form a generalized age replacement policy. The model in 1993 states that if the component fails before its age ($y<t$), it is maintained by perfect repair with the probability p(y) or minimal repair with probability of q(y)= 1- p(y). If not, it is replaced at the first failure after the age (t) or at periodic replacement time T where $0\leq t \leq T$. When the age equals to T and q(y)=1, the policy is again transformed to periodic replacement with minimal repair at failure. Sheu *et al.*(1995) improved the model via including failures with different probabilities as: Type-1 failure with p(z) and Type-2 failure with q(z)=1-p(z). Type-1 failures are the ones which can be recovered by minimal repair, while Type-2 failures are corrected by perfect repair. If only Type-2 failures exist for the conditions, the policy returns to basic age replacement since the replacement of an item refers perfect repair. For the reverse cases that only Type-1 failures occur and for that the

number of failures goes to infinity, policy is again called as periodic replacement with minimal repair at failure.

Another age-dependent preventive maintenance policy called as *repair replacement policy* was identified by Block *et al.* (1993). The study assumes preventive replacement of survived unit at specified operating period or corrective repair of the failed unit perfectly or minimally. The policy followed a conventional way where the aging components are replaced with the identical one in specific time interval prior to failures.

An alternative approach called as *mixed age preventive maintenance policy* was studied by Wang and Pham (1999). In the study, it is assumed that component can be exposed to two different failures after n^{th} imperfect maintenance as: Type-1 which was the total failure of the component requiring perfect (replacement) maintenance, and Type-2 which was the failure that could be fixed by minimal repair. In addition, model assumes that repair activity has a probability of p(y) to be performed as perfectly and q(y)=1-p(y) as minimally. The period covering *n* imperfect repairing also meant replacement age T. Therefore, the condition that equalizes the perfect repairing probability and the number of imperfect repairing to zero reduced the model to *periodic replacement with minimal repair at failure*. On the other hand, certain existence of perfect repairing and lack of imperfect repairing transformed the model to age replacement policy.

In addition to age-dependent preventive maintenance policy, other type of policy is periodic preventive maintenance policy. It includes maintenance activities for certain time intervals, kT. Block replacement policy is one of the common names utilized to describe the replacement of a block or group in predetermined intervals. One approach on periodic replacement with minimal repair at failure policy by Liu *et al.* (1995) offered that the component would be replaced at time (O +1)T where O is the number of imperfect preventive maintenance carried out in every T interval. On the other hand, the model stated that possible failures between the intervals would be fixed by minimal repair. It can be noted that if there is no any imperfect maintenance, the model reduces to classic periodic replacement with minimal repair at failure policy.

An extended block replacement policy proposed by Berg and Epstein (1976) combined the policy and age limitation. According to the model, replacement of the units with ages less than or equal to the replacement period were kept working up to the failure time or the replacement time. Failed components were replaced with the identical new one. If the unit age is not less than periodic time interval, the model is turned to classic block replacement policy.

Tango (1978) differentiated block replacement policy by suggesting that replacement of the failed parts could be done with a used one as well as a new one. The failed component was fixed by replacement with the new one when the failure took place before the prescribed time limit. If the failure time was between the limit time and periodic replacement time, a used spare part was utilized for the replacement.

Nakagawa (1981) modified periodic replacement with minimal repair at failure policy via considering the possible after-failure strategies of the units. Periodic time length was divided into two intervals as the period less than predetermined time point (T_0) and the period between this point and the periodic replacement time (T^*). If the failure exists before the predetermined time point (T_0), maintenance is carried out with minimal repair. Otherwise, in between T_0 and T^*, (policy-1) the failed part is not maintained until the periodic time; or (policy-2) the failed part is replaced with the spare one; or (policy-3) the failed part is replaced with the new one. If the predetermined time point is taken as zero, policy-3 transforms to basic block replacement policy.

In addition to age-dependent and periodic preventive maintenance policies, failure limit, sequential preventive maintenance, repair limit, and repair number counting and reference time are the other types of policies investigated in literature to regulate the maintenance activity of single-unit systems. Failure limit policy can be used to stabilize the failure rate and only carried out when the failures exceed the acceptable limits due to the factors such as, wear and tear, fatigue or other age-based consequences.

Sequential preventive maintenance policy assumes that the time periods for preventive maintenance cannot be kept constant since the unit requires more frequent maintenance due to its age. The models prepared with this approach are based on the minimization of the cost for the next preventive maintenance. Nguyen and Murthy (1981) proposed a policy predicating on the reference time point t_i which was the maximum operating time of unit without failure after $(i-1)^{th}$ repair activity. Also, the component was indicated to be replaced after k^{th} repair due to failure or at age t_i, whichever occurs initially. If k equals to zero, the model is turned to age replacement policy.

Repair limit policy determines the limits between repairing and replacement activities. The policy is divided into two approaches as repair cost limit policy and repair time limit policy (Wang, 2002). Repair cost limit policy states that replacement of a unit can be carried out if the predetermined cost limit is exceeded. On the other side, repair time limit policy as defined by Nakagawa and Osaki (1974) restricts the repairing time such that if the period exceed the limit, failed unit is replaced by the new one instead of repairing.

The policies discussed in this section make various assumptions on scope and boundary of the maintenance activities for single-unit systems. Maintenance manager can choose one of these policies considering working mechanism of system and applicability of the policy for the system.

2.6.4 Maintenance Policies for Multi-Unit Systems

Multi-unit systems cover more than one components in various combinations. If maintenance of individual components is not applicable, maintenance policy for multi-unit systems can be considered. Optimality of the maintenance should be assessed via considering the dependencies between components. Opportunistic maintenance or group maintenance policies can be utilized for multi-unit systems.

Opportunistic maintenance is applicable where the maintenance of one item gives opportunity for repairing, inspection or replacement of the other items (Shenoy and Bhadury, 2005). The phenomenon of *opportunity* may also rise when system is halted due to demand reduction or other external reasons (Budai *et al.*, 2008). There are various researches investigating adaptation of opportunistic maintenance for different modelling types. In this regard, Dekker and Smeitink (1991) implemented opportunistic maintenance concept to block replacement policy. The model defined the opportunity arrivals using renewal process. The study assumes that item replacement is carried out correctively after the failure or preventively only when opportunity arises. In addition, Dekker and Dijkstra (1992) used opportunistic approach for age replacement, similar to block replacement model. Moreover, Cui and Li (2006) extended imperfect shock model to opportunistic maintenance of multi-units system.

On the other hand, group maintenance aims to gather items to be maintained considering three common approaches as (i) replacement of items when any failure occurs, (ii) placing redundant items into system design, and (iii) simultaneous maintenance of the independent items which hold the same failure distribution (Wang and Pham, 2006). For the stochastically compatible independent items, group policy can be established using T-age replacement, m-failures replacement, and combination of T-age and m-failures replacement (m,T) policies. Assaf and Shanthikumar (1987) formed a group maintenance policy for a number of items having exponential PDFs. The model assumed that the quantity of failures could be determined only in inspection and repairing of the failed items was performed perfectly. Love *et al.* (1982) formed a policy for a fleet of machine. Repair limit approach was applied in the model instead of age and block maintenance types. It was assumed that replacement would only take place only when the repair cost limit was exceeded. In another study, Gertsbakh (1989) regarded the number of failure as a limit parameter to initiate the repairing activity. Moreover, Sheu and Jhang (1997) introduced a model covering two phases for (0,T) period and (T, T+W) period. The policy assumed that failure of the individual items were repaired minimally in (0,T) and perfectly in (T, T+W). In the model, group maintenance was only performed in (T, T+W).

2.7 Previous Reliability and Maintenance Studies in Mining

Mining is a machine-intensive sector where various mechanical systems are employed in demanding working environments. They are exposed to various mechanical and electrical failure modes during their lifetimes. These failures lead to time and production losses and delay in production schedule. Maintenance cost of a machine can reach a level between 35–60% of total operating cost in changing working environments (Roy *et al.*, 2001). Detection and control of prominent breakdowns and developing predictive and preventive programs against failures are crucial for longevity of machinery components and sustainability of machinery operations. Draglines are massive earthmovers and sensitivity between machinery breakdowns and production rate is extensively high for draglines. Research studies in the literature are lack of maintenance optimization and component-based reliability modelling for draglines. The existing dragline studies only offer general reliability models without component decomposition and failure mode analysis. This section mentions about the previous reliability and maintenance studies on mining systems.

Zhu *et al.* (1993) developed an artificial intelligence system called as Intelligent Maintenance Support System (IMSS) gathering and interpreting data acquired from sensors installed on the critical parts of trucks in an oil sand mine in Canada. The system collected 47 variables through 21 analog and 26 digital signals with 30 minutes intervals. The data was qualified using the knowledge base of experts, truck manuals and data file. The authors claimed that IMSS gave apprehensible results for fault diagnosis and condition monitoring.

Louit and Knights (2001) performed a discrete simulation to eliminate failures and unplanned malfunction periods for the machine fleet of a gold-silver mine company in Chile using root-cause failure analysis and generating repair standards. The research aimed to reduce hidden costs due to accidents and delays in maintenance and to increase the portion of planned maintenance. Concordantly, breakdown data collected in the field was identified and quantified as planned and unplanned and delays in the maintenance process were classified as lack of required personnel, lack of spare parts, and priorities in the maintenance order. Simulations considered root-cause failure analysis, modification in stock planning, repair standards, additional demand for labor and workshop area, organizational changes, transferring of maintenance staff to operation process, and maintenance contracting.

Veganes and Nuziale (2001) generated a genetic algorithm model for evaluation of mining equipment reliability to reveal aging problem of component, operational conditions, amount and quality of maintenance activities. The model was applied to LHD, using information about failure types, values of time between failures, repair periods, machine age, and the environmental conditions.

Roy *et al.* (2001) worked on the reliability and maintainability performance of four electric rope shovels in India. In the study, shovel system was divided into twelve subsystems. The analyses indicated that electrical and dipper subsystems were the most critical subsystems considering repair durations and failure frequencies.

Lewis and Steinberg (2001) introduced an interactive maintenance management system (IMMS) called as Intellimine which provided a real-time interface serving for continuous data collection and analyses to get alarm about functional anomalies for the machines. It was emphasized that maintenance cost was the greatest controllable cost in the mining sector and 11% and 30% of the direct mining cost in the USA open pits were due to the maintenance process and maintenance staff, respectively. In this study, it was claimed that Intellimine presents a maintenance optimization interface using the real-time data flow to control direct maintenance costs and indirect cost due to production loss and redundant number of spare part and staff.

Samanta *et al.* (2004) carried out a research on reliability of LHD machinery system. In the study, stochastic Markov process was utilized to measure the availability of LHD as a function of reliability and maintenance. The system was divided into six subsystems in serial connection so that failure in one unit could lead to a breakdown of LHD. According to the analyses, transmission, drive unit, and hydraulic mechanism of LHD were determined as the most problematic parts. Steady state availability of the machine was estimated to be 73%.

Marquez (2005) aimed to build a simulation program intending for maintenance policy assessment for truck engine to reduce total cumulative expected cost of maintenance. Unit cost of failure due to expenses of employee, spare parts, rescheduled operations, testing process, and responsible maintenance company were introduced in the model. Simulation algorithm used semi-Markov process to evaluate the behavior of maintenance policies in a continuous-time model.

Gupta *et al.* (2006) used fault tree approach to improve a logic-based reliability model for longwall shearer. Any of the faults located in gear box, cutting drum, electric motor, frame, ranging arm, power pack, and traction unit were supposed to induce breakdown in the shearer. Reliability and functional importance of individual components were evaluated using fault tree analysis.

Vagenas *et al.* (2007) summarized a methodology to determine reliability and optimized maintenance intervals for LHD via combining analytical, statistical, and graphical methods. Trend and serial correlation tests and goodness-of-fits of the subsystem data for Weibull, exponential, and lognormal distributions was evaluated using Kolmogorov-Smirnov and Chi-Squared tests. In the study, it was also stated that Kolmogorov-Smirnov test was more convenient for non-normal distributions.

Barabady and Kumar (2008) focused on the reliability and availability factors of a crushing plant in Jajarm Bauxite Mine of Iran using survival and repair data. The study detected maintenance-critical subsystems with reliability importance factors. These factors were estimated via time-dependent ratio between reliability of system and component. In the study, the crushing plant was divided into six subsystems. Individual lifetimes were estimated using best-fit distributions and non-homogenous Poisson process for non-trend and trend components, respectively.

Uzgören *et al.* (2010) assessed the reliabilities of two draglines and estimated required maintenance intervals for various reliability levels. Reliability assessment in the study was carried out using best-fit distributions since there is not any indication of lifetime trend. Mean time between the failures (MTBF) was found as 97.03 and 75.80 for dragline-1 and dragline-2, respectively. Moreover, maintenance test released that 23.75 and 19.06 hours maintenance intervals were required to keep dragline-1 and dragline-2 in 75% reliability level, respectively. Uzgören and Elevli (2010) also applied non-homogenous Poisson process with power law to find out reliability of draglines with lifetime trend behavior.

Hall and Daneshmend (2010) expressed data gathering and analysis procedures frequently utilized in reliability analyses of mining machines. It was mentioned that Pareto analysis, failure distribution interpretation, and repair time analysis were the common methods in reliability estimations when adequate data was acquired from sources such as, sensor, on-board interface in the equipment, historical failure data sheet, and on-going maintenance and operation schedule. Application of failure mode effects and criticality (FMECA) for small dataset was mentioned in the study.

Gölbaşı *et al.* (2013) explained how to decompose a dragline into subsystems and components considering common failure modes existing in the mechanism. Failure behaviors of draglines were investigated via comparing various bathtub curve characteristics. In the study, variation of annual failure numbers and the resultant downtimes for two draglines in Tunçbilek coal mine were also examined. Upper and lower lifetime bounds of the subsystems for these draglines in 90% confidence interval were estimated with reliability modelling.

Gölbaşı and Demirel (2013) investigated component failure behaviors of two draglines currently operating in Tunçbilek coal mine via reliability importance factors and assessed mean component availabilities. In this sense, twenty two components were detected to induce failures in the draglines. Reliability variations of individual components and their downtime profiles were utilized to determine expected availabilities and expected failure numbers of the components at the end of 24th

operating hours. Regarding the degradation changes of component reliabilities, the most critical components being prone to failure were detected.

Demirel *et al.* (2013) explained functional dependencies between dragline components and system reliability variations using fault tree analysis. In this basis, dragline was decomposed into seven subsystems as dragging, hoisting, rigging, bucket, movement, machinery house, and boom. Following data classification to subsystems, data anomalies were examined by run charts via controlling clustering, mixture, trend and oscillation behaviors of successive data values. Time-dependent subsystem reliabilities were calculated to estimate overall dragline reliability. Methodology of the study was applied to the draglines in Tunçbilek coal mine.

Gölbaşı and Demirel (2015) made a review on quantitative and qualitative methods that can be utilized to detect wear-out periods of mining machineries. Changes in machinery failure rates throughout their lifetimes were discussed on a bathtub curve. Qualitative trend tests such as, graph of cumulative failure numbers versus cumulative time between failure and Duane plot were examined via numerical examples. Detailed evaluation of quantitative trend tests such as, Crow-AMSAA, Laplace, Lewis-Robincon, and reversal arrangement tests were investigated with a sample dataset.

Gölbaşı and Demirel (2015) performed a Monte Carlo simulation for two draglines to reveal downtime profiles of the systems. In the study, trend behaviors for lifetime datasets of individual components were observed using hypothesis testing methods, Crow-AMSAA and Laplace. Lifetime characterizations of the components in either lifetime growth or lifetime deterioration were evaluated with general renewal process. Other components without lifetime trend were characterized using best-fit distributions. Considering these assumptions, time-dependent failure rates of each dragline subsystem were estimated. In addition, downtime profiles of the draglines were determined using component lifetimes, random component repair times, compulsory breaks due to regular inspections and legal shift breaks, and stochastic behavior of energy source problems. Analyses showed that the dragline availabilities changes between 64% and 69%.

2.8 Summary

This section presented an extensive literature survey on maintenance and reliability, and their applications in mining sector. Factors contributing to system effectiveness were also mentioned. The survey basically focus on reliability assessment methods and maintenance policies. In this basis, reliability was discussed including descriptive terms and system reliability methods. Maintenance issue was handled investigating assumptions in maintenance modelling and stochastic maintenance concept. Then, techniques in maintenance optimization were stated for single- and multi-units systems. The literature survey was concluded with previous maintenance and reliability application in mining area.

Dragline covers various electrical and mechanical components leaguing together to ensure its earthmoving ability. Although there are various researches on kinematics and dynamics of dragline components, literature is lack of optimizing maintenance policies for these earthmover. Moreover, dragline reliability in previous researches is estimated roughly without component decomposition and failure mode analysis. This study implements top-to-bottom reliability assessment and optimizes maintenance policies considering preventive replacement policies, optimal inspection intervals and maintenance priority of components. Therefore, deductive reliability methods such as, reliability block diagram, fault tree analysis, and failure modes and effects analysis were extensively discussed in the literature survey. Moreover, maintenance optimization tools such as, delay-time maintenance, age- and block-replacement policies, and stochastic maintenance models were mentioned using mathematical expressions in the literature survey.

CHAPTER 3

PREPROCESSING OF DATA

3.1 Data Acquisition

In this thesis, reliability and maintenance models were developed using objective and subjective data of Page and Marion draglines which are still operative in Tunçbilek Coal Mine, Turkey. Objective data includes information on the maintenance sheets about dragline breakdowns in period between 1998 and 2011, their brief explanations, failure occurrence times, and repair durations. This data was acquired from the mine site under the scope of a research project by Demirel *et al.* (2013). On the other hand, subjective data covers personnel opinions of maintenance experts on the details of maintenance activities at the mine site and their economic consequences.

Maintenance sheets hold 1005 and 1088 number of maintenance activity for Page and Marion draglines, respectively. Following removal of human errors such as, duplicated record and typing errors, data was labelled using thematic and numeric codes according to failure modes. On the other hand, subjective data was acquired via questionnaire forms filled by dragline maintenance experts. These forms deeply investigate expected costs of corrective and preventive maintenance activities, economic consequences of production losses due to system halts, list of activities performed during regular inspections, details of currently applied maintenance policy, and functional and structural dependencies between components in the draglines. The questionnaires cover up-to-date information of year 2015.

3.2 Dragline Subsystems and Data Classification

During its operation, dragline locates its buckets away from the machinery house and strip overburden material by dragging the bucket toward machinery house. Following overburden stripping, loaded bucket is hoisted and dumped to spoil area after a swing movement of machinery. Draglines keep operation going with successive cycles of excavating, hoisting, swinging, and dumping actions.

Precise analysis of a system requires compatible decomposition of system into subsystem considering functional and structural dependencies. In this basis, dragline was decomposed into seven subsystems called as dragging, hoisting, bucket, rigging, machinery house, movement, and boom. Figure 3.1 illustrates a dragline operation and schematic view of dragline subsystems.

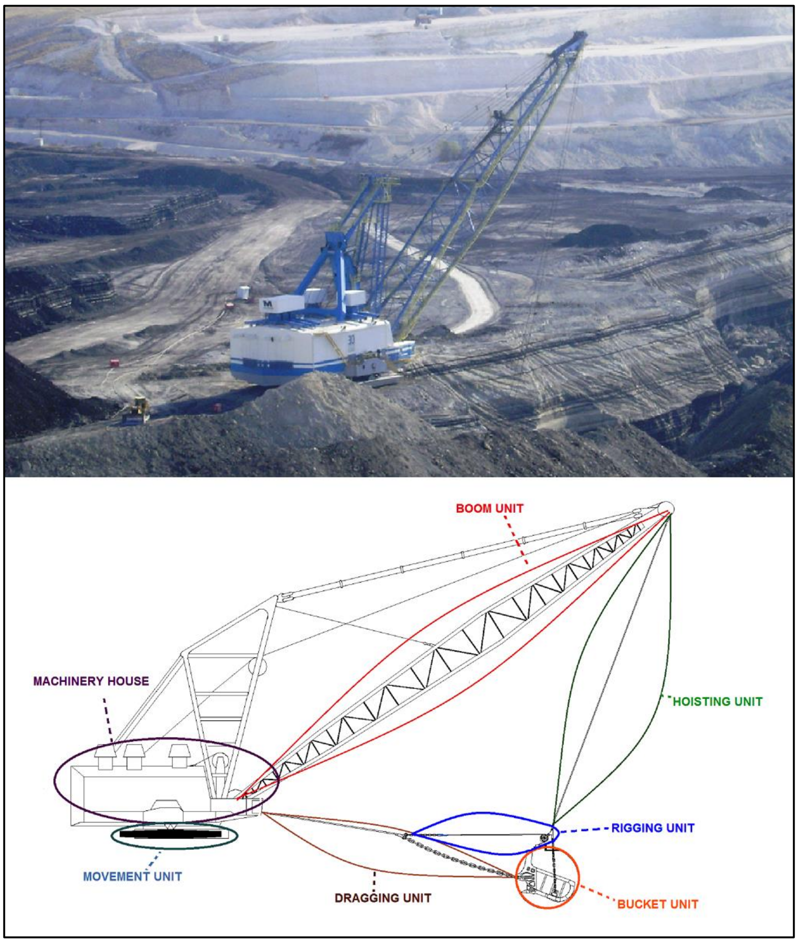


Figure 3.1 A Dragline Operation and Schematic View of Dragline's Subsystems

Following subsystem identification, components inducing breakdown of dragline were assigned to the relevant subsystems. It should be noted that components with no failure record were excluded in the analyses. Main failure-inducing components of the subsystems are:

- Dragging Unit: drag chain, drag rope, drag control, ringbolts, sockets
- Hoisting Unit: hoist rope, hoist control, brake, sockets
- Bucket Unit: bucket body, bucket chain, teeth, pins, ringbolts
- Rigging Unit: rigging rope, pulley, sockets, ringbolts
- Machinery House: generators, motors, lubrication unit, air-conditioning
- Movement Unit: rotation mechanism, walking mechanism, warning mechanism
- Boom Unit: boom chords

After specifying subsystems and their components, related failure data are assigned into each subsystem. Contribution of each subsystem to failure numbers and resultant system halts can be investigated at Pareto Charts in Figure 3.2. Total numbers of failures for 13-years period are 1,005 and 1,088 for Page and Marion draglines, respectively. Total maintenance breakdown durations are observed as 13,954 hours for Page and 16,471 hours for Marion. The chart reveals that dragging is the most frequently failed unit for Page while it is machinery house for Marion. However, machinery house is the unit with the highest repairing durations for both draglines and yields more than 50% of maintenance halts individually.

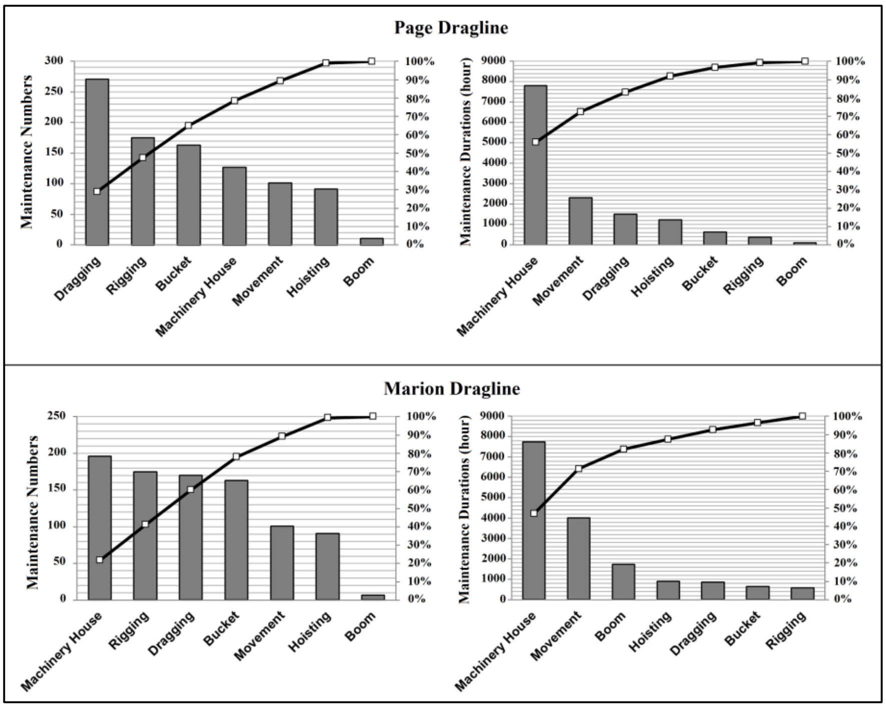


Figure 3.2 Failure Number and Breakdown Duration Distribution for the Draglines

3.3 Data Quality and Lifetime Trend Detection

Accuracy and validity of reliability and maintenance models is directly related to quality and convenience of the processed data. Errors and missing values in a dataset raises deviations in analysis outputs and lead to unexpected results. These anomalies may exist due to consequences of ignoring or skipping observation records, inconsistent data acquisition method, and human errors in data records. This section investigates data anomalies and data behavior using outlier, randomness, and trend tests.

Outliers are inconsistent data values compared to behavior of remaining dataset. They are extreme values, unexpectedly high or low, which lie visibly out of the harmony followed by general of data. Detection and elimination of these values are important since analysis covering outliers causes unfavorable deviations in results. Boxplot, i.e. box and whisker plot, can be utilized as a graphical statistic tool for both understanding of data distribution shape and detection of the extreme data values that can point to outlier existence (Rossi, 2010). Boxplots uses five descriptive statistics as the first quartile (Q_1), median (the second quartile), the third quartile (Q_3), maximum and minimum values of the sample, and number of observations (Figure 3.3). The first quartile, median, and the third quartile are the values indicating 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ percentile points in the distribution, respectively. They are presented on the box shape. On the other hand, minimum and maximum points are at the lower and upper part of the whiskers, lines at the both sides of the box. Minimum point and maximum point define the smallest and the largest data value in the set which fall between the ranges of $Q_1 - 1.5x$IQR and $Q_3 + 1.5x$IQR. IQR is interquartile range between Q_3 and Q_1 values, 50% of area under distribution curve is in this interquartile range. If any data falls above $Q_3 + 1.5x$IQR or below $Q_1 - 1.5x$IQR, it is generally defined as outlier. Box plots are nonparametric test, independent of data distribution type. Therefore, they can be utilized in non-normal lifetime behaviors.

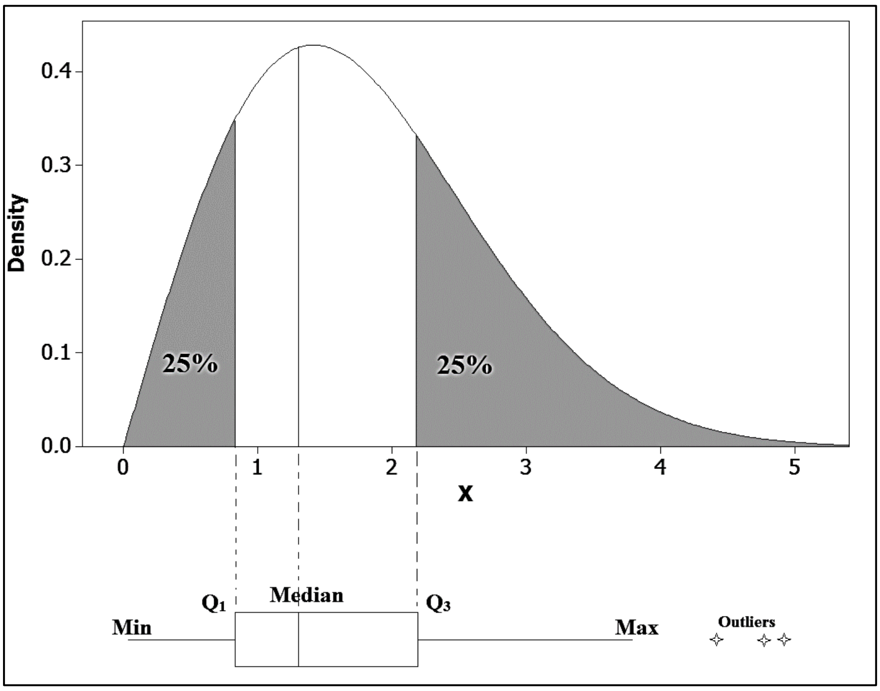


Figure 3.3 Box Plots in Outlier Detection

In the study, box plots were utilized in detection outliers for survival, i.e. TBF, and repair, i.e. TTR, data of individual components of draglines. Figure 3.4 shows sample plot for components of Page dragging unit.

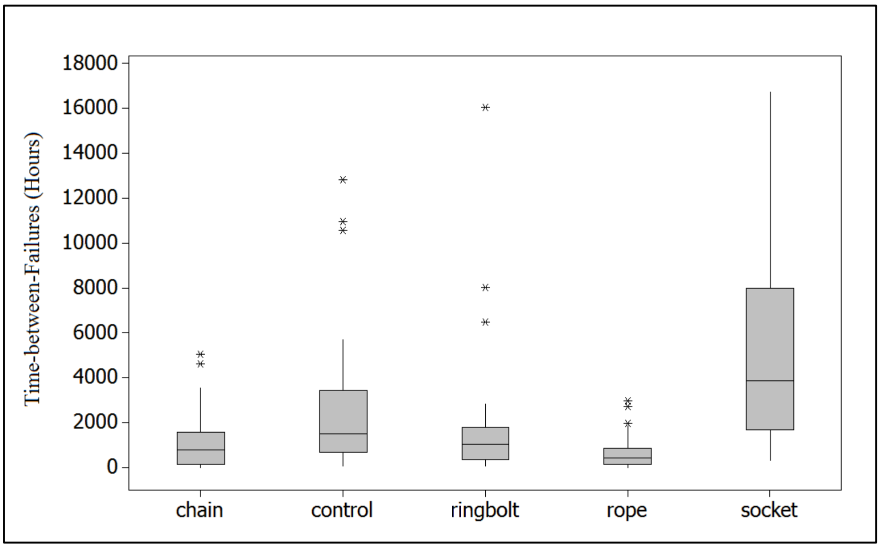


Figure 3.4 Outlier Detection in Page Drag Unit Using Box Plots

Star symbols in Figure 3.4 points to outliers for the individual components of Page drag unit. All outliers are extremely high values compared to other data values in the dataset. The plots also indicate that distributions of components are generally right tailed so data is accumulated towards the origin and large values are also observed in the distributions. It is important that candidate outliers near to whiskers can be due to right skewness in data distribution. Therefore, outlier should also be interpreted subjectively considering general behavior of dataset. For instance, candidate outliers for Page dragging rope in Figure 3.4 are accumulated near to whiskers. Therefore, elimination of these values can disturb natural behavior of the distribution.

Lack of data randomness is another anomaly in statistical analysis since hypothesis testing methods and confidence intervals are failed to explain the relevant analysis in case of using non-random data (Ruppert, 2011). Randomness can be detected using run charts which check trend, oscillation, mixture, and cluster behaviors of data around the median, reference line. Using the charts, each anomaly is tested using p-values and existence of anomaly is rejected if p-value is higher than α for $(1-\alpha)$ confidence interval. Data abnormalities appear as (i) unnatural accumulation of data values around a specific point leading to clustering problem, (ii) unexpected lack of data near to median leading to mixture problem, (iii) excessive ascending and descending ordering of data leading to trend problem, and (iv) rapid upward and downward aligning of data around median leading to oscillation problem. Figure 3.5 illustrates behavior of data abnormalities.

Sample run chart for drag rope component of Page dragline is shown in Figure 3.6. P-values for clustering, mixture, trend, and oscillation is higher than significance level of 0.05 for 95% confidence interval, then it is failed to reject null hypothesis. Therefore, run chart shows that there is no randomness problem in the dataset. For the other components of both draglines, there is also no anomaly indication for data randomness except for data trend. In a reliability study, data trend can be assumed as a characteristic of lifetime behavior instead of data anomaly. Therefore, trend issue was examined in detail using hypothesis testing methods.

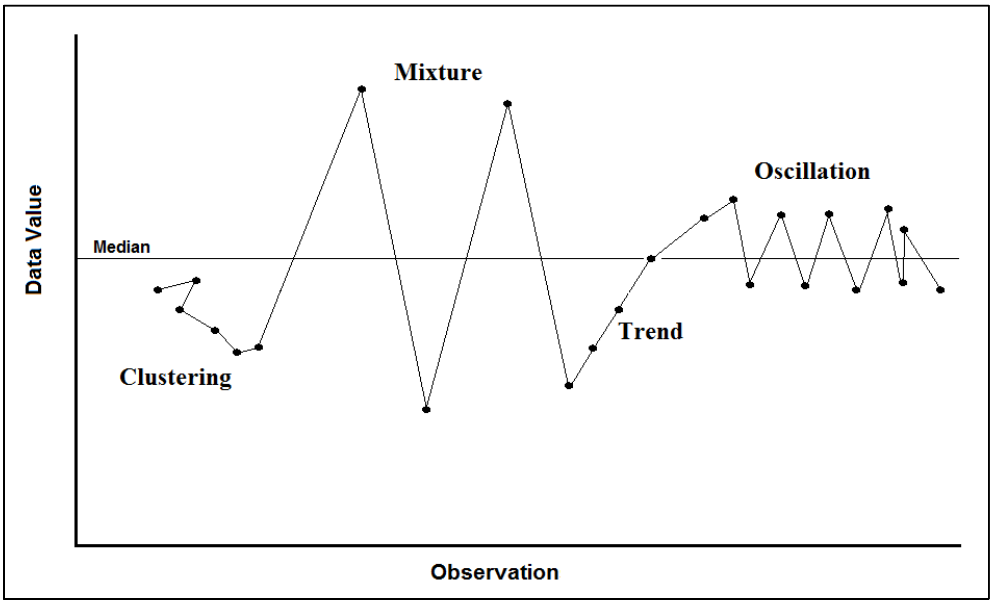


Figure 3.5 Potential Causes of Data Randomness

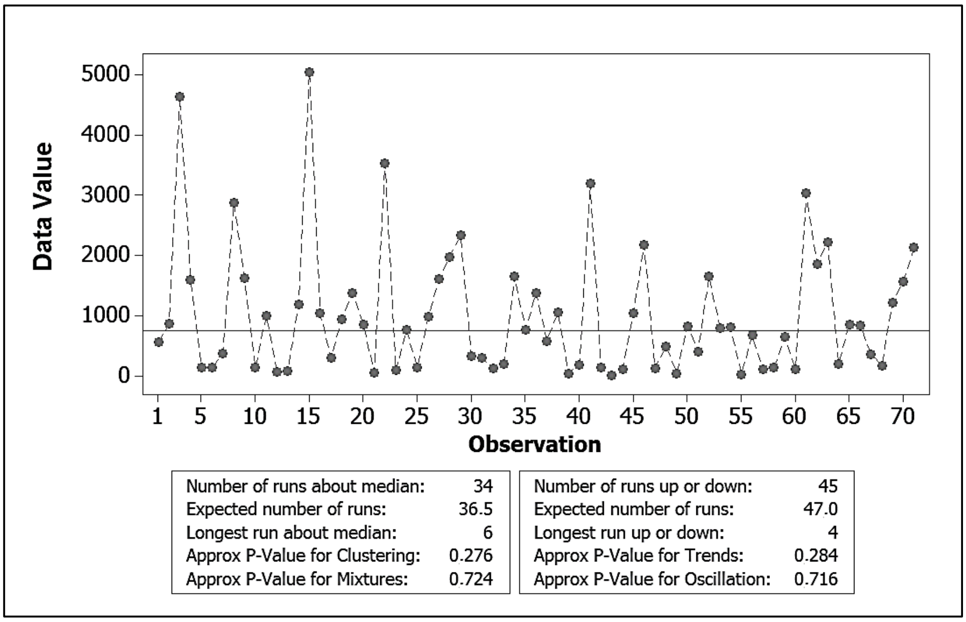
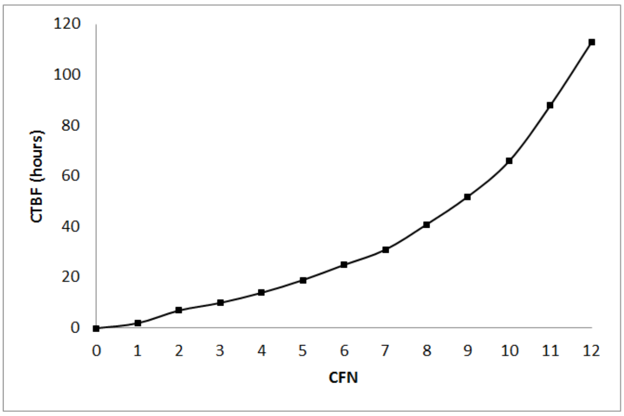


Figure 3.6 Run Chart for Drag Rope Component of Page Dragline

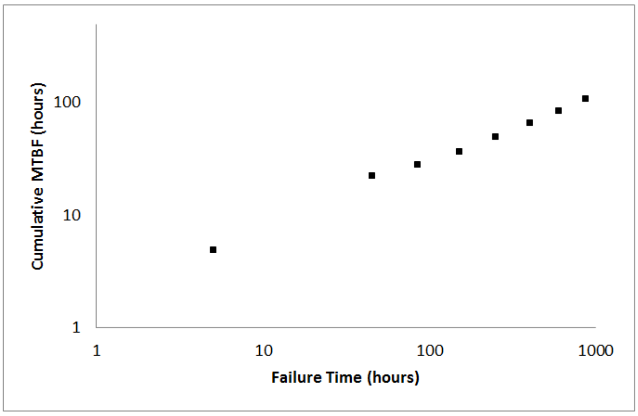
Although trend behavior is tested in run charts, it should be analyzed in detail to check whether repairable components are in lifetime wear-out/improvement period or not. This condition highly affects reliability evaluation method for the components. Effect of lifetime trend on reliability modelling will be discussed in Section 4. This section only focuses on the detection of trend behavior.

Lifetime data trend can be analyzed qualitatively and quantitatively. Qualitative graphs can be generated by plotting (i) cumulative failure numbers (CFN) versus cumulative time between failure (CTBF) and (i) failure times versus cumulative mean time between failures (MTBF) in log-log scale (called as Duane plot). Figure 3.7 illustrates sample plots using these two qualitative methods.



CFN	1	2	3	4	5	6	7	8	9	10	11	12
Survival Time (TBF)	2	5	3	4	5	6	6	10	11	14	22	25
CTBF	2	7	10	14	19	25	31	41	52	66	88	113

(a)



Failure Times	5	45	85	150	250	400	600	870
Cumulative MTBF	5	23	28	38	50	67	86	109

(b)

Figure 3.7 Sample Plot of CFN versus (a) CTBF and (b) Duane Plot

In CFN versus CTBF plot, curvature alignment of ordered data with concave up or concave down behavior may be indicator of potential data trend. For instance, curve in Figure 3.7 (a) is an example of upward trend for given data values. Similarly, Duane plot shows data trend if MTBF follow upward or downward alignment. Duane plot in Figure 3.7 (b) shows that there is not any indication of trend for the stated dataset. Even though the graphical methods are good indicators of degradation or growth of system age, they are generally interpreted subjectively. In this regard, quantitative hypothesis testing methods can be beneficial to deduce more objective results and to validate findings of qualitative plotting methods. Crow/AMSAA, pair-wise comparison nonparametric test (PCNT), Laplace test, and Lewis-Robinson test are frequently used in analysis of data trend for repairable systems (Wang and Coit, 2005). Crow/AMSAA and Laplace methods test whether the data can be fitted in homogenous Poisson process or not where Lewis-Robinson and PCNT methods check suitability of data for ordinary renewal process or not. Recall that homogenous Poisson process (HPP) is subset of ordinary renewal process (ORP) where data follows exponential distribution. Validity of HPP or ORP in these tests can be good evidence of non-trend behavior.

Crow/AMSAA examines whether the data can be fitted in HPP or NHPP. The method uses parameters, β, of failure intensity($\lambda\beta t^{\beta-1}$). Null hypothesis in the test assumes $\beta = 1$, then HPP is validated (constant failure intensity, λ). Alternative hypothesis assumes $\beta \neq 1$, degradation ($\beta < 1$) or growth ($\beta > 1$) of system reliability, and then NHPP is confirmed. Best estimate of β using maximum likelihood estimation is given in Equation 3.1. In the formula, N and T_i are the number of failures and arrival time (cumulative time between failures) of ith failure. (Wang and Coit, 2005)

$$\hat{\beta} = \frac{N}{\sum_{i=1}^{N-1} \ln(\frac{T_N}{T_i})} \tag{3.1}$$

According to the test, null hypothesis ($\beta = 1$) is rejected if $2N/\hat{\beta} < \chi^2_{2N,1-\alpha/2}$ or $2N/\hat{\beta} > \chi^2_{2N,\alpha/2}$, where χ and α are chi-squared distribution and confidence interval, respectively.

Other trend test, PCNT, measures whether the data can be modelled using renewal process or not. Presence of renewal process (null hypothesis) is rejected if $U_p > z_{\alpha/2}$ or $U_p < -z_{\alpha/2}$, U_p can be evaluated using Equation 3.2. In the formula, N is the number of failures and U is the number of cases where $X_j > X_i$ for $j > i$ (Wang and Coit, 2005).

$$U_p = \frac{U - N(N-1)/4}{\sqrt{\frac{(2N+5)(N-1)N}{72}}} \tag{3.2}$$

The third trend test, Laplace test, investigates whether data is well fitted in HPP or NHPP, as in Crow/AMSAA test. Acceptability of HPP (null hypothesis) is rejected if $U_L > z_{\alpha/2}$ or $U_L < -z_{\alpha/2}$. Test statistics, U_L, is stated in Equation 3.3. In the formula, N and T_i are the number of failures and arrival time (cumulative time between failures) of ith failure (Wang and Coit, 2005).

$$U_L = \frac{\sum_{i=1}^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}} \tag{3.3}$$

The last trend test, Lewis-Robinson test, seeks whether data is fitted in renewal process or not. Division of Laplace test statistics, U_p, to coefficient of variance is taken as target test statistics as given in Equation 3.4. Coefficient of variance can be expressed as $\sqrt{Var[X]}/\bar{X}$ where X is TBF data. Again, null hypothesis rejected if $U_{LR} > z_{\alpha/2}$ or $U_{LR} < -z_{\alpha/2}$ (Wang and Coit, 2005).

$$U_{LR} = \frac{U_L}{CV[X]} \tag{3.4}$$

Decisions of these tests can differ in some conditions where rejection value is in the limits. Although Crow/AMSAA is highly robust test, decision about data trend can be made considering results of the other tests, graphical illustration of lifetime trend, and lifetime behavior in recent time. Test hypothesis of quantitative trend tests and their rejection criteria are summarized in Table 3.1. These tests will be utilized in Section 4. for the dataset of each component for both draglines.

Table 3.1 Summary of Quantitative Trend Tests (Wang and Coit, 2005)

Test Name	Hypothesis	Test Hypothesis	Rejection Criteria
Crow/AMSAA	$H_0 = HPP$ $H_1 = NHPP$	$\hat{\beta} = \frac{N}{\sum_{i=1}^{N-1} \ln(\frac{T_N}{T_i})}$	$2N/\hat{\beta} < \chi^2_{2N,1-\alpha/2}$ $2N/\hat{\beta} > \chi^2_{2N,\alpha/2}$
Laplace	$H_0 = HPP$ $H_1 = NHPP$	$U_L = \frac{\sum_{i=1}^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}}$	$U_L > z_{\alpha/2}$ $U_L < -z_{\alpha/2}$
Lewis-Robinson	$H_0 = Renewal$ $H_1 = Not\ Renewal$	$U_{LR} = \frac{U_L}{\sqrt{Var[X]}/\bar{X}}$	$U_{LR} > z_{\alpha/2}$ $U_{LR} < -z_{\alpha/2}$
PCNT	$H_0 = Renewal$ $H_1 = Not\ Renewal$	$U_p = \frac{U - N(N-1)/4}{\sqrt{\frac{(2N+5)(N-1)N}{72}}}$	$U_p > z_{\alpha/2}$ $U_p < -z_{\alpha/2}$

CHAPTER 4

RELIABILITY OF WALKING DRAGLINES

4.1 Introduction

Energy demand in the global world and continual coal production in high quantities have been a requirement to enhance dragline performance. Productivity of these earthmovers is concerned by many interrelated components leaguing together to generate the system. Estimation of component reliability is the main tool to forecast the availability and reliability of the whole machinery. Deductive investigation approach is generally utilized in reliability investigations to reveal the root-causes of system failures. Components are the bottom elements of such a bottom-to-top reliability investigation. Precise construction of functional dependencies between components and subsystems is the primary issue to develop a system reliability model.

Dragline is a repairable system as other mining machineries. In the study, reliability block diagrams (RBD) were utilized to describe top-to-bottom relationships in subsystems and overall system. Reliability estimations of individual components were achieved regarding their lifetime trends and repairability conditions. Component repairability conditions were determined considering their maintenance type and failure modes. On the other hand, lifetime wear-out or growth, i.e. trend, behavior of components were detected via graphical and hypothesis testing methods as discussed in Section 3.3. Repairable component with lifetime trend were processed using general renewal process (GRP). Reliability of stationary repairable components and non-repairable component were estimated via best-fit distributions. In addition to reliability estimation, general renewal process was also utilized to examine maintenance effectiveness on dragline subsystems. Methodology to be utilized in this section can be viewed from Figure 4.1

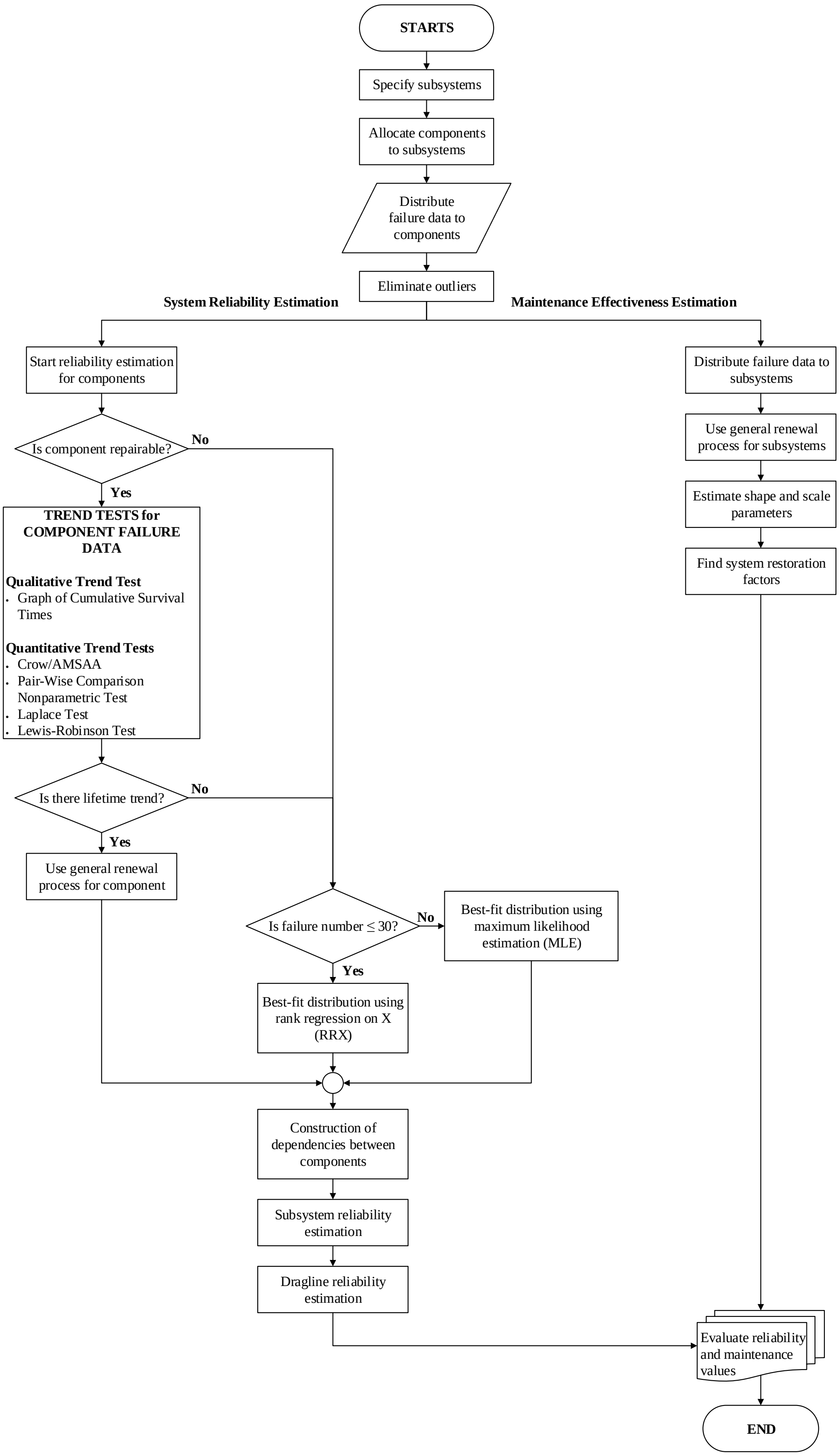


Figure 4.1 Methodology of the System Reliability Analysis

4.2 Reliabilities of Draglines' Subsystems

This section covers reliability and maintenance effectiveness estimations for individual subsystems of draglines. In the study, reliability modelling of draglines were achieved via reliability block diagrams and regarded both component reliabilities and their functional effects on the systems. Dragline is a combination of subsystems called as dragging, hoisting, bucket, rigging, machinery house, movement, and boom. Subsystem components are configured in a particular design to ensure different functionalities of dragline. Lifetime performance of each component has different effect on subsystem according to their functional and structural features.

Reliability estimation methods of components are affected from their repairability and lifetime trend behaviors (Figure 4.1). Repairability conditions can be investigated considering failure modes and resultant maintenance types where lifetime trend can be discussed using hypothesis tests and graphical lifetime illustrations. If a component is always replaced with an identical one in case of failure, it is called as non-repairable component. Corrective repairing for these components are generally not practical and economic. Since there is no any lifetime aging/growth behavior for non-repairable components, reliability of them can be estimated using best-fit distributions of time-to-failure values. On the other hand, a component is called as repairable if replacement of it after all failures is structurally and economically impossible. If component is detected to be repairable, then lifetime trend behavior should be examined. Components without any non-stationary deterioration or growth in their lifetimes are called as non-trend components. In this case, it is understood that the component is almost maintained to as good as new condition and they behave like non-repairable components. Therefore, best-fit distributions of time between failures values can be utilized for these components. If there is increasing/decreasing lifetime trend, reliability of these non-stationary components can be estimated using general renewal process (GRP). It should be noted that a repairable component can cover non-repairable sub-components. Therefore, repairability condition can change according to the definition boundary of components. Repairability assumptions of dragline components can be viewed in Table 4.1. Lifetime trend behavior of the components will be discussed in Sections 4.2.1-4.2.7.

Table 4.1 Repairability Conditions of Dragline Components

	Component	Failure Mode	Repair Type	Repairability
Dragging	Chain assembly	Breakage	Replacing and welding of individual chain	Repairable
	Ringbolt	Breakage	Welding	Repairable
	Rope-mode01	Rupture	Replacement	Non-repairable
	Rope-mode02	Dislocation from pulley	Recovering the mechanism	Repairable
	Control	General malfunction	General repair	Repairable
	Socket	Breakage	Welding	Repairable
Hoisting	Brake	Fail to brake	Mechanical repair	Repairable
	Rope-mode01	Rupture	Replacement	Non-repairable
	Rope-mode02	Dislocation from pulley	Recovering the mechanism	Repairable
	Socket	Breakage	Welding	Repairable
	Control	General malfunction	General repair	Repairable
Bucket	Bucket body	Wear and tear	Welding	Repairable
	Chain assembly	Breakage	Replacing and welding of individual chain	Repairable
	Digging teeth	Dropping, breakage	Replacing and welding of individual tooth	Repairable
	Pins	Breakage	Replacement of individual pins	Repairable
	Ringbolt	Breakage	Welding	Repairable
Rigging	Socket	Breakage	Welding	Repairable
	Ringbolt	Breakage	Welding	Repairable
	Rope-mode01	Rupture	Replacement	Non-repairable
	Rope-mode02	Dislocation from pulley	Recovering the mechanism	Repairable
	Pulley-mode01	Irrecoverable malfunction	Replacement	Non-repairable
	Pulley-mode02	Mechanical disintegration	Recovering the mechanism	Repairable
Machinery House	Generators	General malfunction	Removal of brush dust, fixing armatures, bearings or couplings	Repairable
	Motors	General malfunction	Removal of brush dust, fixing armatures, bearings or couplings	Repairable
	Lubrication	General malfunction	Fixing injectors, valves, pumps, air compressors or timing mechanism	Repairable
	Air conditioning	General malfunction	General repair	Repairable
Movement	Rotation	General malfunction	Fixing transmission box, bearings, felts, pinion gears, turret traversing mechanism, rails or flanges	Repairable
	Walking	General malfunction	Fixing transmission box, bearings, felts, walking axle, journal bearing, pins or steel construction of walking feet	Repairable
	Warning	General malfunction	Fixing connection couplings or warning brushes	Repairable
Boom	Boom chords	Fracture	Preventive welding	Repairable

As seen in Table 4.1, rope components of dragging, hoisting and rigging units are non-repairable components. However, these components may exhibit two different failure modes as rupture and dislocation from mechanism. If rupture exists, rope is replaced with a new one. On the other hand, dislocation from mechanism is recovered with repairing activity without component replacement. Rupture mode in the study were called as rope-mode1 to specify its non-repairable condition. Moreover, components such as, chain, pin, digging tooth are generally maintained with sub-component replacement. They were assumed as repairable sets including non-repairable individual components. For instance, pin component is repairable set which covers individual non-repairable pins.

4.2.1 Dragging Unit

Overburden stripping is achieved through dragging of dragline bucket. Dragging unit comprises individual components utilized for pull-back action of bucket toward machinery house in order to fill the bucket with loose ground material. Dragging chain, dragging rope, control elements, socket, and ringbolt are the main components of this unit. Reliability of dragging unit were evaluated via reliability estimation of these components. Then, effect of maintenance to subsystem recovery was discussed using general renewal process.

As stated in Figure 4.1, repairability condition and existence of lifetime trend effect reliability assessment method. In this sense, drag rope-mode01 is only non-repairable component in dragging units (Table 4.1). For repairable components, lifetime trend behaviors were analyzed using graphical trend tests (Figures 4.2-4.3) and hypothesis tests in 90% confidence interval (Tables 4.2-4.3). Trend tests indicated that chain assembly and rope-mode2 are the candidate components for lifetime trend in Marion dragging unit. Rope-mode2 slightly yields alternative hypothesis for PCNT and Lewis Robinson tests. Figure 4.2 also supports that this component is at the beginning of trend behavior. Therefore, it was assumed non-trend component. Eventually, chain assembly is only trend component in Marion dragging system. Reliability of it was assessed using GRP. On the other hand, there is no any candidate trend-component in Page dragging unit.

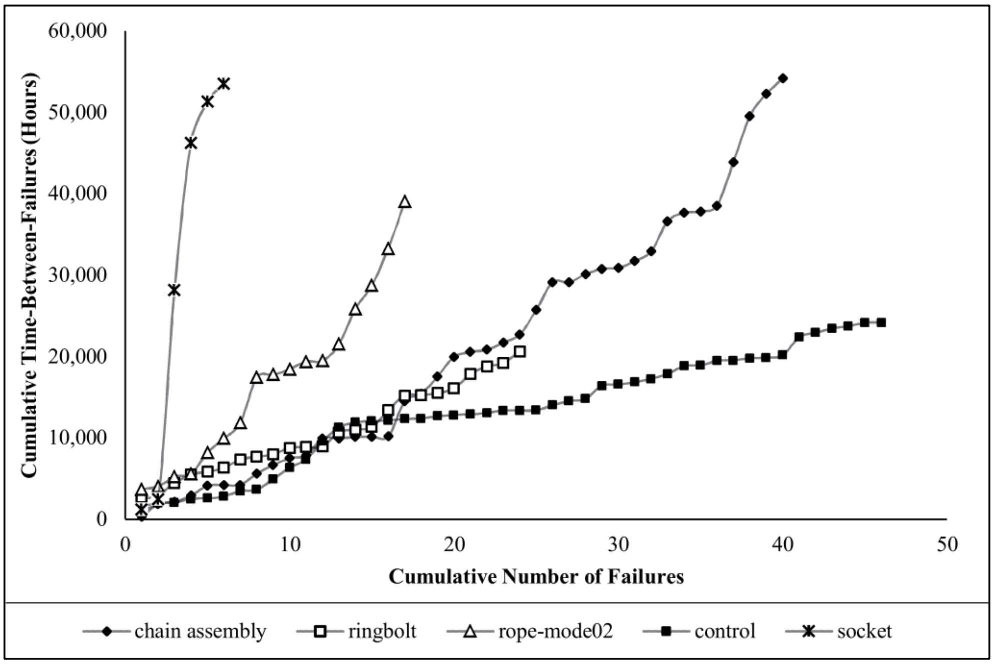


Figure 4.2 Graphical Lifetime Trend Test for Marion Dragging Unit

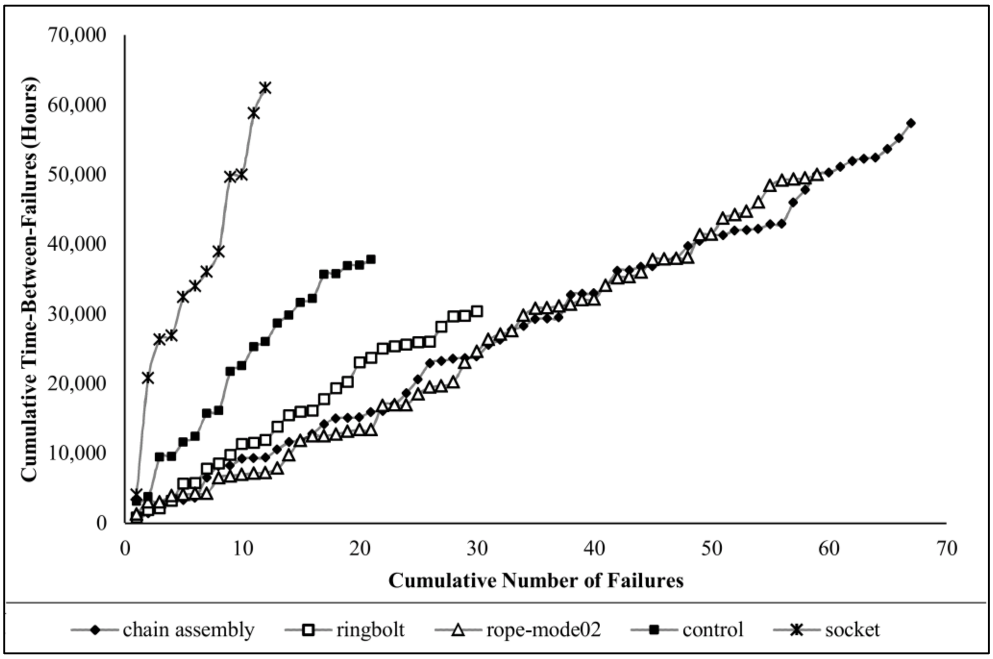


Figure 4.3 Graphical Lifetime Trend Test for Page Dragging Unit

Table 4.2 Quantitative Lifetime Trend Analysis for Marion Dragging Unit

Test Name	Test Parameters	Dragging Unit Components				
		Chain Assembly	**Ringbolt**	**Rope Mode02**	**Control**	**Socket**
Crow AMSAA	$2N/\hat{\beta}$	108.2	37.3	35.9	73.5	15.5
	$\chi^2_{2N,1-\alpha/2}$	60.4	33.1	21.6	70.9	5.2
	$\chi^2_{2N,\alpha/2}$	101.9	65.2	48.6	115.4	21.0
		Reject H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
Laplace	U_L	-2.76	0.14	-1.38	1.07	-0.13
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	2.05	-0.25	-1.68	-0.63	0.56
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Reject H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	-2.58	0.17	1.65	0.98	-0.11
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Reject H_0	Accept H_0	Accept H_0
	DECISION	Trend	Non-trend	Non-trend	Non-trend	Non-trend

Table 4.3 Quantitative Lifetime Trend Analysis for Page Dragging Unit

Test Name	Test Parameters	Dragging Unit Components				
		Chain Assembly	**Ringbolt**	**Rope Mode02**	**Control**	**Socket**
Crow AMSAA	$2N/\hat{\beta}$	134.8	54.0	118.6	28.9	16.6
	$\chi^2_{2N,1-\alpha/2}$	108.3	43.2	93.9	28.1	13.8
	$\chi^2_{2N,\alpha/2}$	162.0	79.1	144.4	58.1	36.4
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
Laplace	U_L	-0.59	0.43	-0.54	1.37	0.58
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	0.48	-0.77	-0.51	-1.27	-0.27
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	-0.63	0.56	0.77	1.46	0.63
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend	Non-trend

As discussed in Figure 4.1, reliability parameters of non-trend repairable parts and non-repairable components can be estimated using best-fit distributions where trend repairable parts can be processed using general renewal function. Regarding these assumptions, lifetime characteristic parameters of individual components are estimated as in Table 4.4.

Table 4.4 Lifetime Parameters of Dragging Unit Components

	MARION		PAGE	
Chain	General Renewal Process		Weibull-3P	
	Beta	0.90	Beta	0.92
	Eta	626.68	Eta	812.30
	Restoration Factor	0.00	Gamma	15.79
Control	Weibull-3P		Weibull-2P	
	Beta	0.90	Beta	0.93
	Eta	485.70	Eta	1,820.23
	Gamma	11.50		
Ringbolt	Weibull-3P		Weibull-2P	
	Beta	1.04	Beta	1.25
	Eta	820.81	Eta	1,085.00
	Gamma	51.95		
Rope-Mode01	Weibull-3P		Loglogistic	
	Beta	2.18	Mu	6.72
	Eta	1,848.27	Sigma	0.45
	Gamma	-388.95		
Rope-Mode02	Weibull-3P		Weibull-3P	
	Beta	0.95	Beta	0.77
	Eta	2,451.80	Eta	732.24
	Gamma	13.96	Gamma	9.84
Socket	Lognormal-2P		Weibull-2P	
	(LN) Mean	8.40	Beta	0.97
	(LN) Std	1.45	Eta	5,509.90

Table 4.4 indicates that failure behavior of dragging components can be qualified using Weibull distribution commonly as well as lognormal and loglogistic distributions and general renewal process. Weibull distribution can be identified with either two or three descriptive parameters. Shape (beta) and scale (eta) parameters are common for both Weibull-2P and -3P. Shape parameter describes alignment of the distribution curve. Weibull distribution holds exact behavior of normal or exponential distribution in case that shape parameter is equal to 3.5 or 1, respectively. Therefore, a shape parameter less than 1 refers high failure frequency in early times and monotonic decrease of graph line from the origin. If shape parameter is greater than 1, density function takes bell-shape curve and peak point of the function shifts to the right. Besides, growth in shape factor is also related to failure rate such that this situation can point to possible wear-

out initiation in the system. The second descriptive parameter, scale, is a specific characteristic lifetime where failure probability of the component is exactly equal to 63.2%. Unlike two parametric one, Weibull-3P also includes an additional parameter called as location parameter (gamma). It denotes amount of curve shift away from the origin. Positive location parameter moves the curve right hand side of the origin where negative parameter shifts it to the left hand side of the origin. Positive location parameter is called as failure free time since it refers a particular lifetime where failure probability is zero prior to it.

Large majority of the dragging components were best fitted to Weibull distribution. These components generally exhibit quasi-exponential behavior with shape parameter (Beta) near to 1. It points to the accumulation of data near to the origin and monotonic decrease of curve away from the origin. With shape parameter larger than 1, Marion rope-mode01 and Page ringbolt have bell-shape distributions.

Lognormal distribution was fitted for Marion socket component. Inherently, lognormal distribution has an increasing trend up to the peak point and then it starts to go down. It is derived version of normal distribution. It is generally good fitted for the wear-out failure data in which rapid rise of failure rate is observed. Therefore, failure behavior of Marion socket component is expected to show alteration with rising lifetime duration.

General renewal process (GRP) was applied only for Marion dragging chain. This stochastic process utilizes chronological failure points of system in a time period and it does not use survival time frequency as in best-fit distributions. Other common stochastic methods, ordinary renewal and non-homogenous Poisson processes assume that system is recovered to as good as new and as bad as old conditions after maintenance, respectively. Therefore, ordinary renewal process assumes that repairing activities are carried out perfectly and no aging effect is observed in the system where non-homogenous Poisson process supposes that system is returned to the state just before the failure with minimal repairing. Therefore, systems with non-homogenous Poisson process continue to age consistently. On the other hand, general renewal process introduces q-value which is Kijima's imperfect maintenance parameter as discussed in Section 2.5.3. This parameter is the degree of repair which can take value between 0 and 1. Restoration factor can also be utilized alternatively since restoration factor (RF) = 1-q. It assumes that recovered system can be any state between as good as new and as bad as old. It is a flexible stochastic process compared to other methods. Besides, general renewal process reduces to ordinary renewal process or non-homogenous Poisson process if q parameters equals to exact 0 or 1, respectively. GRP is identified using shape and scale parameters as in Weibull-2P. Marion dragging socket has shape parameter with 0.9 and exhibit quasi-exponential behavior. Besides, restoration factor with exact zero refers that this component shows as bad as old condition after maintenance with minimal repair. Reliability curves of dragging components for both draglines can be investigated in Figures 4.4-4.5.

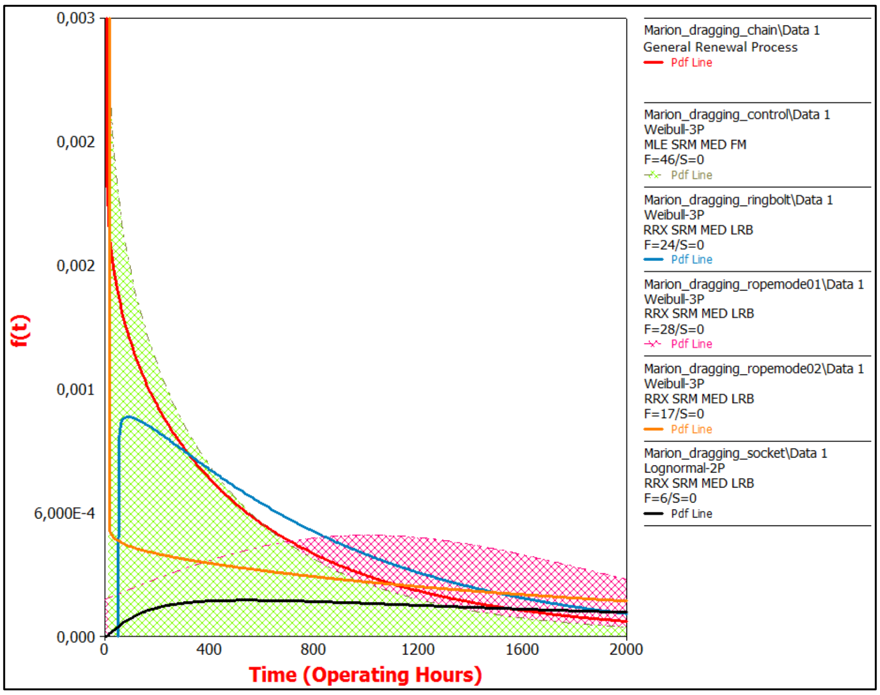


Figure 4.4 Probability Density Functions of Marion Dragging Unit Components

Using lifetime parameters, expected lifetime values (area under reliability curves) of the components were determined as in Table 4.5. Calculations revealed that socket components for both dragline exhibit the longest lifetimes in the dragging unit. On the other hand, drag control for Marion and drag chain for Page are components with the least working lifetimes. All components for dragging units are expected to survive more than 500 hours operating time

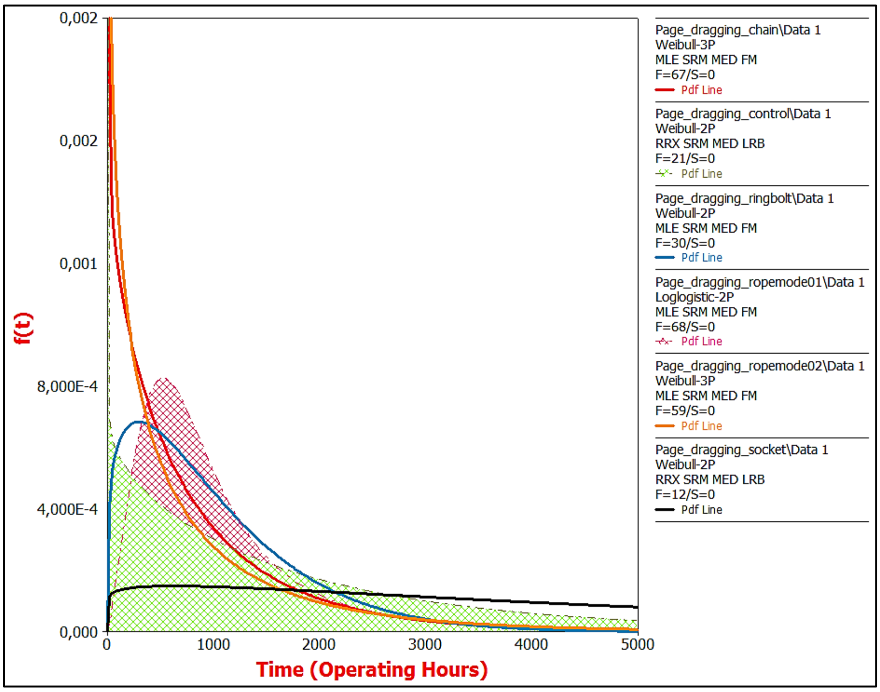


Figure 4.5 Probability Density Functions of Page Dragging Unit Components

Table 4.5 Expected Lifetime Durations (Hours) of Dragging Unit Components

	Dragging Unit Components					
	Chain	**Control**	**Ringbolt**	**Rope-Mode01**	**Rope-Mode02**	**Socket**
Marion	659	524	859	1,248	1,189	12,686
Page	858	1,880	1,011	2,521	860	5,204

Reliability of dragging units can be estimated considering dependencies between components. Functionality of a dragging unit is interrupted in failure of any component. Therefore, the component are connected to each other in series order and subsystem reliability can be calculated with multiplication of component reliabilities as in Equation 4.1.

$$R_{Drag}(t) = R_{Chain}(t).R_{Control}(t).R_{Ringbolt}(t).R_{RopeM1}(t).R_{RopeM2}(t).R_{Socket}(t) \quad (4.1)$$

Reliability behaviors of dragging units and components can be examined in Figures 4.6-4.7. The graphical illustrations show that reliability of Marion dragging unit falls down slightly sharper compared to Page. Expected lifetime duration of Marion and Page dragging units are 176 and 210 hours, respectively.

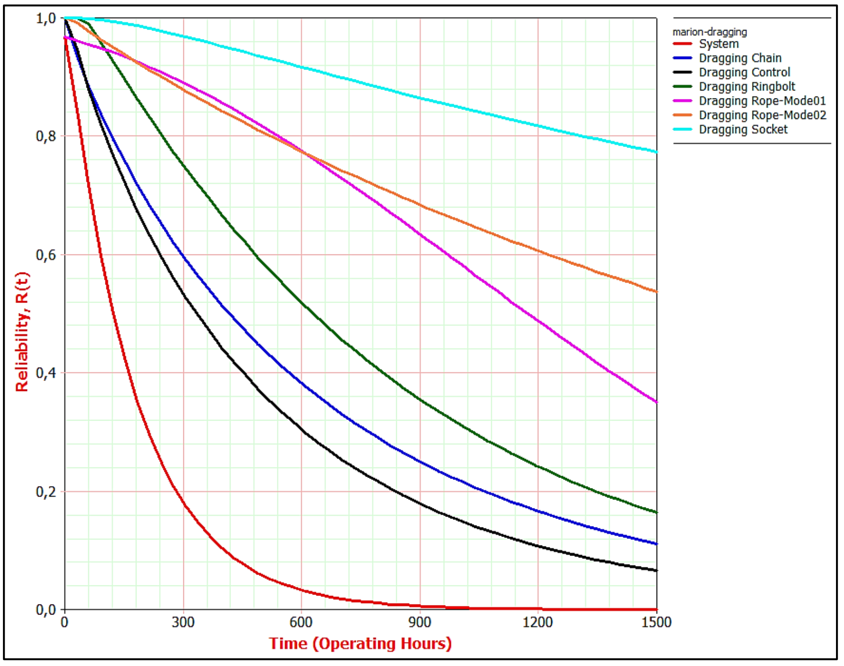


Figure 4.6 System and Component Reliability Curves of Marion Dragging Unit

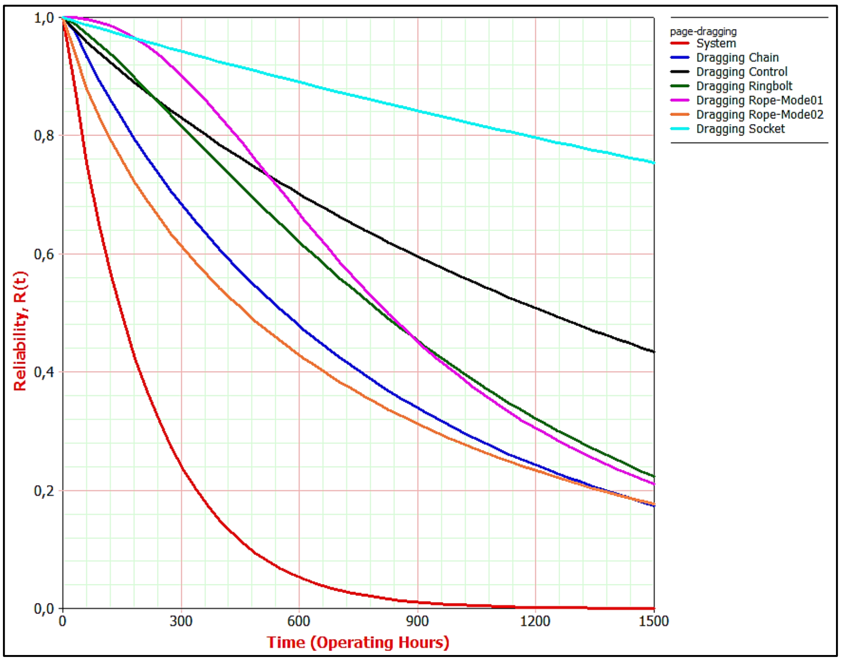


Figure 4.7 System and Component Reliability Curves of Page Dragging Unit

For quantitative investigation, reliability variations of subsystems between 0-150 operating hours can be investigated in Table 4.6.

Table 4.6 Reliability Variation of Dragging Units in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion Dragging Reliability	0.87	0.77	0.66	0.57	0.49	0.43
Page Dragging Reliability	0.90	0.80	0.71	0.63	0.56	0.50

Table 4.6 showed that reliabilities of dragging units for Marion and Page drop below 50% after 125 and 150 operating hours, respectively. In addition to reliability modelling, maintenance effectiveness for the units were also measured using general renewal process. The method was utilized with failure data of subsystem without any component decomposition. It allowed to gain a holistic view on maintenance effectiveness for the units. In this basis, GRP parameters and restoration factors can be examined in Table 4.7

Table 4.7 Maintenance Restoration Effectiveness for Dragging Units

	General Renewal Function Parameters				
	Shape (Beta)	**Lambda**	**Scale (Eta)**	**Degree of Repair**	**Restoration Factor**
Marion	0.64	0.48	117.76	0.57	0.43
Page	0.75	0.02	180.68	0.36	0.64

It can be understood from Table 4.7 that maintenance activities recover Marion and Page dragging units to as good as new condition with 43% and 64%, respectively. These values indicate that maintenance policy for the units may be improved to prevent the potential effects of system aging in future period.

4.2.2 Hoisting Unit

Working elements of hoisting unit are utilized to lift the full bucket following dragging action. Brake, rope, socket, and control components are the main parts of the unit.

Socket was excluded in the reliability analysis of Marion hoisting unit due to lack of failure information.

Current maintenance activities show that hoist rope is the only non-repairable component in hoisting unit (Table 4.1). Repairable components of the unit were pre-processed with qualitative and quantitative trend tests to detect their lifetime behaviors. Graphical illustration of cumulative time between failures values for hoisting units can be viewed in Figures 4.8-4.9. Quantitative evaluation of lifetime trend via hypothesis tests in 90% confidence interval can be investigated in Tables 4.8-4.9.

In Marion hoisting unit, brake and rope-mode02 components are candidate trend-component. For brake component, only Crow AMSAA and Laplace tests defense trend behavior via rejecting the null hypothesis. Considering the test decisions and regular lifetime decrease illustrated in Figure 4.8, this component was assumed as trend component. On the other hand, rope-mode02 was assumed to be non-trend component since majority of the test accepts null hypothesis and there is not consistent lifetime increase/decrease in the graph (Figure 4.8). For Page hoisting unit, there is strong trend indication for rope-mode02 and control components.

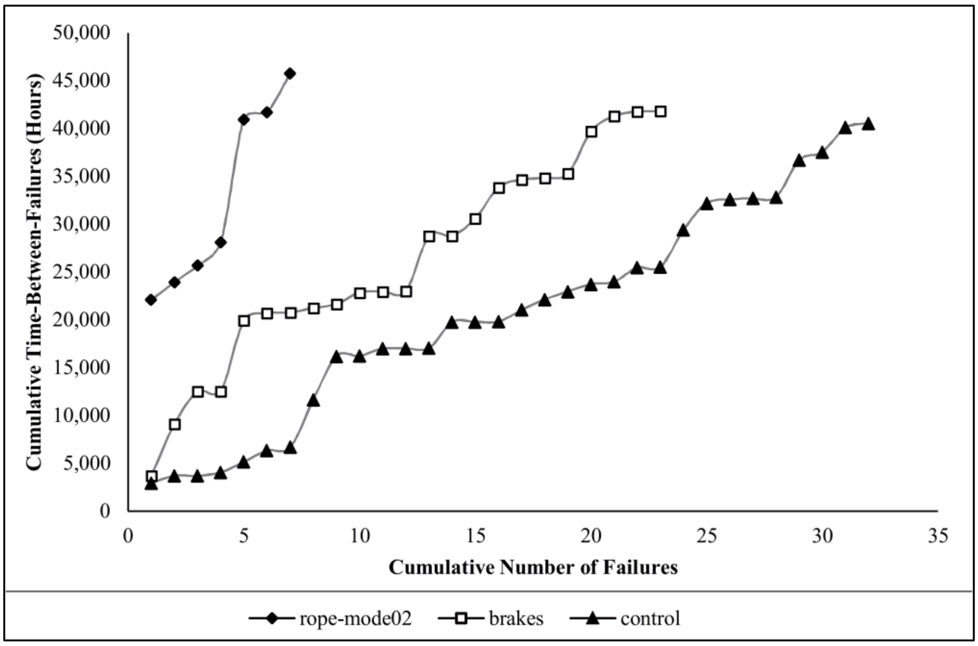


Figure 4.8 Graphical Lifetime Trend Test for Marion Hoisting Unit

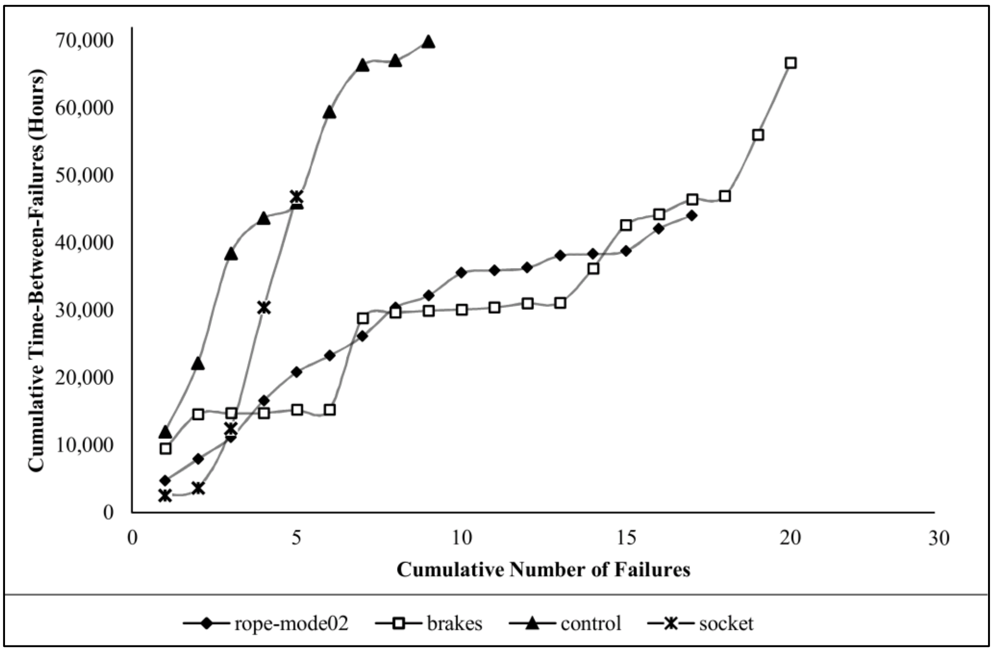


Figure 4.9 Graphical Lifetime Trend Test for Page Hoisting Unit

Table 4.8 Quantitative Lifetime Trend Analysis for Marion Hoisting Unit

Test Name	Test Parameters	Hoisting Unit Components			
		Rope Mode02	**Brakes**	**Control**	**Socket**
Crow AMSAA	$2N/\hat{\beta}$	5.3	24.4	57.0	No Available Data
	$\chi^2_{2N,1-\alpha/2}$	6.6	31.4	46.6	
	$\chi^2_{2N,\alpha/2}$	23.7	62.8	83.7	
		Reject H_0	Reject H_0	Accept H_0	
Laplace	U_L	1.40	1.77	-0.04	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Accept H_0	Reject H_0	Accept H_0	
PCNT	U_p	-0.45	-0.92	0.45	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Accept H_0	Accept H_0	Accept H_0	
Lewis Robinson	U_{LR}	1.22	1.47	-0.04	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Accept H_0	Accept H_0	Accept H_0	
	DECISION	Non-trend	Trend	Non-trend	-

Table 4.9 Quantitative Lifetime Trend Analysis for Page Hoisting Unit

Test Name	Test Parameters	Hoisting Unit Components			
		Rope Mode02	**Brakes**	**Control**	**Socket**
Crow AMSAA	$2N/\hat{\beta}$	19.9	34.7	9.3	14.4
	$\chi^2_{2N,1-\alpha/2}$	21.6	26.5	9.4	3.9
	$\chi^2_{2N,\alpha/2}$	48.6	55.8	28.9	18.3
		Reject H_0	Accept H_0	Reject H_0	Accept H_0
Laplace	U_L	1.69	-0.78	1.32	-1.63
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	1.45	1.43	-1.67	1.47
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Reject H_0	Accept H_0
Lewis Robinson	U_{LR}	2.71	-0.61	1.88	-2.00
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Reject H_0	Accept H_0
	DECISION	Trend	Non-trend	Trend	Non-trend

Regarding the trend tests, hoisting brake for Marion and hoisting control and rope-mode02 for Page were processed using general renewal process where reliability of the other components were estimated via best-fit distributions (Table 4.10).

Table 4.10 Lifetime Parameters of Hoisting Unit Components

	MARION		**PAGE**	
Brake	General Renewal Process		Lognormal-2P	
	Beta	0.65	(LN) Mean	6.83
	Eta	1,443.72	(LN) Std	1.99
	Restoration Factor	0.90		
Control	Weibull-2P		General Renewal Process	
	Beta	0.71	Beta	1.65
	Eta	1,042.13	Eta	10,566.22
			Restoration Factor	0.80
Rope-Mode01	Normal-2P		Loglogistic-2P	
	Mean	2,851.59	Mu	7.44
	Std	1,640.61	Sigma	0.23
Rope-Mode02	Lognormal-2P		General Renewal Process	
	(LN) Mean	8.17	Beta	1.52
	(LN) Std	1.30	Eta	7,361.11
			Restoration Factor	0.00
Socket	No information		Weibull-2P	
			Beta	0.87
			Eta	10,402.66

For Marion, control and brake components exhibit quasi-exponential behaviors with shape parameters less than 1. Rope components with both failure modes hold bell-shape distributions. For Page dragline, all components except for socket follow bell-shape lifetime curves. Trend-components were processed using general renewal process and their restoration factors were acquired as 90%, 80%, 0% for Marion hoisting brake, Page hoisting control and rope-mode02, respectively. These values indicated that maintenance for Marion hoisting brake and Page hoisting control was renewed these components to almost as good as new condition. However, they can be improved with more effective repair policies. On the other hand, Page rope-mode02 was detected to be maintained to as bad as old state. Maintenance generally recovered the component to condition just prior to failure. Therefore, more conservative policies may be performed to prevent the halts induced by this component. In addition to lifetime parameters, related lifetime curves can also be investigated in Figures 4.10-4.11.

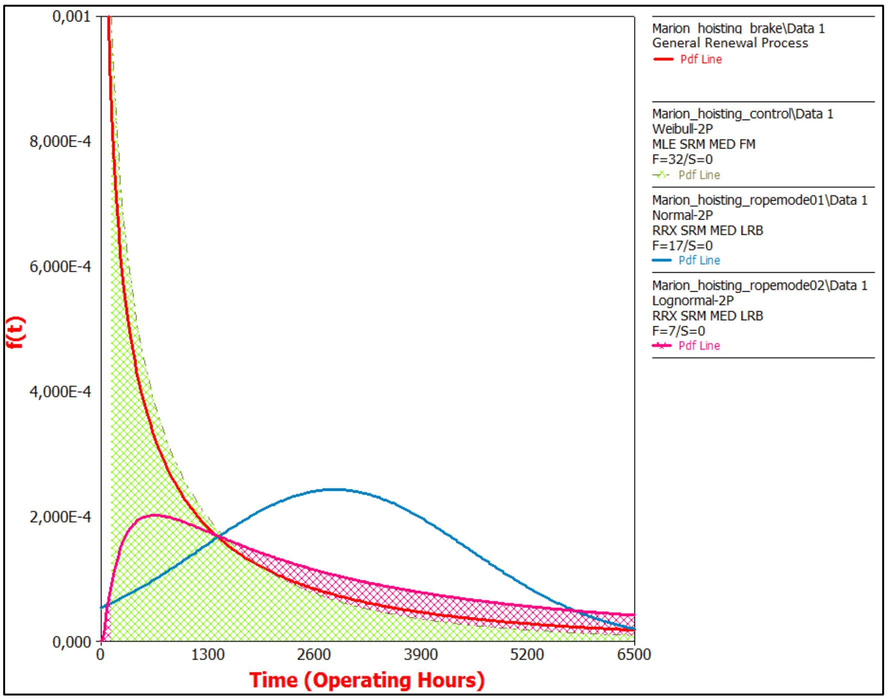


Figure 4.10 Probability Density Functions of Marion Hoisting Unit Components

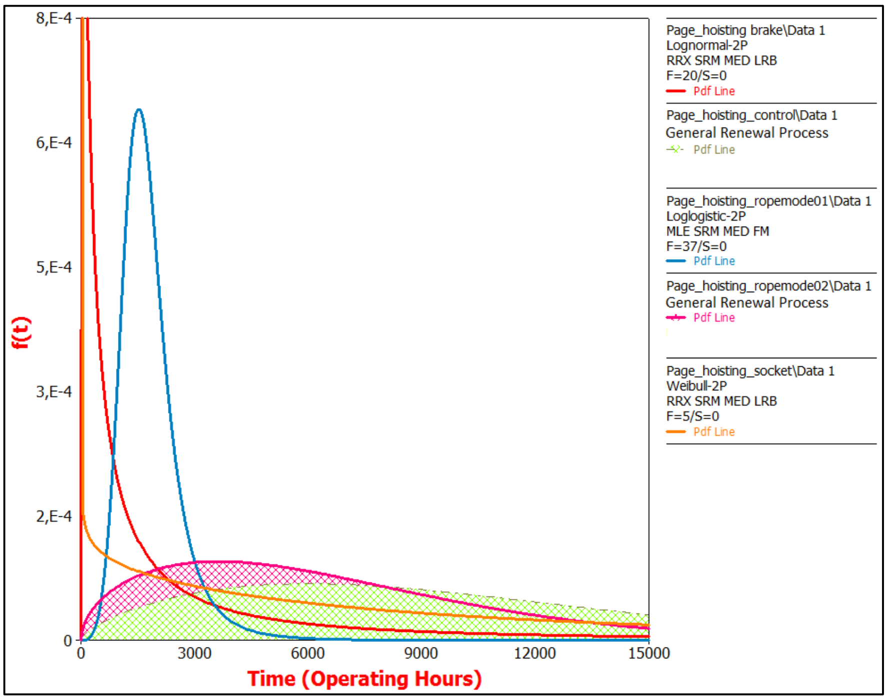


Figure 4.11 Probability Density Functions of Page Hoisting Unit Component

Areas under the probability density functions gave the expected lifetimes of components as stated in Table 4.11. According to the values, all components are expected to operate more than about 1,300 hours without failure. Control component for Marion and rope-mode01 for Page are the components with the lowest working lifetime and the highest maintenance frequency.

Table 4.11 Expected Lifetime Duration (Hours) of Hoisting Unit Components

	Hoisting Unit Components				
	Brake	**Control**	**Rope-Mode01**	**Rope-Mode02**	**Socket**
Marion	1,972	1,295	2,852	8,144	-
Page	6,642	9,448	1,848	6,634	11,162

Breakdown of any component leads to non-functionality of whole hoisting unit. Therefore, they are connected to each other with series order as shown in Equation 4.2. Component and hoisting system curves can be seen in Figures 4.12-4.13 for both draglines. Mean lifetimes of the units for Marion and Page were calculated as 431 and 830 operating hours, respectively.

$$R_{Hoisting}(t) = R_{Brake}(t).R_{Control}(t).R_{RopeM1}(t).R_{RopeM2}(t).R_{Socket}(t) \quad (4.2)$$

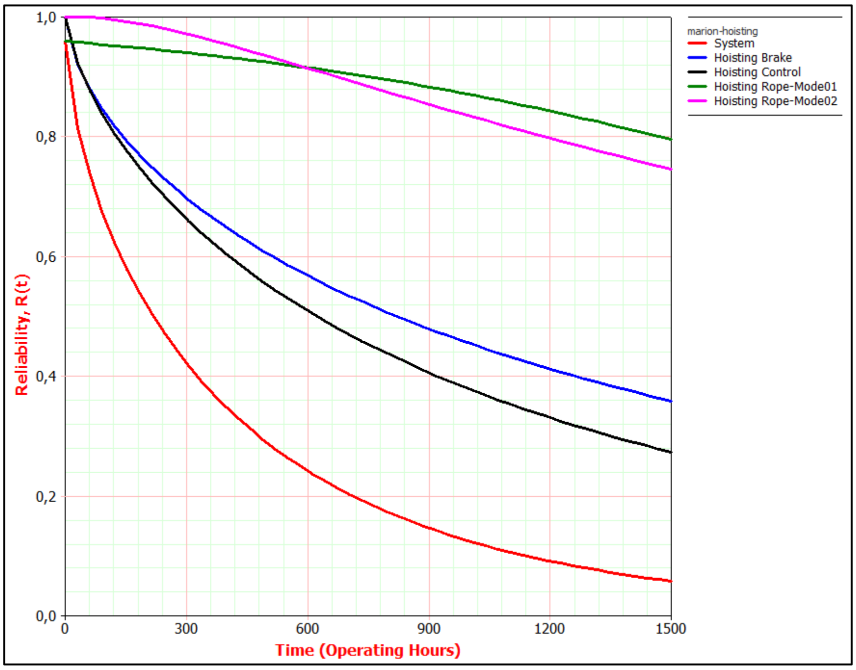


Figure 4.12 System and Component Reliability Curves of Marion Hoisting Unit

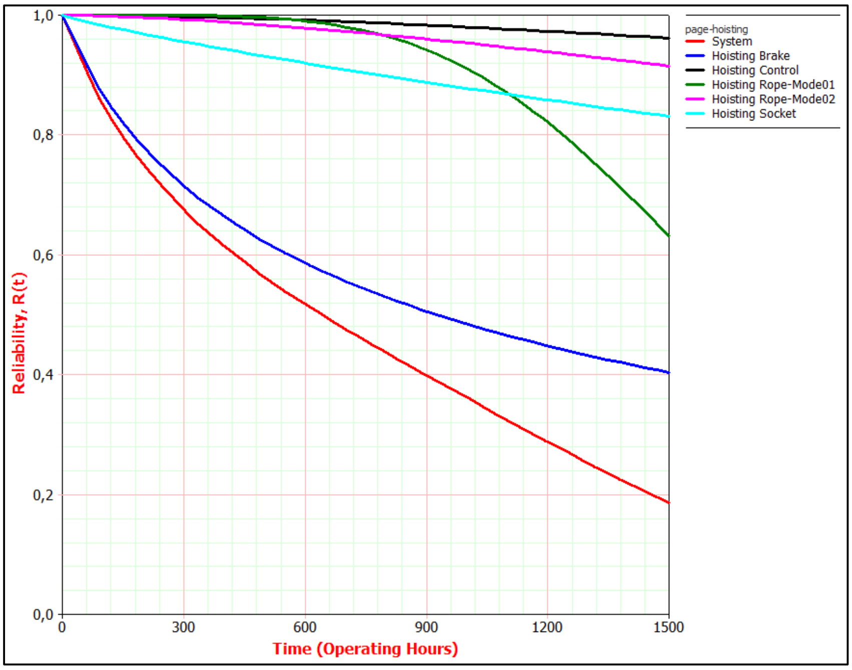


Figure 4.13 System and Component Reliability Curves of Page Hoisting Unit

Figures 4.12-4.13 showed that system reliability dropped below 50% at 218th and 641th operation hours for Marion and Page, respectively. Reliability variations in 150 operating hours can also be seen in Table 4.12.

Table 4.12 Reliability Variation of Hoisting Units in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion Hoisting Reliability	0.83	0.76	0.71	0.66	0.62	0.58
Page Hoisting Reliability	0.96	0.92	0.88	0.85	0.82	0.79

In addition to reliability assessment, general renewal process was also applied to evaluate maintenance effectiveness for the units. Restoration factors in Table 4.13 reveals that both hoisting units are restored to almost as good as new condition after maintenance activities.

Table 4.13 Maintenance Restoration Effectiveness for Hoisting Units

	General Renewal Function Parameters				
	Shape (Beta)	**Lambda**	**Scale (Eta)**	**Degree of Repair**	**Restoration Factor**
Marion	0.81	6.40E-3	520.87	3.30 E-3	0.99
Page	1.09	8.00E-4	729.357	0.00	1.00

4.2.3 Bucket Unit

During overburden stripping, resistance of formation against earthmoving activity is absorbed by the bucket and transmitted to other units of dragline such as, drag chain, hoist chain, rigging, and boom. Bucket is the source and initiation area of external forces during operation. Therefore, lifetime investigation of bucket unit elements is critically important to forecast possible failures in this stress intensive region. Bucket unit covers various mechanical parts such as, main bucket body, chain, digging teeth, pin, and ringbolt.

Since individual chain, digging tooth, and pin are generally replaced with new ones in case of any failure, they are individually non-repairable parts. However, sets of identical parts can be referred as repairable since such a set cannot be replaced completely after failures. Therefore, all bucket components were considered and graphical and hypothesis tests were utilized to measure lifetime trend for these components as shown in Figures 4.14-4.15 and Tables 4.14-4.15, respectively.

In Marion bucket unit, only pin component has slight indication of trend. Considering the hypothesis test values and graphical illustration, this component was assumed as non-trend component. On the other hand, teeth, ringbolt, and bucket main body components in Page bucket unit were detected to show lifetime trend. Regarding the reliability assessment methodology in Figure 4.1, reliabilities of trend-components were estimated using general renewal process since they follow nonstationary lifetime behavior. On the other side, reliabilities of the other components were estimated using best-fit distributions.

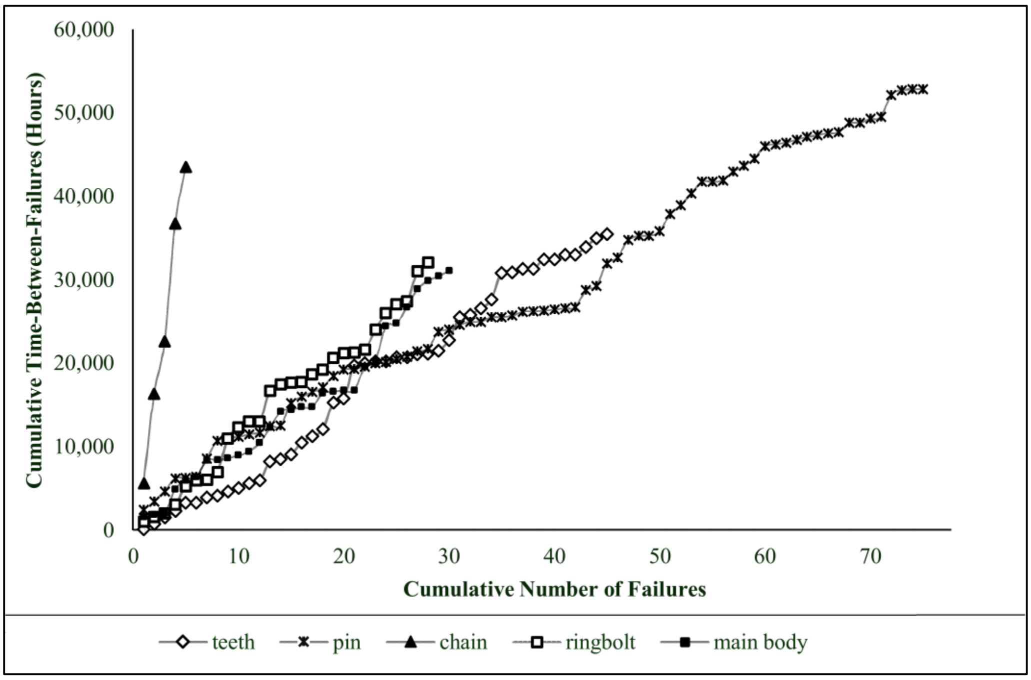


Figure 4.14 Graphical Lifetime Trend Test for Marion Bucket Unit

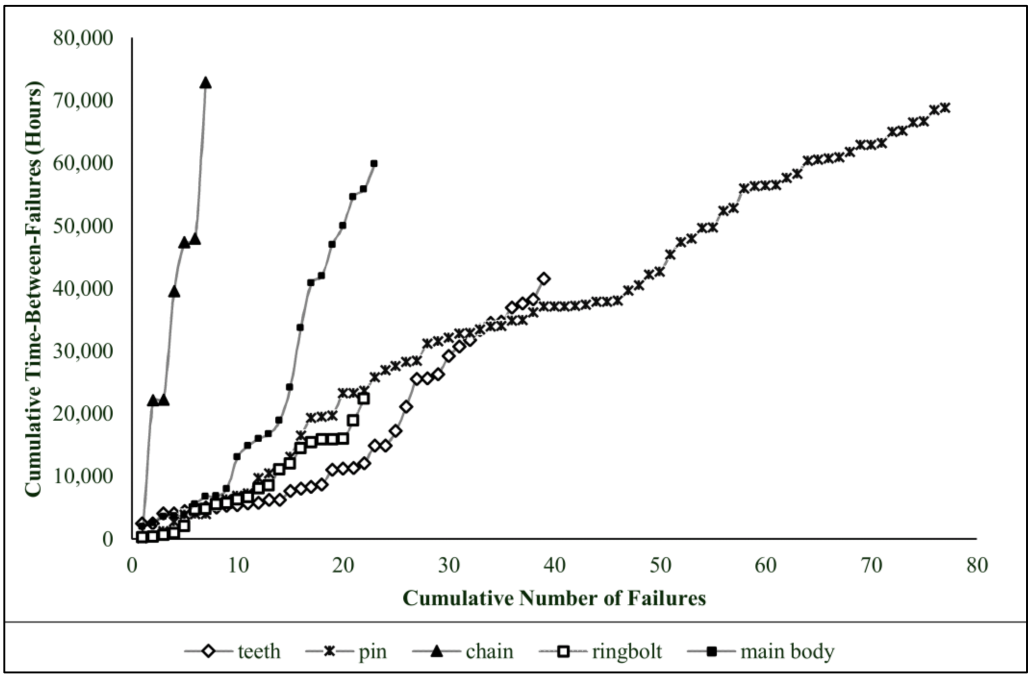


Figure 4.15 Graphical Lifetime Trend Test for Page Bucket Unit

Table 4.14 Quantitative Lifetime Trend Analysis for Marion Bucket Unit

Test Name	**Test Parameters**	**Bucket Unit Components**				
		Teeth	**Pin**	**Chain**	**Ringbolt**	**Main Body**
Crow AMSAA	$2N/\hat{\beta}$	97.8	117.9	7.7	56.5	58.5
	$\chi^2_{2N,1-\alpha/2}$	69.1	122.7	3.9	39.8	43.2
	$\chi^2_{2N,\alpha/2}$	113.1	179.6	18.3	74.5	79.1
		Accept H_0	Reject H_0	Accept H_0	Accept H_0	Accept H_0
Laplace	U_L	-0.16	1.17	-0.23	-0.52	-0.67
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	-0.29	-1.28	0.98	0.16	0.62
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	-0.14	1.11	-0.55	-0.54	-0.67
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0	Accept H_0
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend	Non-trend

Table 4.15 Quantitative Lifetime Trend Analysis for Page Bucket Unit

Test Name	Test Parameters	Hoisting Unit Components				
		Teeth	**Pin**	**Chain**	**Ringbolt**	**Main Body**
Crow AMSAA	$2N/\hat{\beta}$	98.58	151.92	18.10	62.57	66.26
	$\chi^2_{2N,1-\alpha/2}$	58.65	126.31	6.57	29.79	31.44
	$\chi^2_{2N,\alpha/2}$	99.62	183.96	23.68	60.48	62.83
		Accept H_0	Accept H_0	Accept H_0	Reject H_0	Reject H_0
Laplace	U_L	-1.90	0.57	-0.76	-2.05	-2.32
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Reject H_0	Reject H_0
PCNT	U_p	2.63	-0.48	0.75	0.82	2.40
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Reject H_0	Reject H_0
Lewis Robinson	U_{LR}	-1.69	0.56	-0.73	-1.95	-2.44
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Accept H_0	Reject H_0
	DECISION	Trend	Non-trend	Non-trend	Trend	Trend

Considering lifetime trend analyses and assumptions on reliability assessment, lifetime parameters of the bucket units were determined as in Table 4.16.

Table 4.16 Lifetime Parameters of Bucket Unit Components

	MARION		**PAGE**	
Chain	Exponential-2P		Weibull-2P	
	Lambda	0,0002	Beta	0.61
	Gamma	4,528.10	Eta	11,528.17
Main Body	Weibull-3P		General Renewal Process	
	Beta	0.89	Beta	0.72
	Eta	959.10	Eta	788.92
	Gamma	20.75	Restor. Factor	0.00
Pin Set	Weibull-3P		Weibull-3P	
	Beta	0.86	Beta	0.91
	Eta	640.40	Eta	873.43
	Gamma	12.66	Gamma	31.31
Ringbolt	Weibull-3P		General Renewal Process	
	Beta	0.99	Beta	0.86
	Eta	1,114.85	Eta	988.83
	Gamma	28.47	Restor. Factor	0.85
Teeth	Weibull-2P		General Renewal Process	
	Beta	0.88	Beta	0.76
	Eta	740.79	Eta	942.78
			Restor. Factor	0.97

Table 4.16 signifies that bucket components can generally be characterized using Weibull parameters. The lifetime values show that all components of Marion bucket unit exhibit exact- or quasi-exponential behavior since all shape parameters are in the range of 0.85-1.00. This condition refers that these components continue to their useful lifetimes without any wear-out. Besides, Marion chain component with high location parameter (gamma) points that probability of this component to fail before 4,530 operating hour is almost zero. Moreover, Page ringbolt and teeth components evaluated using general renewal process hold restoration factors of 0.85 and 0.97. Comparative lifetime curves of the components can be investigated from Figures 4.16-4.17.

Mean survival times of the components without exposing to any failure are given in Table 4.17. Chain and pin components are the bucket unit element with the highest and the lowest lifetimes for both draglines, respectively.

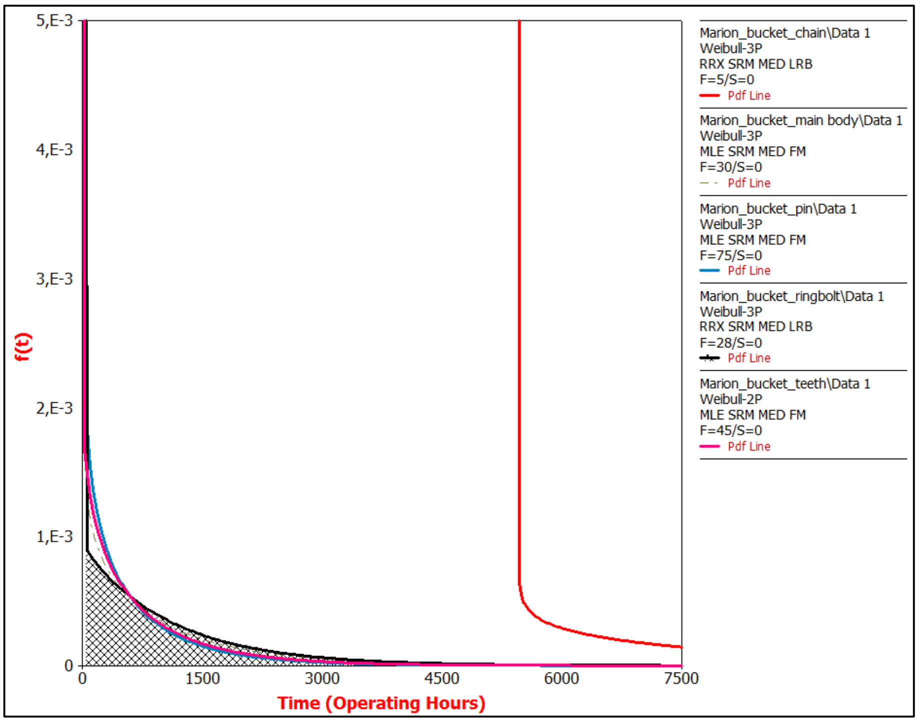


Figure 4.16 Probability Density Functions of Marion Bucket Unit Components

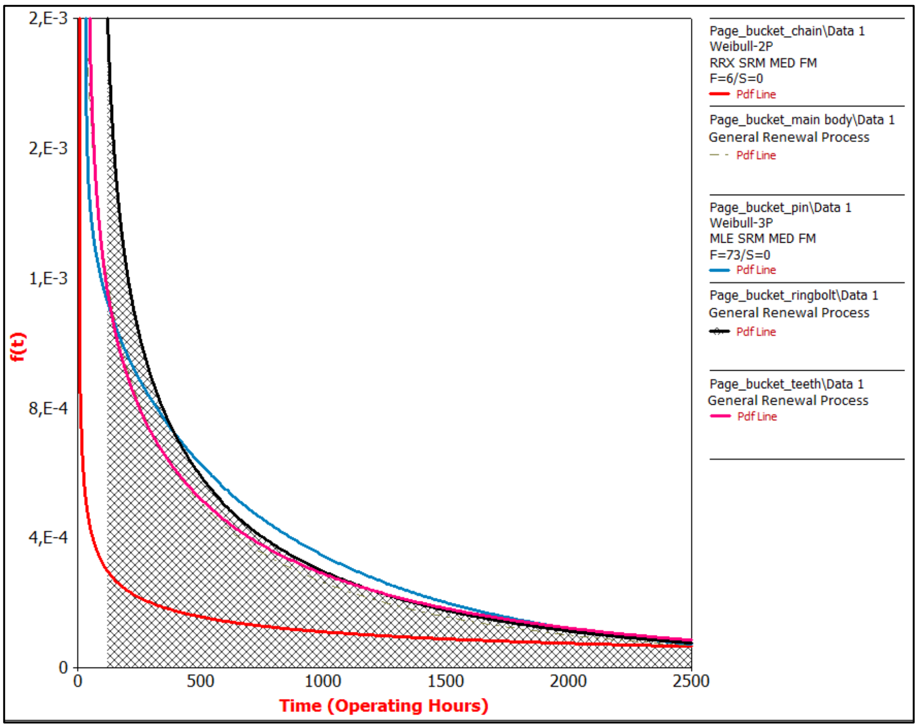


Figure 4.17 Probability Density Functions of Page Bucket Unit Components

Table 4.17 Expected Lifetime Duration (Hours) of Bucket Unit Components

	Bucket Unit Components				
	Chain	**Main Body**	**Pin**	**Ringbolt**	**Teeth**
Marion	9,528	1,038	706	1,145	787
Page	17,149	943	897	1,101	1,215

Bucket unit reliability was calculated using Equation 4.3. Reliability curves of the components and bucket unit can be viewed in Figures 4.18-4.19. It is seen that survival probabilities of Marion and Page bucket units fall below 50% after 131th and 121th operation hours, respectively. Moreover, expected lifetimes of the units for Marion and Page were determined as 200 and 188 operating hours, respectively.

$$R_{Bucket}(t) = R_{Chain}(t).R_{Main\ Body}(t).R_{Pin}(t).R_{Ringbolt}(t).R_{Teeth}(t) \quad (4.3)$$

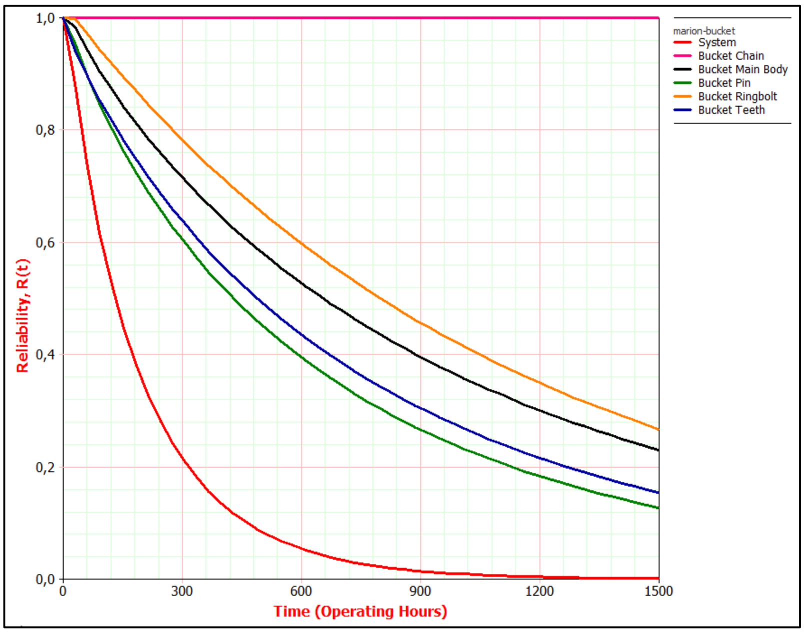


Figure 4.18 System and Component Reliability Curves of Marion Bucket Unit

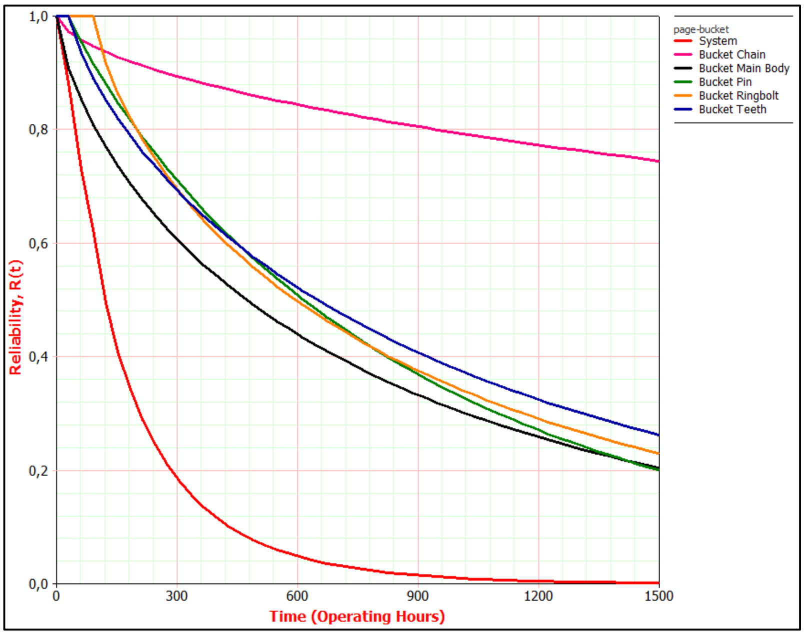


Figure 4.19 System and Component Reliability Curves of Page Bucket Unit

For detailed investigation, reliability variations of the bucket units between 0-150 operation hours can be investigated from Table 4.18.

Table 4.18 Reliability Variation of Bucket Units in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion Bucket Reliability	0.91	0.78	0.68	0.59	0.52	0.45
Page Bucket Reliability	0.90	0.78	0.68	0.58	0.49	0.42

Following the reliability assessment, efficiency of maintenance activities for the units were evaluated using general renewal process. It can be seen from Table 4.19 that maintenance activities restore Marion bucket unit to as good as new condition where Page bucket is maintained to as bad as old condition. Therefore, maintenance policy for Page bucket is required to be improved against future wear-out problems.

Table 4.19 Maintenance Restoration Effectiveness for Bucket Units

	General Renewal Function Parameters				
	Shape (Beta)	**Lambda**	**Scale (Eta)**	**Degree of Repair**	**Restoration Factor**
Marion	1.15	1.50 E-3	281.50	0.00	1.00
Page	0.82	2.20 E-2	102.69	1.00	0.00

4.2.4 Rigging Unit

Rigging mechanism is utilized to balance and discharge bucket. After filling the bucket, rigging rope suspended from pulley is stretched by the dragging engine. By this way, bucket mouth is slightly moved upward to prevent spillage of material from bucket before completing the swing movement. After completion of dragline rotation to the dump area, bucket mount is released downward to remove loose material in the bucket. Pulley, rope, and connection parts such as, socket and ringbolt are the main elements of rigging unit.

There are two non-repairable components in the unit as rigging rope and rigging pulley. As stated in Table 4.1, non-repairable failure modes of these components were called as mode01. Therefore, best-fit distributions were utilized to evaluate reliability of rope-mode01 and pulley-mode01 in the study. On the other hand, other components in repairable condition were pre-processed using qualitative (Figures 4.20-4.21) and quantitative (Tables 4.20-4.21) trend tests. The tests concluded that socket for Marion and pulley-mode02 for Page are the components with lifetime trend. Reliability of these components were assessed using general renewal process where the other repairable components were evaluated with best-fit distribution.

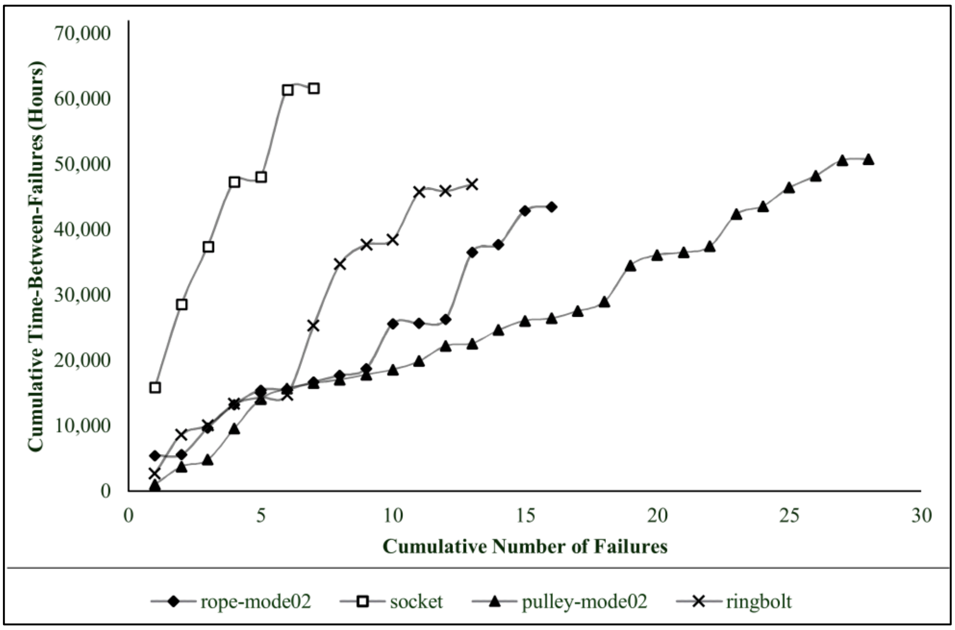


Figure 4.20 Graphical Lifetime Trend Test for Marion Rigging Unit

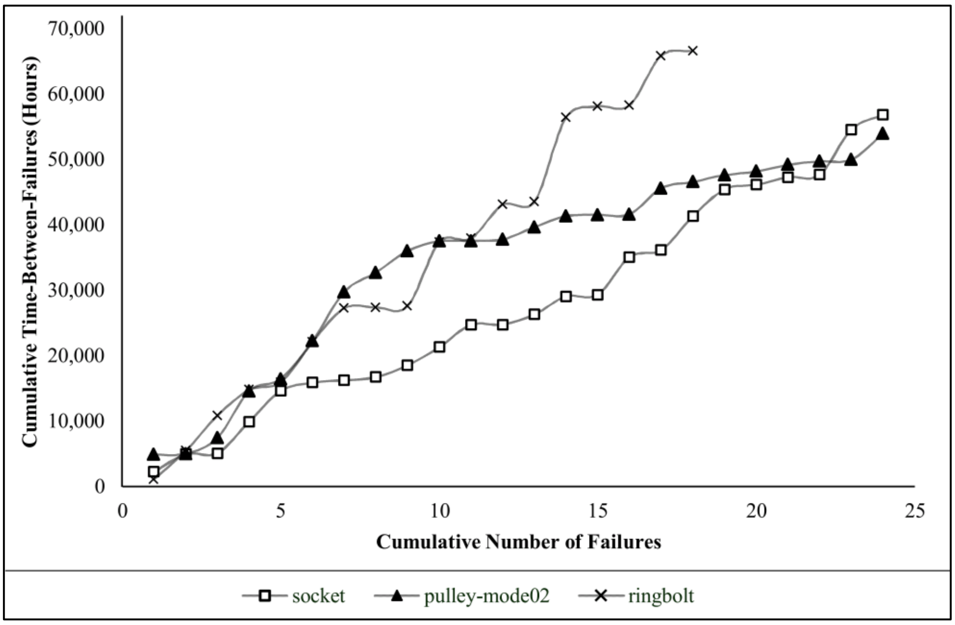


Figure 4.21 Graphical Lifetime Trend Test for Page Rigging Unit

Table 4.20 Quantitative Lifetime Trend Analysis for Marion Rigging Unit

Test Name	Test Parameters	Rigging Unit Components			
		Socket	**Ringbolt**	**Rope Mode02**	**Pulley Mode02**
Crow AMSAA	$2N/\hat{\beta}$	6.26	22.11	26.85	49.62
	$\chi^2_{2N,1-\alpha/2}$	6.57	15.38	20.07	39.80
	$\chi^2_{2N,\alpha/2}$	23.68	38.89	46.19	74.47
		Reject H_0	Accept H_0	Accept H_0	Accept H_0
Laplace	U_L	1.24	0.22	-0.26	0.11
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	-1.65	-0.85	-0.24	0.14
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	1.78	0.22	-0.45	0.12
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0	Accept H_0
	DECISION	Trend	Non-trend	Non-trend	Non-trend

Table 4.21 Quantitative Lifetime Trend Analysis for Page Rigging Unit

Test Name	Test Parameters	Rigging Unit Components			
		Socket	**Ringbolt**	**Rope Mode02**	**Pulley Mode02**
Crow AMSAA	$2N/\hat{\beta}$	45.71	35.11	No Available Data	29.19
	$\chi^2_{2N,1-\alpha/2}$	33.10	23.27		33.10
	$\chi^2_{2N,\alpha/2}$	65.17	51.00		65.17
		Accept H_0	Accept H_0		Reject H_0
Laplace	U_L	-0.50	-0.16		2.18
	$z_{\alpha/2}$	1.64	1.64		1.64
		Accept H_0	Accept H_0		Reject H_0
PCNT	U_p	0.40	-0.11		-1.93
	$z_{\alpha/2}$	1.64	1.64		1.64
		Accept H_0	Accept H_0		Reject H_0
Lewis Robinson	U_{LR}	-0.60	-0.16		2.18
	$z_{\alpha/2}$	1.64	1.64		1.64
		Accept H_0	Accept H_0		Reject H_0
	DECISION	Non-trend	Non-trend	-	Trend

Lifetime behaviors of Marion socket and Page pulley-mode02 were estimated using general renewal function due to lifetime data trend. Other rigging components for both

Marion and Page were analyzed using best-fit distributions. The lifetime parameters can be investigated from Table 4.22.

Table 4.22 Lifetime Parameters of Rigging Unit Components

	MARION		PAGE	
Socket	General Renewal Process		Weibull-2P	
	Beta	0.81	Beta	1.06
	Eta	6,790.10	Eta	2,420.09
	Restor. Factor	0.00		
Ringbolt	Weibull-2P		Weibull-2P	
	Beta	0.92	Beta	0.80
	Eta	3,608.02	Eta	3,438.39
Rope-Mode01	Loglogistic-2P		Weibull-3P	
	Mu	5.78	Beta	1.52
	Sigma	0.48	Eta	595.15
			Gamma	51.93
Rope-Mode02	Weibull-2P		No Available Data	
	Beta	0.79		
	Eta	2,494.63		
Pulley-Mode01	Normal-2P		Lognormal-2P	
	Mean	3,765.18	(LN) Mean	9.52
	Std	2,953.95	(LN) Std	0.42
Pulley-Mode02	Weibull-3P		General Renewal Process	
	Beta	1.28	Beta	0.65
	Eta	1,935.42	Eta	1,176.41
	Gamma	28.84	Restor. Factor	0.72

Lifetimes of rigging components exhibit different characteristics of Weibull, lognormal, normal, and loglogistic distributions. Components with non-Weibull behavior hold bell-shaped lifetime curves that can be indicator of possible wear-outs. Trend-components, Marion socket and Page pulley-mode02, have restoration factors of 0.00 and 0.72, respectively. This values indicate that Marion socket is maintained minimally to the condition just before failures. On the other hand, Page pulley is restored to as good as new condition with a rate of 72%. In addition, loglogistic distribution of Marion rope-mode01 holds right tailed and bell-shape curve. Loglogistic is the logarithmic type of logistic distribution having heavily tailed, i.e. long tailed, quasi-normal behavior. Rigging is one of the dragline units where wear-out condition can be frequently observed. Using lifetime parameters, probability density curves of the rigging components were created as shown in Figures 4.22-4.23.

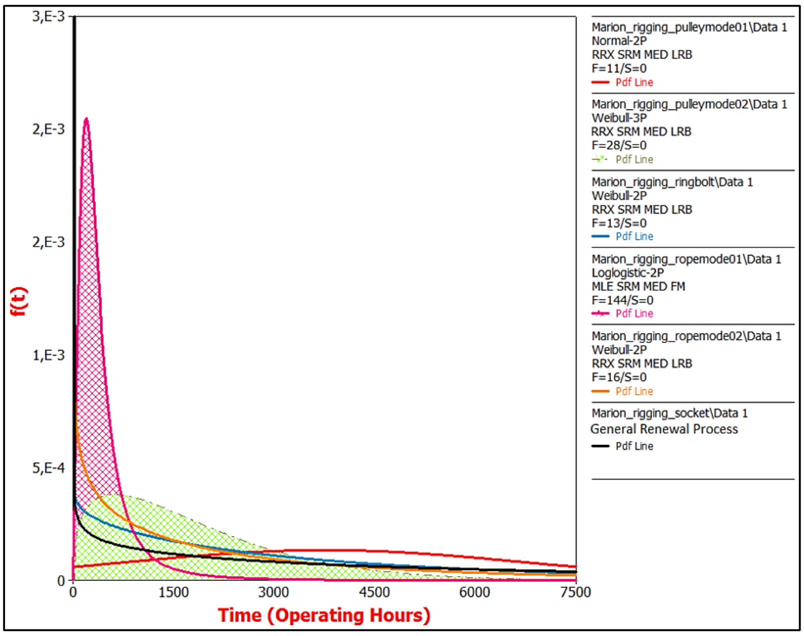


Figure 4.22 Probability Density Functions of Marion Rigging Unit Components

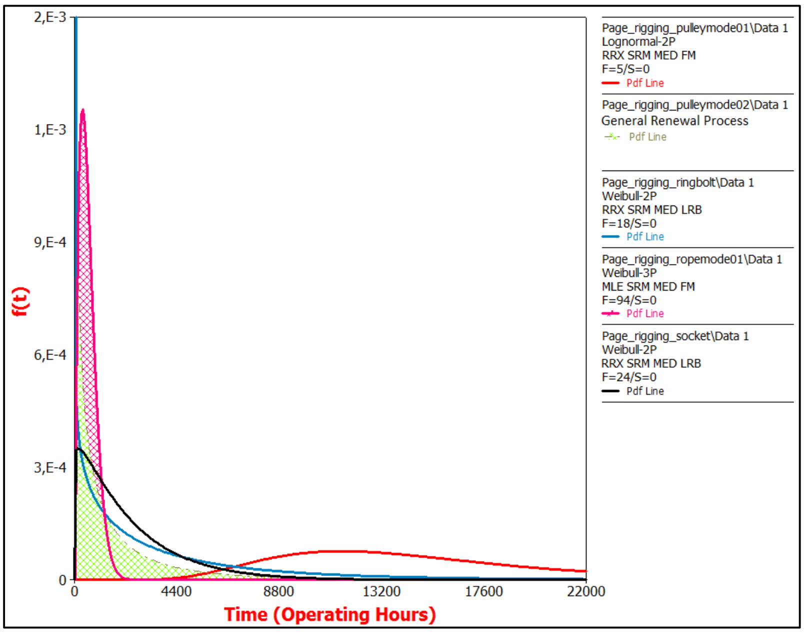


Figure 4.23 Probability Density Functions of Page Rigging Unit Components

Expected lifetimes of the components, i.e. areas under the probability density curves, of the components were calculated as in Table 4.23. The lifetime values points to that rope-mode01 is the most maintenance intensive element in the rigging units of both dragline. On the other side, socket and pulley-mode01 require the least number of maintenance activities in Marion and Page rigging mechanisms, respectively.

Table 4.23 Expected Lifetime Duration (Hours) of Rigging Unit Components

	Rigging Unit Components					
	Socket	**Ringbolt**	**Rope Mode01**	**Rope Mode02**	**Pulley Mode01**	**Pulley Mode02**
Marion	7,626	3,752	489	2,864	3,765	1,820
Page	2,363	3,906	588	-	14,902	1,607

Following component reliability estimations, system reliability of the rigging units were calculated using Equation 4.4. Reliability curves for the units and their components can be assessed from Figures 4.24-4.25. The curves revealed that failure probability overtakes surviving probability after 187th and 225th operation hours for Marion and Page, respectively. Moreover, it was estimated that Marion and Page rigging units have mean operating lifetimes of 248 and 320 hours, respectively.

$$R_{Rigging}(t) = R_{PulleyM1}(t).R_{PulleyM2}(t).R_{Ringbolt}(t).R_{RopeM1}(t).R_{RopeM2}(t).R_{Socket}(t) \quad (4.4)$$

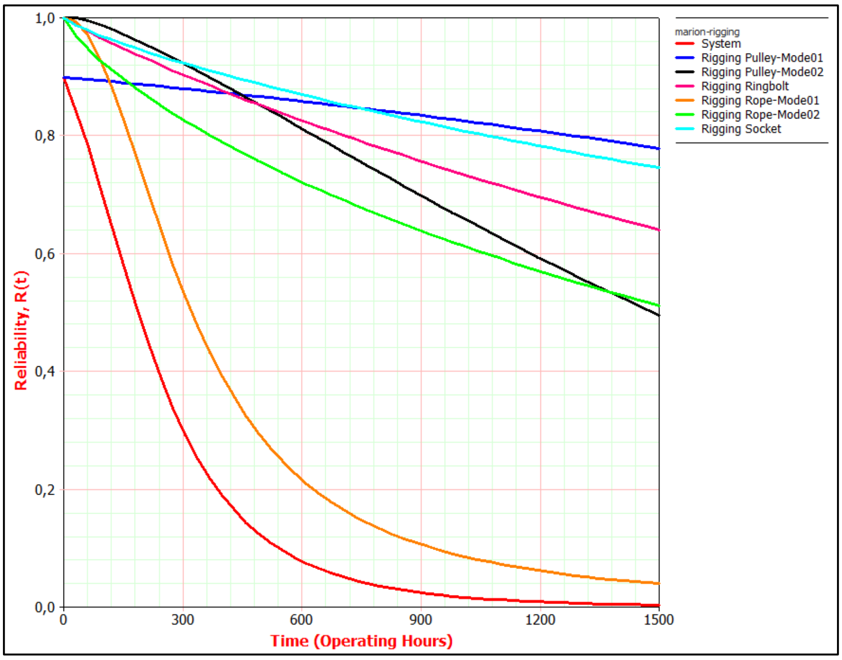


Figure 4.24 System and Component Reliability Curves of Marion Rigging Unit

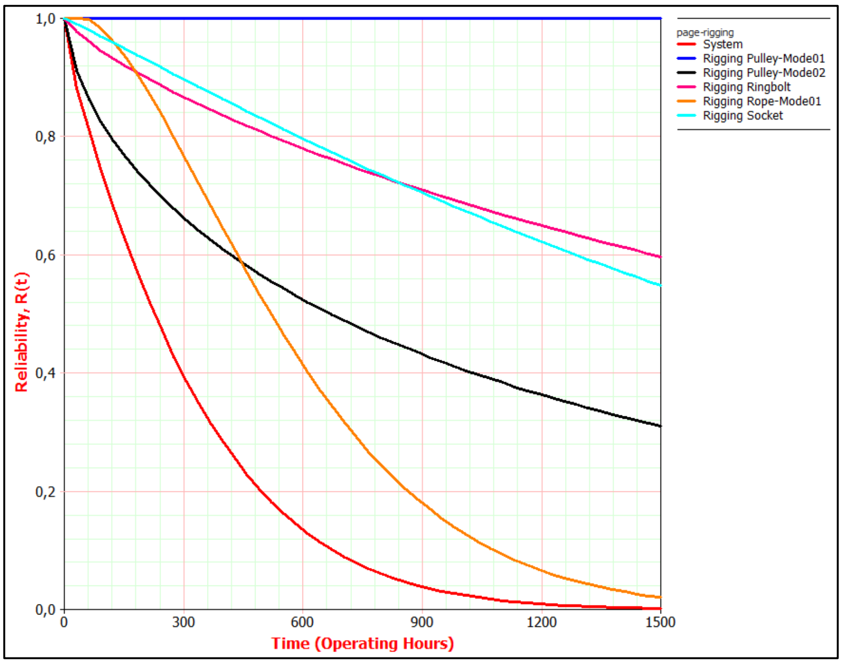


Figure 4.25 System and Component Reliability Curves of Page Rigging Unit

For detailed analysis, reliability changes of the units in 0-150 operation hours can be viewed from Table 4.24. Rapid deterioration of Marion rigging unit compared to Page can be concluded from the reliability values.

Table 4.24 Reliability Variation of Rigging Units in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion Rigging Reliability	0.85	0.80	0.75	0.70	0.64	0.58
Page Rigging Reliability	0.90	0.84	0.78	0.73	0.68	0.63

In addition to reliability modelling, general renewal process was applied to time between failures datasets of the units to discuss maintenance effectiveness on the unit lifetimes. Relevant failure data was analyzed holistically without any component decomposition. Restoration values can be examined from Table 4.25.

Table 4.25 Maintenance Restoration Effectiveness for Rigging Units

	General Renewal Function Parameters				
	Shape (Beta)	**Lambda**	**Scale (Eta)**	**Degree of Repair**	**Restoration Factor**
Marion	1.24	8.00E-4	292.12	0.00	1.00
Page	1.19	8.00E-4	407.37	0.00	1.00

Restoration factors in Table 4.25 revealed that maintenance policy applied for rigging mechanisms restores these units to as good as new condition.

4.2.5 Machinery House Unit

Dragline machinery house (MH) is composed of: i) motors to perform hoisting, dragging, swing, and walking movements, ii) relevant generators, iii) lubrication unit for oil feeding, and iv) air conditioning parts. Unlike the other units, machinery house covers plenty of electrical appurtenances in order to ensure power requirement of dragline. It is the transition area where electrical energy is converted to mechanical energy to sustain the functionality of dragline. Failure of machinery house elements may cause longer downtimes compared to downtimes induced by the other units.

Dragline machinery house includes capital-intensive components which are rarely renewed during dragline lifetime period. They are repairable mechanisms and maintained via inspecting and recovering electrical and mechanical elements embedded in the mechanisms. Therefore, lifetime trend behaviors of all components were analyzed prior to reliability estimation.

Lifetime trends of the components were investigated graphically (Figures 4.26-4.27) and quantitatively (Tables 4.26-4.27). Test results showed that there is a strong evidence of lifetime trend for generator and motor components in Page machinery house. On the other hand, hypothesis tests indicated that there is no any lifetime trend for Marion machinery house components. Air conditioning is excluded in the analyses for Page since there is no any available failure data.

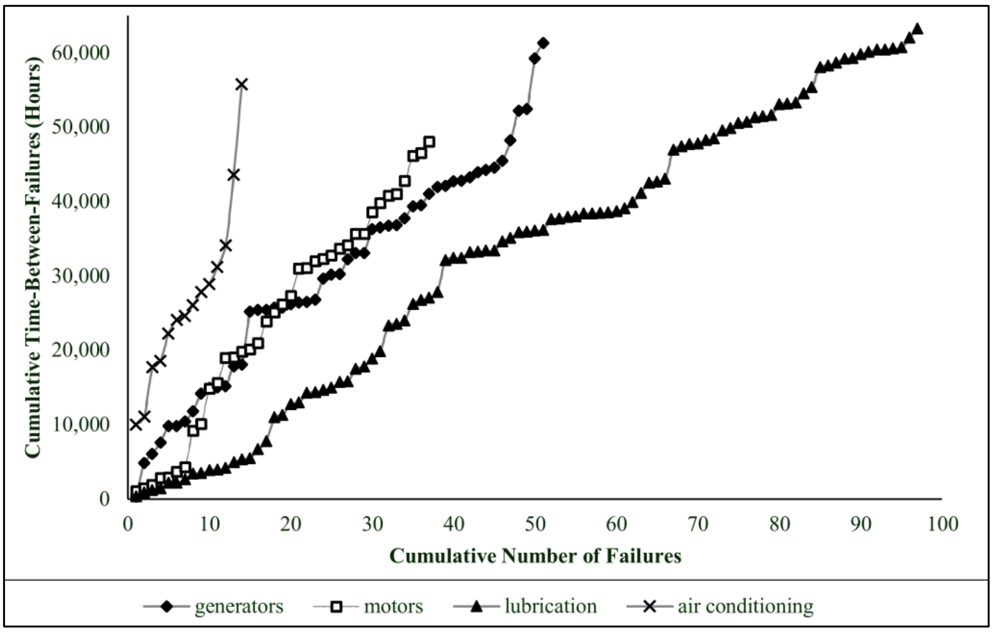


Figure 4.26 Graphical Lifetime Trend Test for Marion MH Unit

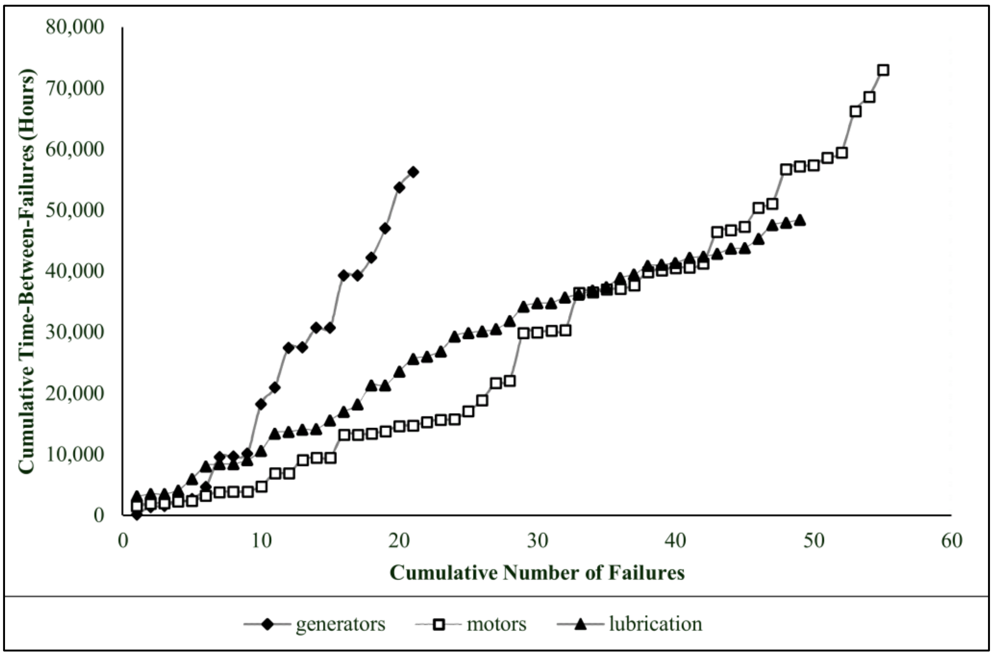


Figure 4.27 Graphical Lifetime Trend Test for Page MH Unit

Table 4.26 Quantitative Lifetime Trend Analysis for Marion MH Unit

Test Name	Test Parameters	Machinery House Components			
		Generators	**Motors**	**Lubrication**	**Air Conditioning**
Crow AMSAA	$2N/\hat{\beta}$	93.47	76.38	199.68	23.19
	$\chi^2_{2N,1-\alpha/2}$	79.70	55.19	162.78	16.93
	$\chi^2_{2N,\alpha/2}$	126.57	95.08	227.50	41.34
		Accept H_0	Accept H_0	Accept H_0	Accept H_0
Laplace	U_L	-0.38	-0.04	0.43	-0.73
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0
PCNT	U_p	0.61	0.73	-0.50	0.93
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	-0.29	-0.05	0.34	-0.75
	$z_{\alpha/2}$	1.64	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0	Accept H_0
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend

Table 4.27 Quantitative Lifetime Trend Analysis for Page MH Unit

Test Name	Test Parameters	Machinery House Components			
		Generators	**Motors**	**Lubrication**	**Air Conditioning**
Crow AMSAA	$2N/\hat{\beta}$	66.53	153.06	79.12	No Available Data
	$\chi^2_{2N,1-\alpha/2}$	28.14	86.79	76.16	
	$\chi^2_{2N,\alpha/2}$	58.12	135.48	122.11	
		Reject H_0	Reject H_0	Accept H_0	
Laplace	U_L	-1.98	-3.33	1.15	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Accept H_0	Reject H_0	Accept H_0	
PCNT	U_p	1.27	2.55	-0.64	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Reject H_0	Reject H_0	Accept H_0	
Lewis Robinson	U_{LR}	-1.87	-2.33	1.31	
	$z_{\alpha/2}$	1.64	1.64	1.64	
		Reject H_0	Reject H_0	Accept H_0	
	DECISION	Trend	Trend	Non-trend	-

Considering data trend analyses, lifetime parameters of machinery house components were estimated as in Table 4.28.

Table 4.28 Lifetime Parameters of MH Unit Components

	MARION		PAGE	
Generator	Weibull-3P		General Renewal Process	
	Beta	0.78	Beta	0.77
	Eta	829.20	Eta	1,472.23
	Gamma	12.33	Restor. Factor	0.00
Lubrication	Lognormal-2P		Exponential-2P	
	(LN) Mean	5.81	Lambda	0.001
	(LN) Std	1.27	Gamma	13.00
Motor	Exponential-2P		General Renewal Process	
	Lambda	0.0008	Beta	0.71
	Gamma	20.42	Eta	758.44
			Restor. Factor	0.99
Air Conditioning	Lognormal-2P		No Available Data	
	(LN) Mean	7.93		
	(LN) Std	1.04		

As seen in Table 4.28, Page components exhibit quasi- or exact-exponential data behaviors due to low shape parameters. On the other hand, lubrication and air conditioning in Marion unit hold bell-shape distributions where generator and motor have exponential curve. Lifetime characteristic curves can be viewed in Figures 4.28-4.29.

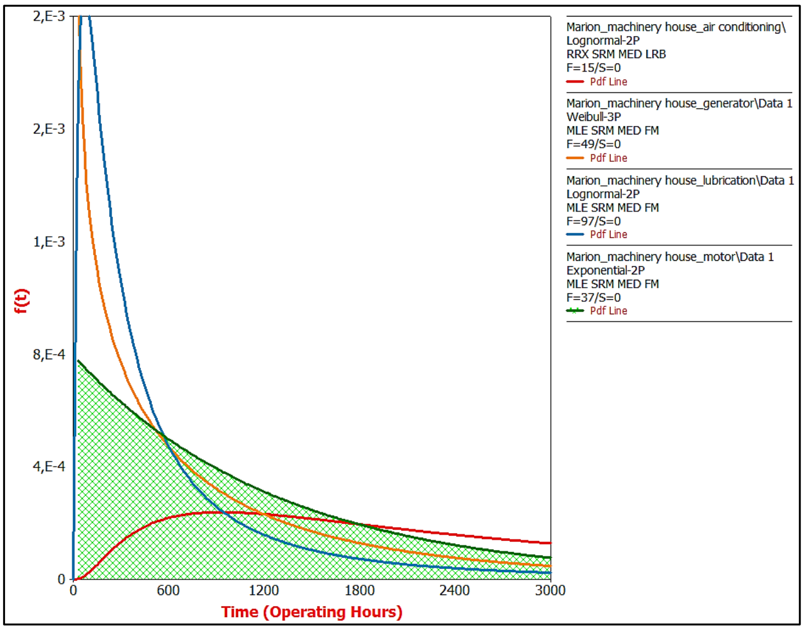


Figure 4.28 Probability Density Functions of Marion MH Components

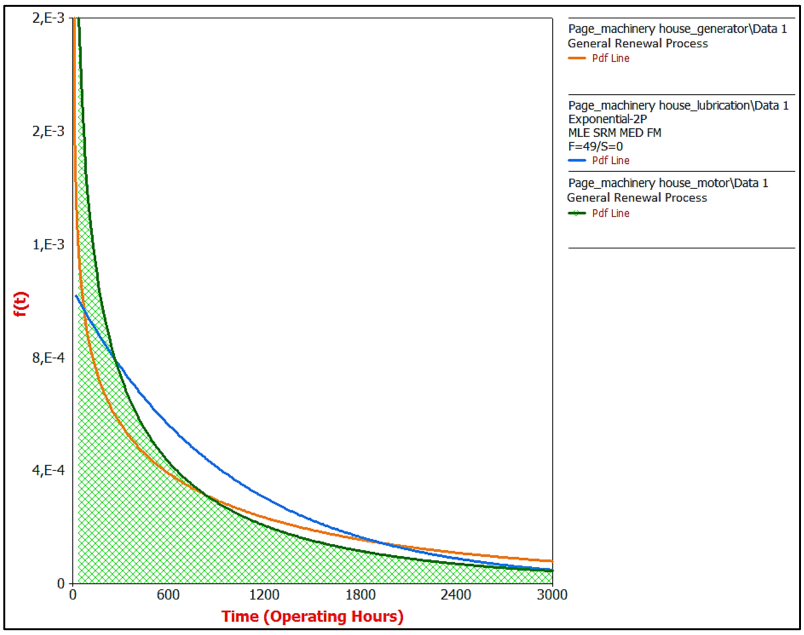


Figure 4.29 Probability Density Functions of Page MH Components

Mean lifetime estimations in Table 4.29 show that air conditioning is the component with the highest lifetime without failure for both draglines. The condition that there is no failure data for Page air conditioning is also evidence of its high reliability. On the other hand, lubrication and motor are expected to fail more frequently compared to other components of the draglines, respectively.

Table 4.29 Expected Lifetime Duration (Hours) of MH Unit Components

	Machinery House Components			
	Generator	**Lubrication**	**Motor**	**Air Conditioning**
Marion	972	743	1,297	4,773
Page	1,716	989	947	-

Overall system reliability for machinery house can be calculated using Equation 4.5. Time-dependent reliability variation of machinery house units and their elements can be investigated in Figures 4.30-4.31.

$$R_{\text{Machinery House}}(t) = R_{\text{Generator}}(t).R_{\text{Lubrication}}(t).R_{\text{Motor}}(t).R_{\text{Air Conditioning}}(t) \qquad (4.5)$$

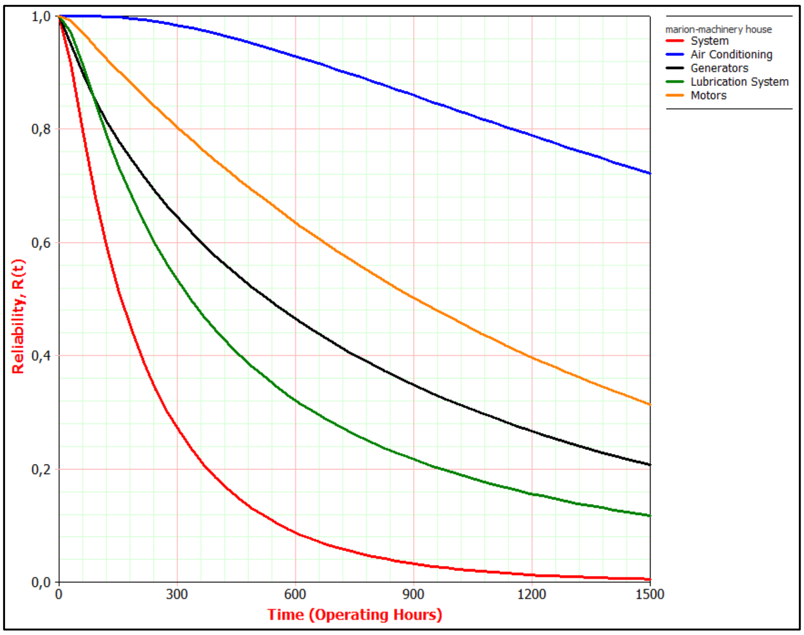


Figure 4.30 System and Component Reliability Curves of Marion MH Unit

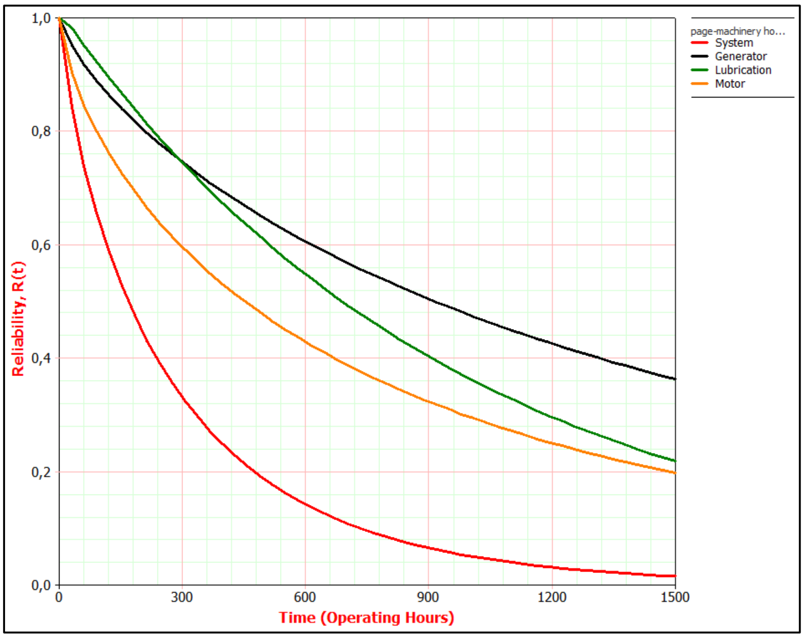


Figure 4.31 System and Component Reliability Curves of Page MH Unit

Mean lifetime estimation for the units revealed that machinery house can operate without any failure along 245 and 294 hours for Marion and Page, respectively. For detailed inquiry, reliability variation of the units between 0-150 operating hours can also be viewed from Table 4.30. It is seen from the table that machinery house reliabilities fall below 50% after 150 hours.

Table 4.30 Reliability Variation of MH Unit in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion MH Reliability	0.94	0.83	0.74	0.65	0.58	0.52
Page MH Reliability	0.87	0.77	0.70	0.64	0.58	0.53

Maintenance effectiveness for machinery house units were also examined in addition to reliability estimation. General renewal process results are given in Table 4.31. Restoration factors indicate that Marion machinery house is maintained as good as new where Page machinery house is restored to as bad as old condition. It can be concluded from these scores that more conservative maintenance policies should be applied for Page machinery house to prevent future wear-out problems.

Table 4.31 Maintenance Restoration Effectiveness for MH Units

	General Renewal Function Parameters				
	Shape (Beta)	**Lambda**	**Scale (Eta)**	**Degree of Repair**	**Restoration Factor**
Marion	1.07	2.80 E-3	241.79	0.00	1.00
Page	0.87	8.90 E-3	222.72	1.0	0.00

4.2.6 Movement Unit

A dragline achieves its movement abilities via rotation and walking components working coordinately. Regarding production plans in coal mines, this earthmover gets suitable operational position with eccentric walking mechanism through the forward throwing action of the feet. After positioning, dragline keeps production with a successive cycle of fill, rotate, and dump actions. Swing period between fill and dump activities is performed with rotation components. In addition to walking and rotation components, a warning system is also included in the movement mechanism to give a warning during operations.

Rotation, walking, and warning mechanisms hold various electrical and mechanical elements operating coordinately to achieve the positioning and swing movement of dragline at the work area. These mechanisms sometimes lose their functionalities due to malfunctioning condition of the sub-constituents. They are maintained in inspections and failures via repairing, overhauling, and replacement of sub-components. Since they are repairable mechanisms, their datasets were pre-processed to detect lifetime trend with graphical methods (Figures 4.32-4.33) and hypothesis tests (Tables 4.32-4.33). For Marion movement unit, rotation and walking mechanisms were detected to be candidate for lifetime trend. All hypothesis tests points to lifetime trend in the rotation component where there is small indication of lifetime trend for walking. Therefore, rotation was assumed as trend-component alone. In Page movement unit, hypothesis test values in Table 4.33 and alignment of lifetime data in Figure 4.33 showed a potential trend behavior for rotation and warning. Therefore, they were also assumed as trend-components.

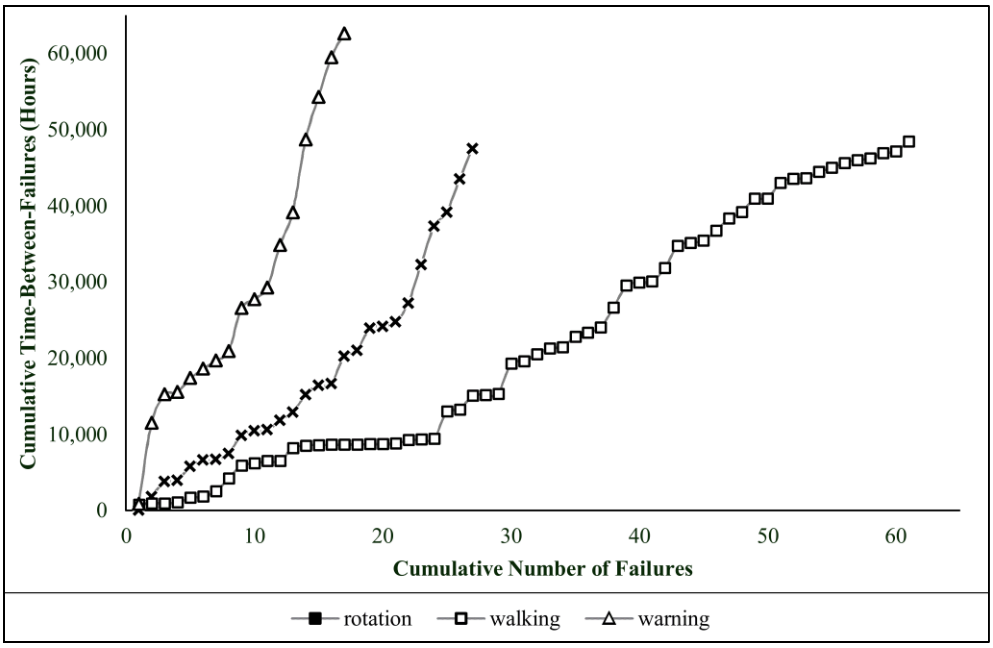


Figure 4.32 Graphical Lifetime Trend Test for Marion Movement Unit

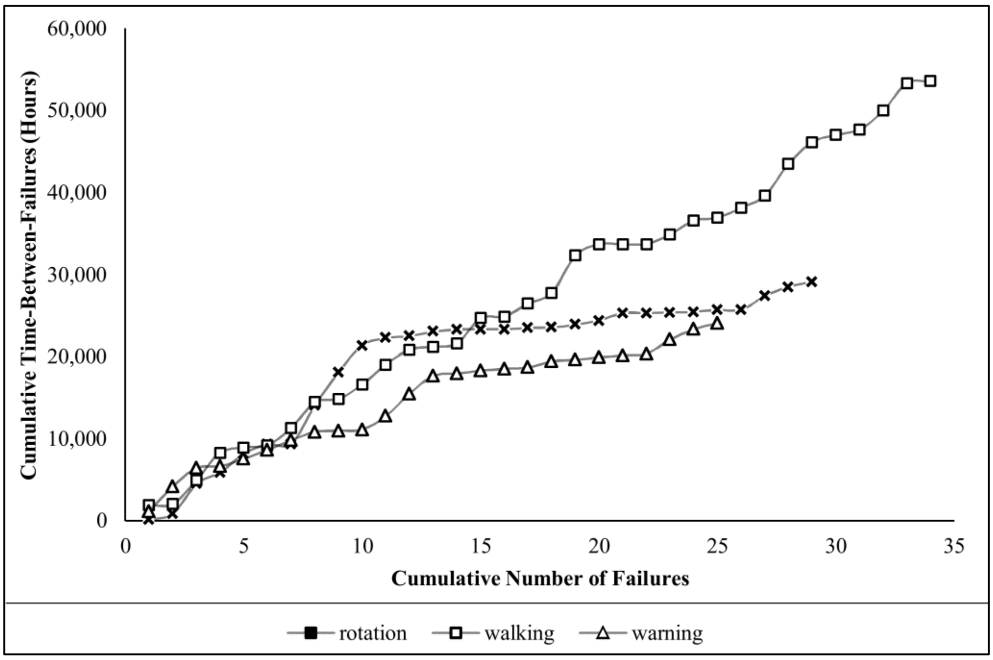


Figure 4.33 Graphical Lifetime Trend Test for Page Movement Unit

Table 4.32 Quantitative Lifetime Trend Analysis for Marion Movement Unit

Test Name	Test Parameters	Movement Unit Components		
		Rotation	**Walking**	**Warning**
Crow AMSAA	$2N/\hat{\beta}$	78.93	148.66	35.01
	$\chi^2_{2N,1-\alpha/2}$	38.12	97.49	21.66
	$\chi^2_{2N,\alpha/2}$	72.15	148.78	48.60
		Reject H_0	Accept H_0	Accept H_0
Laplace	U_L	-2.63	-1.52	-0.85
	$z_{\alpha/2}$	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0
PCNT	U_p	2.73	2.17	1.40
	$z_{\alpha/2}$	1.64	1.64	1.64
		Reject H_0	Reject H_0	Accept H_0
Lewis Robinson	U_{LR}	-3.02	-1.30	-1.02
	$z_{\alpha/2}$	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0
	DECISION	Trend	Non-trend	Non-trend

Table 4.33 Quantitative Lifetime Trend Analysis for Page Movement Unit

Test Name	Test Parameters	Movement Unit Components		
		Rotation	Walking	Warning
Crow AMSAA	$2N/\hat{\beta}$	40.82	61.71	32.88
	$\chi^2_{2N,1-\alpha/2}$	41.49	50.02	34.76
	$\chi^2_{2N,\alpha/2}$	76.78	88.25	67.50
		Reject H_0	Accept H_0	Reject H_0
Laplace	U_L	2.83	0.02	1.53
	$z_{\alpha/2}$	1.64	1.64	1.64
		Reject H_0	Accept H_0	Accept H_0
PCNT	U_p	-1.61	-0.25	-1.03
	$z_{\alpha/2}$	1.64	1.64	1.64
		Accept H_0	Accept H_0	Accept H_0
Lewis Robinson	U_{LR}	2.15	0.03	1.71
	$z_{\alpha/2}$	1.64	1.64	1.64
		Reject H_0	Accept H_0	Reject H_0
	DECISION	Trend	Non-trend	Trend

Estimated lifetime parameters of the components are given in Table 4.34. Rotation for both draglines and warning component for Page dragline were processed using general renewal process where the other parts were evaluated by best-fit distributions.

Table 4.34 Lifetime Parameters of Movement Unit Components

	MARION		**PAGE**	
Rotation	General Renewal Process		General Renewal Process	
	Beta	0.78	Beta	0.47
	Eta	782.44	Eta	490.65
	Restor.	0.00	Restor. Factor	0.78
Walking	Weibull-3P		Weibull-2P	
	Beta	0.72	Beta	1.12
	Eta	647.48	Eta	1,635.68
	Gamma	14.40		
Warning	Exponential-2P		General Renewal Process	
	Lambda	0.0003	Beta	1.43
	Gamma	332.50	Eta	3,322.29
			Restor. Factor	0.00

Lifetime characteristics illustrated in Table 4.34 indicate that Marion rotation and walking mechanisms follow quasi-exponential behavior with low shape parameter. On the other hand, Page walking and warning mechanisms hold bell-shape distributions, signifying wear-out symptoms in the mechanism. Besides, Page rotation mechanism has very low shape parameter that is an indicator of early mortalities in the sub-constituents. Probability density functions of the components can be viewed in Figures 4.34-4.35.

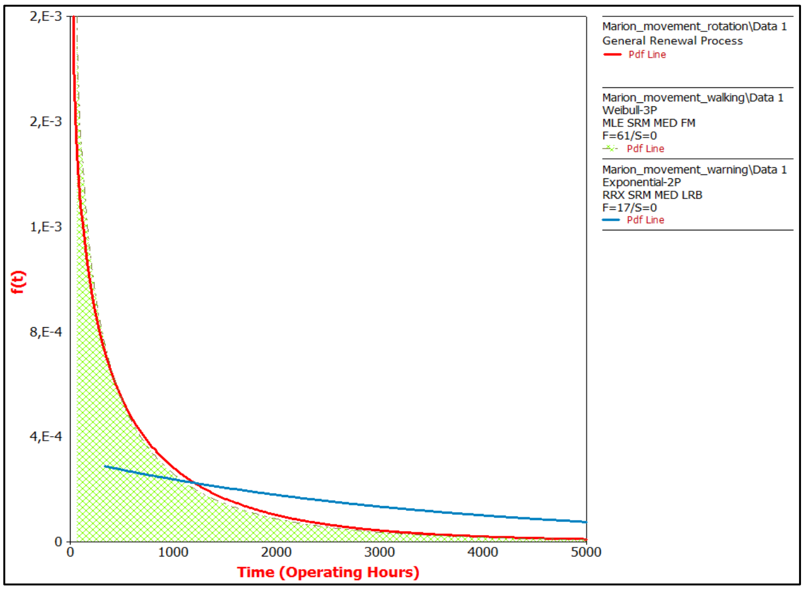


Figure 4.34 Probability Density Functions of Marion Movement Components

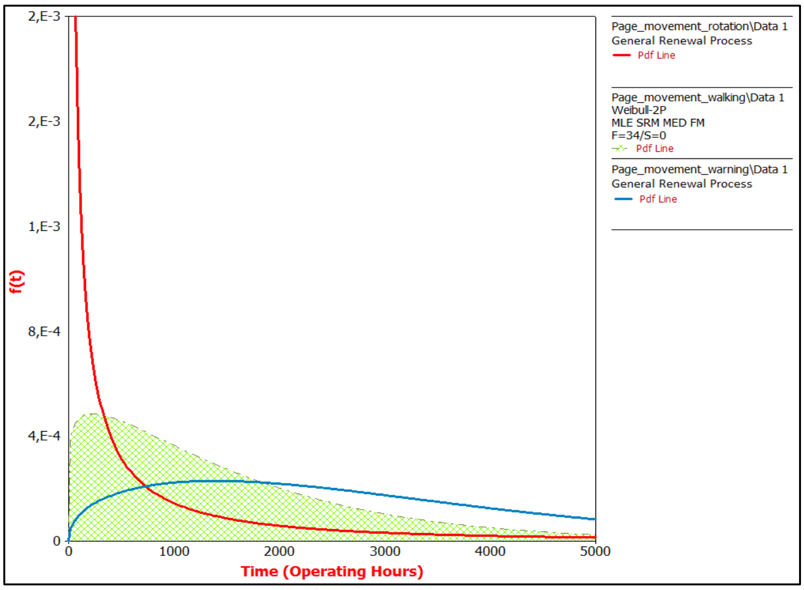


Figure 4.35 Probability Density Functions of Page Movement Components

Mean lifetimes of the components are given in Table 4.35. They are expected to survive without any failure more than 800 and 1,100 hours for Marion and Page, respectively. Warning is the component with the longest lifetime for both draglines. On the other hand, walking and rotation are the most failure-intensive components of Marion and Page movement units, respectively.

Table 4.35 Expected Lifetime Duration (Hours) of Movement Unit Components

	Movement Components		
	Rotation	**Walking**	**Warning**
Marion	903	808	3,812
Page	1,107	1,569	2,927

Using lifetime parameters of individual components, overall system reliability can be assessed using Equation 4.6. Time-dependent reliability curves for the components and the units can be observed from Figures 4.36-4.37. The units are expected to operate along 323 and 391 hours continuously for Marion and Page, respectively.

$$R_{Movement}(t) = R_{Rotation}(t).R_{Walking}(t).R_{Warning}(t) \quad (4.6)$$

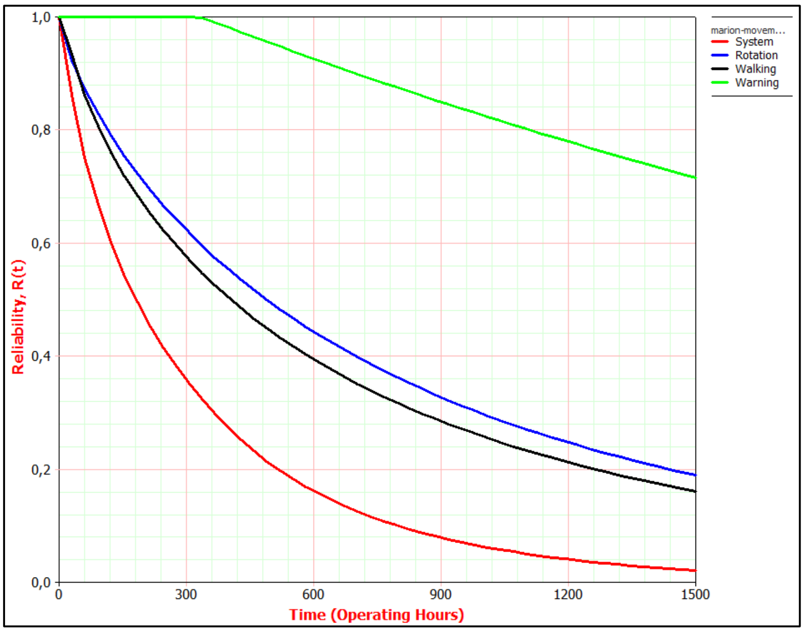


Figure 4.36 System and Component Reliability Curves of Marion Movement Unit

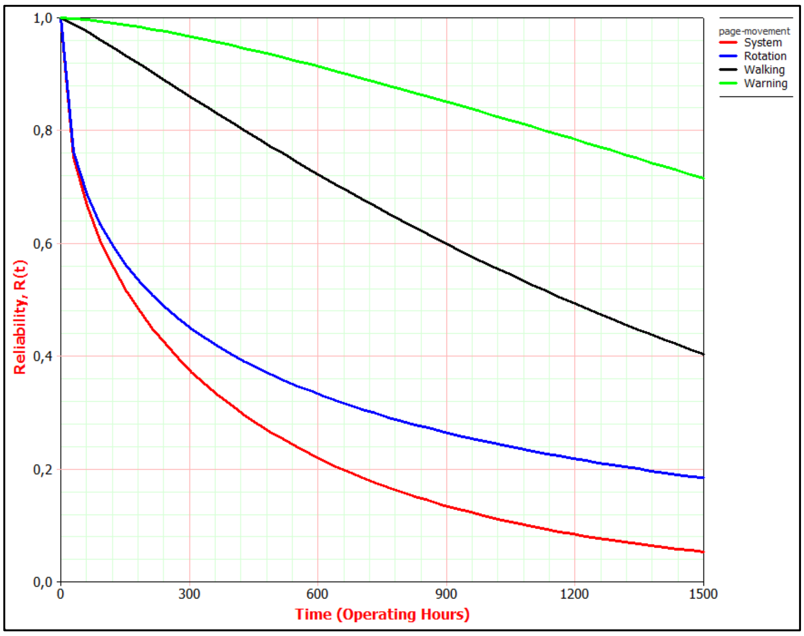


Figure 4.37 System and Component Reliability Curves of Page Movement Unit

Reliability changes of the systems in small-scale time interval (0-150 hours) can also be seen in Table 4.36. The reliability values point to rapid deterioration of Page movement unit compared to Marion.

Table 4.36 Reliability Variation of Movement Units in 0-150 Operating Hours

	Time (Operating Hours)					
	25	**50**	**75**	**100**	**125**	**150**
Marion Movement Reliability	0.89	0.79	0.71	0.65	0.60	0.55
Page Movement Reliability	0.77	0.69	0.64	0.59	0.55	0.52

Movement units were also analyzed to detect the effectiveness of maintenance activities on the units. General renewal process was applied to datasets of movement units without component decomposition. Analysis results can be viewed in Table 4.37. It is seen that Page movement unit is recovered to good as new condition with only 38% while Marion movement is only restored to as bad as old state. Therefore, the values showed that maintenance activities on movement units should be applied conservatively and more preventively.

Table 4.37 Maintenance Restoration Effectiveness for Movement Units

	General Renewal Function Parameters				
	Shape (Beta)	Lambda	Scale (Eta)	Degree of Repair	Restoration Factor
Marion	0.84	1.00E-2	236.76	1.00	0.00
Page	0.75	1.26E-2	339.05	0.62	0.38

4.2.7 Boom Unit

A dragline holds a boom structure with a length varying from 37 to 128 meters to build an operation radius in removal of overburden from stripping area to dumping area. Boom is a structural body which provides a circular operational area via suspending bucket with rope passing through pulley mechanism at the tip of boom body. Although failure frequency in boom is quite lower than the other units, any failure due to fatigue or fracture in this structural body can cause catastrophic failure of dragline and result in long-time halts. Maintenance records on this unit only cover previous preventive welding activities. Therefore, analysis results only give an idea for expected system halts where boom requires preventive welding. In the reliability analysis, this unit is handled holistically without any part decomposition process. Lifetime parameters of boom units were estimated using general renewal process can be viewed in Table 4.38. It is observed that booms are maintained preventively with an interval of about 10,500 operating hours and they are returned to as good as new condition.

Table 4.38 Boom Unit Lifetime Parameters using General Renewal Function

	General Renewal Function Parameters				
	Shape (Beta)	Lambda	Scale (Eta)	Degree of Repair	Restoration Factor
Marion	1.32	4.46E-6	11,502.86	0.00	1.00
Page	0.62	3.90E-3	7,391.10	0.00	1.00

4.3 System Reliability of Draglines

Each individual subsystem discussed in Section 4.2 leagues together to develop the main dragline system. They are functionally connected to each other in series dependency. Any breakdown induced due to failure of any subsystem leads to malfunctioning of the whole dragline. Therefore, reliability of dragline can be estimated using Equation 4.7.

$$R_{\mathrm{Dragline}}(t) = \prod_1^7 R_i(t) \tag{4.7}$$

In Equation 4.7, R_i is the reliability of each individual subsystem, dragging, hoisting, bucket, rigging, machinery house, movement, and boom. Using this time-dependent functional interrelation, reliabilities of draglines are found graphically as in Figures 4.38-4.39.

Variation of dragline system reliabilities in 0-24 hours operating hours can be seen in Table 4.39. It is observed that system reliability of draglines drops below 50% after 22.61th and 21.09th operating hours. This values mean that probability of dragline to fail overtakes the probability of dragline to operate without failures at the end of each workday. Expected lifetimes of Marion and Page draglines are 34.04 and 35.62 hours, respectively.

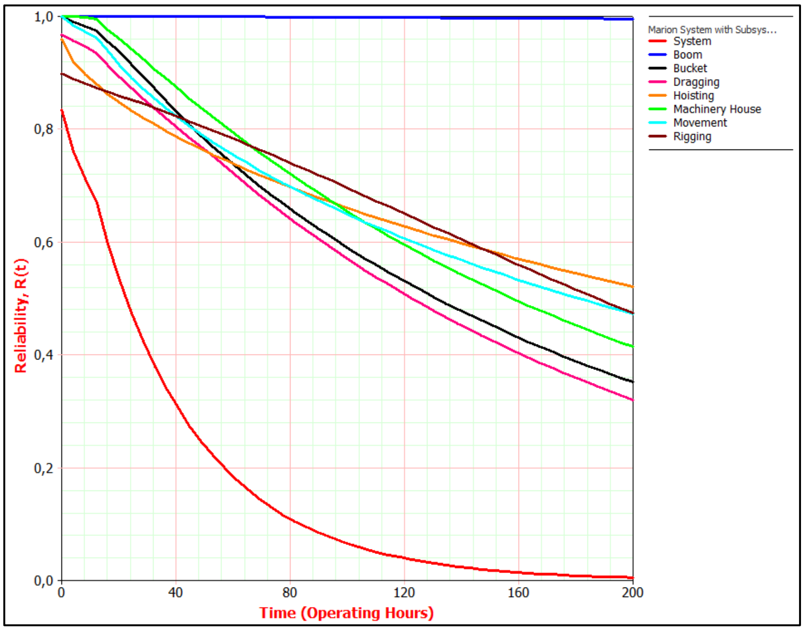


Figure 4.38 System Reliability of Marion Dragline

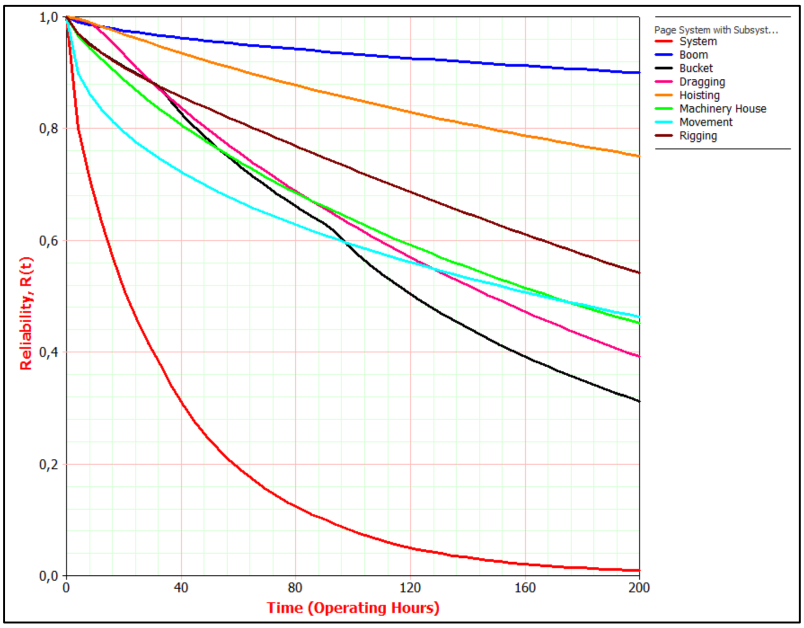


Figure 4.39 System Reliability of Page Dragline

Table 4.39 Time-Dependent Reliability and Mean Lifetimes of Draglines

	Operation Time (Hour)					
	4	**8**	**12**	**16**	**20**	**24**
Marion System Reliability	0.76	0.71	0.67	0.60	0.54	0.48
Page System Reliability	0.80	0.71	0.64	0.57	0.51	0.47

Although previous subsystem analyses in Sections 4.2 showed that subsystems for both dragline exhibit different characteristics, Table 4.39 stated that functionality of overall systems exhibit similar deterioration rates. This condition proves importance of deductive reliability analysis which concerns top-to-bottom component-based reliability modelling. If dragline reliability in the study was handled holistically without component decomposition, it would be concluded that dragline components have similar reliability behavior. Regarding this assumption, preventive maintenance policies would be generated commonly for both dragline. However, root-cause reliability analysis in the study showed that main weaknesses in the mechanisms differs machine to machine even they are operated in similar operations. In this sense, Section 5 will present optimization of maintenance policies of both draglines considering their component characteristics.

CHAPTER 5

PREVENTIVE MAINTENANCE POLICIES FOR WALKING DRAGLINES

5.1 Introduction

Preventive maintenance policies allow decision makers to reduce maintenance costs and to control health of machinery components via optimizing maintenance actions in finite or infinite time intervals. Scope of the policies may cover optimizing inspection periods, determining preventive replacement criterion for system components, keeping system reliability over prescribed limits or developing breakdown maintenance policy. Moreover, these policies may be modelled mathematically to maximize the values of profit, reliability, and availability or minimize cost or downtime amounts in prescribed intervals. This study considered cost as a minimization criterion since it is a rational and realistic parameter to measure direct and indirect economic consequences of system halts. Initially, annual failure profiles of the draglines were built up for current maintenance policy using Monte Carlo simulation. In optimization part, feasibility of preventive component replacements was discussed first via age replacement policies. Replacement interval curves were drawn for changing preventive and corrective costs. Then, a time-counting algorithm was created considering replacement decisions, random lifetime and repair behaviors of components, economic consequences of failures, and scheduled compulsory halts. A sensitivity analysis was performed in the algorithm to find out optimal inspection interval which minimizes overall cost of maintenance. In addition to the algorithm, a risk-based reliability allocation model was constructed to measure cost-effective maintenance criticalities of individual components. This model provided a perspective about which component reliability should be improved with priority. The methodology applied in this section can be viewed in Figure 5.1.

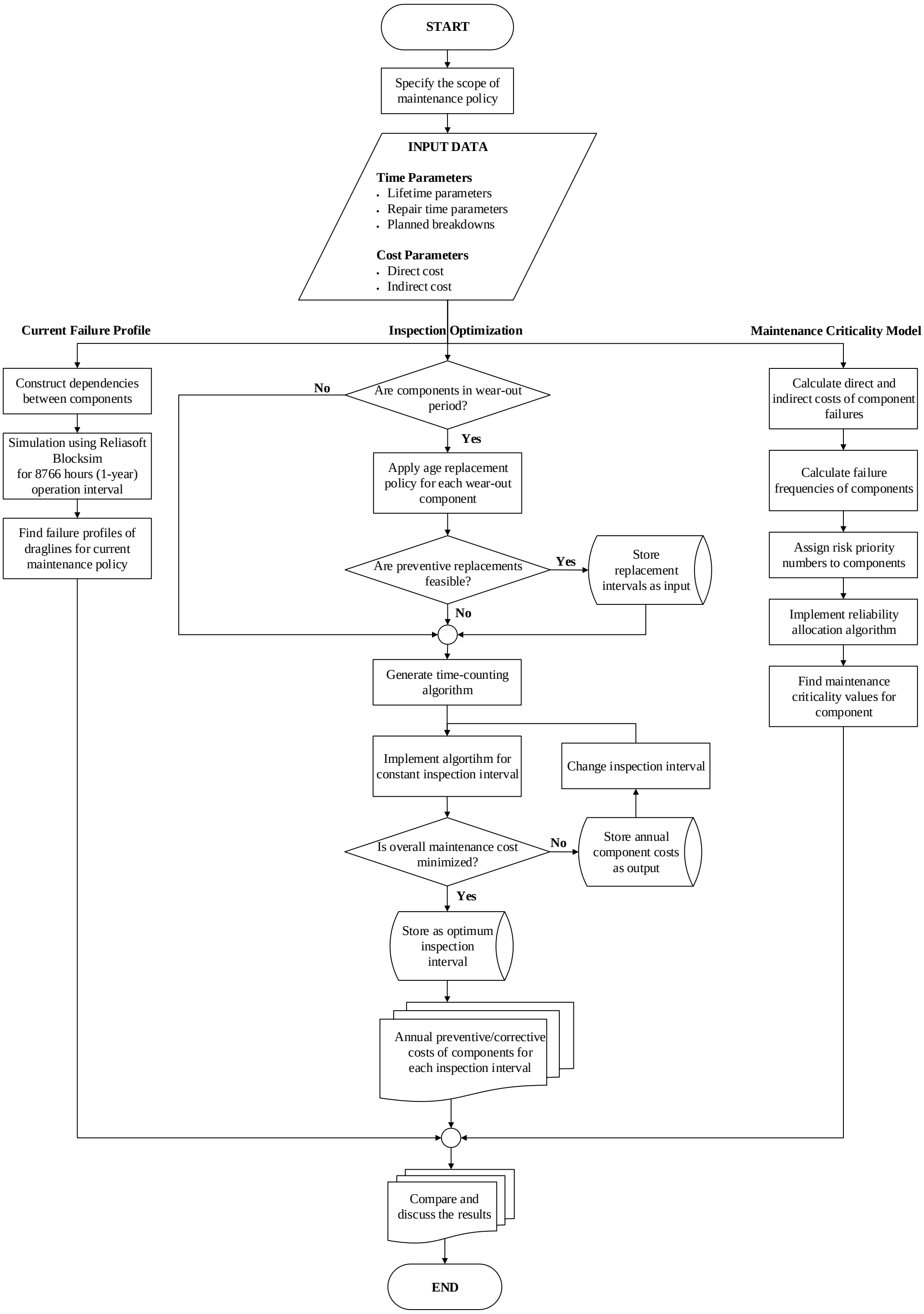


Figure 5.1 Methodology of the Maintenance Optimization

5.2 Current Conditions and Economic Aspects of the Maintenance Activities in Tunçbilek Coal Mine

In the literature, case studies about maintenance policies are generally based on the maximization of operational factors such as, reliability and availability, without considering cost effect. Maintenance cost analyses are rarely observed in the literature since cost values can be acquired rarely or cost-free models are easy to implement. However, cost is an important parameter in order to build realistic and applicable maintenance models in industries. This study utilized cost values in the maintenance optimization part. In this basis, this section informed about the details of current maintenance applications for the draglines in Tunçbilek coal mine and direct and indirect economic consequences of component failures. In addition, a simulation was generated using Monte Carlo technique to reveal the current failure profiles of the draglines.

General conditions of dragline operations and maintenance activities at the mine site can be assessed as follows:

i. Draglines operate in 3 shifts with 8-hours working periods.
ii. In each shift, there is a compulsory break of 30 minutes due to legal worker rights. Therefore, effective utilization time of a dragline is 22.5 hours a day.
iii. Operative conditions of draglines can be halted due to: a) component failures, b) regular inspections, c) interruptions on energy transmission line, d) unfavorable weather conditions, e) lack of sufficient maintenance staff, and f) problems in acquisition of spare parts.
iv. Draglines are maintained in three main ways: a) corrective maintenance when component is failed, b) 8 hours regular inspections every 160 hours, and c) general shutdown maintenance for detailed maintenance and overhauling.

Cost of any maintenance activity can be measured using direct and indirect factors. Direct cost is physical cost of activity paid directly to the collaborators such as, spare part suppliers, maintenance staff, energy providers, and machine hiring companies. On the other hand, indirect cost is the economic consequences of any failure due to production losses, changes in stock market value, and penalties of unmet commitments. Underestimating indirect cost may lead to misleading results since indirect cost generally overtakes direct cost in production industries. In this study, maintenance cost of each failure was estimated using Equations 5.1 and 5.2. Direct cost is the physical repair cost of each component and obtained from maintenance experts. Labor cost is excluded in direct cost since labors in the mine are employed with fixed monthly salary not hourly rate. Indirect cost utilized in this study is the production loss induced by component failures.

$$\text{Unit Failure Cost} = C_{\text{Repair Direct}} + C_{\text{Repair Indirect}} \tag{5.1}$$

$$C_{\text{Repair Indirect}} = TTR_{\text{component}} \, x \, \frac{V_{\text{bucket}} x F}{S} \, x \, \frac{1}{\frac{T_{\text{cycle}}}{\eta_{\text{operation}}}} \, x \, C_{\text{per bank m}^3} \tag{5.2}$$

Indirect costs were determined regarding financial loss per minute and time to repair (TTR) values of individual components. Table 5.1 shows how unit production loss was calculated for both draglines in the study. In Table 5.1, fill and swell factors and operator efficiencies are belonged to Tunçbilek coal mine, obtained from Özdoğan (1984).

Table 5.1 Unit Production Losses ($) of the Draglines

FACTORS	PAGE	MARION
Bucket Capacity, V_{bucket} (m^3)	15.29	30.58
Fill Factor, F	0.85	0.85
Swell Factor, S	1.45	1.45
Bank Overburden Volume per Cycle (m^3)	8.96	17.93
Cycle Time, T_{cycle} (min)	0.75	0.87
Operation/Operator Efficiency, $\eta_{operation}$ (%)	73	73
Bank Overburden Volume per Minute (m^3)	8.72	15.05
Unit Production Loss ($/bank m^3)	0.60	0.60
Production Loss per Minute ($)	5.23	9.03

TTR value in Equation 5.2 can be estimated using best-fit distributions of component repair durations. Since the datasets of individual components are good fitted in lognormal distribution, all TTR values are expressed using ln-mean and ln-standard deviation values as shown in Table 5.2. Mean time to repair, MTTR, values are also stated in the table.

Table 5.2 Repair Time Distributions and MTTR Values of Dragline Components

UNITS	COMPONENTS	MARION			PAGE		
		LN-Mean	**LN-Std**	**MTTR (hours)**	**LN-Mean**	**LN-Std**	**MTTR (hours)**
Dragging	Dragging Chain	0.96	0.53	3.01	1.16	0.71	4.11
	Dragging Ringbolt	0.48	0.49	1.82	0.75	0.75	2.80
	Dragging Rope-Mode01	1.64	0.80	7.11	1.22	0.77	4.56
	Dragging Rope-Mode02	0.35	0.59	1.69	0.60	0.80	2.50
	Dragging Control	1.16	1.17	6.38	0.76	1.14	4.08
	Dragging Rope Socket	0.16	0.37	1.25	0.52	0.80	2.31
Hoisting	Hoisting Rope-Mode01	2.40	0.69	13.99	2.05	0.78	10.54
	Hoisting Rope-Mode02	0.49	0.35	1.74	0.37	0.70	1.84
	Hoisting Brake	0.59	1.07	3.18	0.43	0.78	2.08
	Hoisting Control	0.85	1.32	5.60	0.77	1.56	7.25
	Hoisting Rope Socket	-	-	-	1.24	1.36	8.77
Rigging	Rigging Rope-Mode01	0.44	0.58	1.83	0.11	0.53	1.28
	Rigging Rope-Mode02	0.48	0.59	1.91	0.49	0.69	2.08
	Rigging Rope Socket	0.16	0.70	1.49	0.33	0.52	1.59
	Rigging Pulley-Mode01	0.72	0.69	2.59	0.83	0.69	2.92
	Rigging Pulley-Mode02	0.31	0.78	1.84	0.36	0.61	1.73
	Rigging Ringbolt	0.51	0.64	2.05	0.02	0.46	1.13
Bucket	Teeth	-0.02	0.64	1.21	0.82	0.83	3.20
	Bucket Pin Set	0.08	0.61	1.30	0.03	0.57	1.21
	Bucket Chain Assembly	1.22	1.03	5.74	0.81	0.52	2.59
	Bucket Ringbolts	0.43	0.63	1.88	0.70	0.77	2.70
	Bucket Body	1.00	1.21	5.68	0.48	0.83	2.28
Movement	Rotation Mechanism	0.55	1.09	3.14	0.59	0.96	2.89
	Walking Mechanism	1.46	1.56	14.63	0.84	1.39	6.07
	Warning Mechanism	1.23	1.27	7.70	1.46	1.58	14.86
Machinery House	Generators	2.63	1.95	92.7	3.96	1.40	139.38
	Motors	2.76	1.73	70.07	2.98	1.70	83.16
	Lubrication Mechanism	0.76	1.04	3.65	0.20	0.68	1.53

Direct and expected indirect costs were calculated using Equations 5.1-5.2 as given in Table 5.3 Direct costs were up-to-date values of year 2015, acquired from dragline maintenance experts. Indirect costs were calculated using MTTR values in Table 5.2. It should be noted that indirect cost values can differ according to random TTR values of the distributions in Table 5.2. This issue will be discussed in Section 5.3.2 in detail.

Table 5.3 Direct and Expected Indirect Costs of Dragline Component Failures

UNITS	COMPONENTS	MARION			PAGE		
		Direct Cost ($)	Indirect Cost ($)	Total Cost ($)	Direct Cost ($)	Indirect Cost ($)	Total Cost ($)
Dragging	Dragging Chain	1,114	1,630	2,744	568	1,291	1,859
	Dragging Ringbolt	56	986	1,042	80	879	959
	Dragging Rope-Mode01	1,132	3,850	4,982	644	1,432	2,076
	Dragging Rope-Mode02	0	915	915	0	785	785
	Dragging Control	500	3,455	3,955	386	1,281	1,668
	Dragging Rope Socket	95	677	772	80	725	805
Hoisting	Hoisting Rope-Mode01	1,216	7,576	8,791	705	3,310	4,015
	Hoisting Rope-Mode02	0	942	942	0	578	578
	Hoisting Brake	45	1,722	1,767	45	653	699
	Hoisting Control	591	3,032	3,623	523	2,277	2,800
	Hoisting Rope Socket	-	-	-	80	2,754	2,834
Rigging	Rigging Rope-Mode01	98	991	1,089	107	402	509
	Rigging Rope-Mode02	0	1,034	1,034	0	653	653
	Rigging Rope Socket	34	807	841	25	499	524
	Rigging Pulley-Mode01	843	1,402	2,245	447	917	1,364
	Rigging Pulley-Mode02	655	996	1,651	459	543	1,002
	Rigging Ringbolt	164	1,110	1,274	105	355	459
Bucket	Teeth	109	655	764	84	1,005	1,089
	Bucket Pin Set	659	704	1,363	386	380	766
	Bucket Chain Assembly	295	3,108	3,404	186	813	1,000
	Bucket Ringbolts	614	1,018	1,632	245	848	1,093
	Bucket Body	309	3,076	3,385	227	716	943
Movement	Rotation Mechanism	3,977	1,700	5,678	2,955	908	3,862
	Walking Mechanism	2,205	7,922	10,127	1,795	1,906	3,702
	Warning Mechanism	291	4,170	4,460	227	4,667	4,894
Machinery House	Generators	364	50,197	50,560	300	43,775	44,075
	Motors	186	37,943	38,129	159	26,118	26,277
	Lubrication Mechanism	341	1,976	2,317	273	481	753

In Table 5.3, direct costs of the components with mode02 was assumed as zero since they are failed due to dislocation from mechanism. Therefore, these type of failure modes were assumed to induce production loss alone. From Table 5.3, it is also realized that failure cost raises dramatically for the components with long-term repair duration such as, generators, motors, and rope replacements. Since, indirect costs of dragline component failures are generally greater than direct costs since time-dependent production loss of dragline is incontrovertibly high.

Combining lifetime characteristics of components stated in Section 4.2, expected repair durations in Table 5.2, and compulsory breaks in shifts and inspections, current maintenance policy was simulated using Reliasoft Blocksim software with Monte Carlo technique. As stated at the beginning of the section, draglines are assumed to be operative for 22.5 hours a day and inspected for 8 hours every 160 hours. Simulation outputs and sample simulation windows can be investigated in Table 5.4 and Figures 5.2-5.3, respectively.

Table 5.4 Annual Downtime Profiles of the Draglines

	PAGE	**MARION**
Mean Availability	0.64	0.69
Std Deviation (Mean Availability)	0.04	0.03
Expected Number of Failures	158.05	161.54
Std Deviation (Number of Failures)	12.48	11.53
System Uptime (Hours)	5,601.69	6,045.92
System Downtime (Hours)	3,164.31	2,720.08

Simulation results in Table 5.4 revealed Page and Marion draglines are expected to halt due to component failures for 158 and 161 times, annually. These failures and scheduled breaks cause downtimes with 3,164 and 2,720 hours for Page and Marion, respectively. Therefore, Page can operate with an availability of 64±4 % while Marion can keep its operation going with an availability of 69±3%. Economic consequences of dragline breakdowns will be discussed in detail in Section 5.3.2, regarding direct and indirect costs of maintenance events estimated in this section.

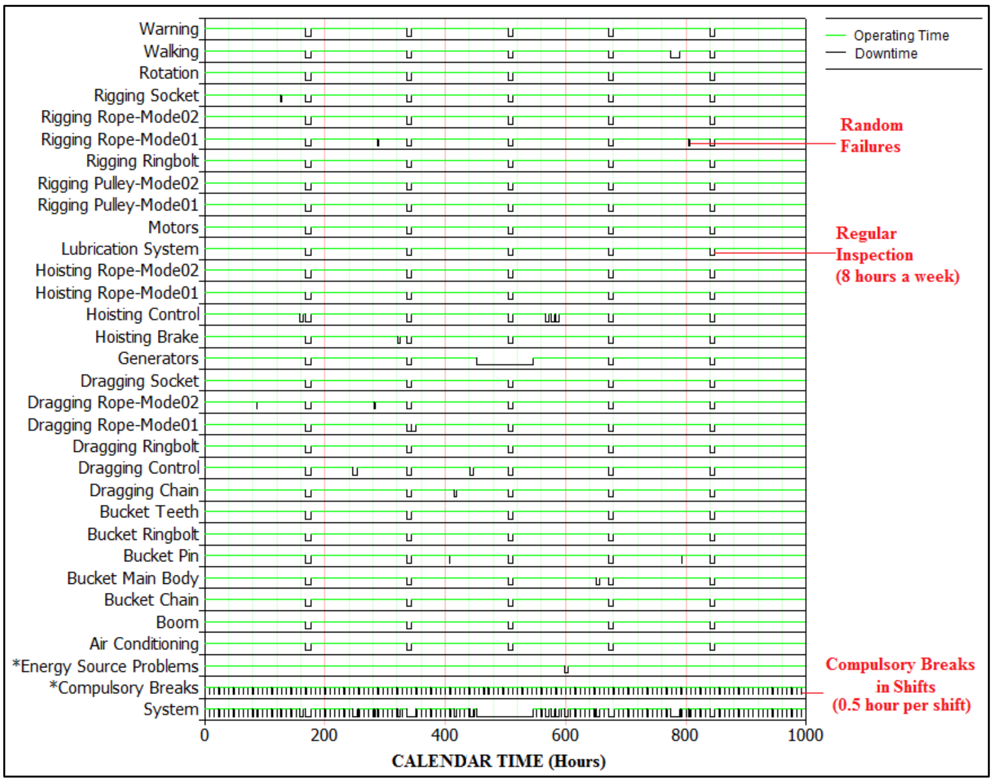


Figure 5.2 Sample Simulation Window for Marion System

Figure 5.3 Sample Simulation Window for Page System

The simulation assumed that dragline operations are halted for 8 hours every 160 hours for regular inspection. Number of failures and their occurrence frequency are highly effected from inspection intervals. Length of inspection intervals is critical to detect the approaching failures in advance and to maintain components preventively. If inspections are carried out in short intervals, this condition increases frequency of system halts due to inspections and resultant production loss. If inspections are performed in long intervals, then inspections cannot catch defects in components and production loss due to corrective maintenance again raises dramatically. Therefore, inspection intervals should be determined in accordance with system characteristics so that overall economic consequences of maintenance can be reduced. In addition to inspection intervals, implementation of preventive component replacements during operation hours is another tool for maintenance policies. Moreover, detection of maintenance criticalities for components can also be utilized to improve the maintenance policies. In this sense, understanding about how individual components contribute to system reliability can raise the awareness about maintenance criticalities of component. In this basis, Section 5.3 will present cost-effective maintenance optimization of the draglines via preventive replacement policies, optimization of inspection intervals and risk-based reliability allocation of the components.

5.3 Cost-Effective Maintenance Optimization of the Draglines

System components deteriorate in operations due to interaction effects such as, corrosion, wear and tear, cracking, erosion, fatigue, and skin damage. Underestimating conservative and preventive activities in maintenance policies causes these components to lose their operational effectiveness with increasing failure rates. In this sense, reliability-based analyses can help to improve maintenance policies via i) supporting reliability of subsystems and its constituents above the planned limits and ii) taking precautions against failure via inspections, repairs, component replacements, servicing, and overhauling operations.

Components in a system league together in various structural and economical dependencies. Therefore, integration of reliability to system maintenance policy requires pre-estimation of components lifetime behavior. Success of the policy may be ensured only with precise estimation of component reliability and identification of functional relationships between subsystems and components. This section utilized lifetime characteristics of dragline components estimated in Section 4.2.

In the study, maintenance strategy of draglines was optimized via (i) generating a decision platform for age-replacements of wear-out components , (ii) development of an optimization algorithm for inspection intervals to minimize overall maintenance cost, and (iii) determination of maintenance-critical components with a risk-based reliability allocation model.

5.3.1 Investigation of Component Replacement Decisions

Preventive replacement decisions in maintenance policies can be handled in two ways as replacement of capital equipment and replacement of individual component. Since replacement of dragline is out of scope in this study, it will be focused on the determination of replacement intervals for critical system components. Preventive replacement decisions can be applied for components in deterioration period. If a component exhibits random failure behavior without any aging condition, these parts are not considered under age-replacement decisions. Prerequisites for the applicability of age-replacement policies are as follows:

i. The component should be in wear-out period. For Weibull distribution, shape parameter (β) is good indicator of determining whether component is in early stages of its lifetime, in its useful lifetime with random failure patterns, or in deterioration period with wear-out problems. The condition of $\beta > 1$ refers the occurrence of unexpected failures since the component leaves behind its useful lifetime. For other distributions, component failure rates should be analyzed to check whether they follow an increasing failure rate or not. It should be noticed that Weibull distribution with shape parameter of 3.5 exhibits exact normal distribution. Therefore, components holding normally distributed lifetime parameters are candidate components in wear-out period, inherently. This condition is also valid for other quasi-normal distributions such as, lognormal, logistic, and loglogistic.

ii. Total cost of preventive replacement should be less than it is for corrective replacement cost. It is obvious that preventive replacement generally brings the component into as good as new condition and reduces the virtual age of overall system via renewing the used part with the new one. However, it is economically unnecessary if preventive replacement causes higher loss of money compared to corrective replacement. It is important that preventive and corrective replacement costs should include both indirect and direct costs for an applicable replacement policy.

Components with shape parameter less than 2 are sometimes considered out of preventive replacement modelling since they are assumed to be at the initial phases of wear-out periods. However, all dragline components with potential wear-out problem were considered under scope of the study. Their convenience for replacement policy were discussed regarding replacement intervals and changing cost conditions.

Table 5.5 summarizes economic consequences of preventive and corrective replacement for the candidate components potentially in wear-out period. These values were estimated considering indirect and direct costs of component replacements. Direct costs for preventive and corrective replacements are common and they are up-to-date values of year 2015. However, indirect cost is expected to be lower for preventive replacement since it is more organized and pre-scheduled activity. On the other hand, corrective maintenance can lead to higher time losses due to negative administrative or maintenance factors. Indirect costs of the replacements were calculated using Equation 5.2. In Tunçbilek coal mine, there is no any record about how replacement duration differs according to the maintenance type. However, dragline maintenance experts stated that preventive replacement can save a time up to 60 minutes. Therefore, a time reduction of 60 minutes was considered as limit reduction in indirect costs of preventive replacements. Sensitivity of preventive replacement decisions for different ratios between corrective and preventive replacement costs will be discussed later.

Table 5.5 Costs of Corrective and Preventive Component Replacements

	Components	Lifetime Parameters		Direct Replace. Cost ($)	Total Corrective Replace. Cost ($)	Total Preventive Replace. Cost ($)
MARION	Dragging Ringbolt	Weibull	Beta: 1.04 Eta: 820.81 Gamma: 51.95	1,089	2,075	1,533
	Dragging Rope-Mode01	Weibull	Beta: 2.18 Eta: 1,848.27 Gamma: -388.95	1,132	4,982	4,440
	Dragging Socket	Lognormal	(LN) Mean:8.40 (LN) Std: 1.45	1,202	1879	1,337
	Hoisting Rope-Mode01	Normal	Mean:2,851.59 Std:1,640.61	1,216	8,792	8,250
	Rigging Rope-Mode01	Loglogistic	Mu: 5.78 Sigma: 0.48	98	1,089	547
	Rigging Pulley-Mode01	Normal	Mean: 3,765.18 Std: 2,953.95	843	2,245	1,703
	Mach. House Lubrication	Lognormal	(LN) Mean:5.81 (LN) Std: 1.27	Not Practical to Replace Completely		
	Mach. House Air Condition	Lognormal	(LN) Mean:7.93 (LN) Std: 1.04	Not Practical to Replace Completely		
PAGE	Dragging Ringbolt	Weibull	Beta: 1.25 Eta: 1,085.00	614	1,493	1,179
	Dragging Rope-Mode01	Loglogistic	Mu: 6.72 Sigma: 0.45	644	2,076	1,762
	Hoisting Rope-Mode01	Loglogistic	Mu: 7.44 Sigma: 0.23	705	4,015	3,701
	Hoisting Brake	Lognormal	(LN) Mean: 6.83 (LN) Std: 1.99	1,268	1,921	1,607
	Hoisting Control	General Ren. Pro	Beta: 1.65 Eta: 10,566.22	Not Practical to Replace Completely		
	Rigging Rope-Mode01	Weibull	Beta: 1.52 Eta: 595.15 Gamma: 51.93	107	509	195
	Rigging Pulley-Mode01	Lognormal	(LN) Mean: 6.83 (LN) Std: 1.99	447	1,364	1,050
	Rigging Socket	Weibull	Beta: 1.06 Eta: 2,420.09	189	688	374
	Movement Walking	Weibull	Beta: 1.12 Eta: 1,635.68	Not Practical to Replace Completely		
	Movement Warning	General Ren. Pro.	Beta: 1.43 Eta: 3,322.29	Not Practical to Replace Completely		

Optimal replacement intervals for the components in wearing period were estimated using age replacement policy. The intervals were derived via minimizing of unit maintenance cost regarding both unit costs of corrective and preventive replacement and their occurrence probabilities in prescribed time interval. Recalling Section 2.6.2, age replacement policy is summarized as in Table 5.6.

Table 5.6 Age-Replacement Policy Equations

Equation	**Description**
$A_c(t_0) = \frac{c_c F(t_0) + c_p R(t_0)}{\int_0^{t_0} R(t)\, dt}$	Unit cost equation
$h_c(t_0) = r(t_0) \int_0^{t_0} R(t)\, dt - R(t_0) - \frac{c_p}{c_c - c_p}$	Numerator of the derived $A_c(t_0)$ function
$h_c(t_0^*) = 0$	Optimum replacement interval criterion
$\boldsymbol{c_c}$ Cost of unit corrective replacement $\boldsymbol{c_p}$ Cost of unit preventive replacement $\boldsymbol{F(t)}$ Failure probability of component for time t $\boldsymbol{R(t)}$ Survival probability of component for time t $\boldsymbol{r(t)}$ Failure rate $\boldsymbol{t_0^*}$ Optimum Replacement Interval	

The ratio between corrective and preventive replacement costs has a great effect on the component replacement intervals. If the preventive replacement cost is close to corrective maintenance cost, the length of interval may exceed expected component lifetime. At that condition, preventive replacement decision fails even if the length of interval seems economically feasible. Decision curve of an age replacement policy is expected to be plotted as in Figure 5.4 if all conditions are satisfied. The minimum point on the curve gives preventive replacement interval which minimizes maintenance cost.

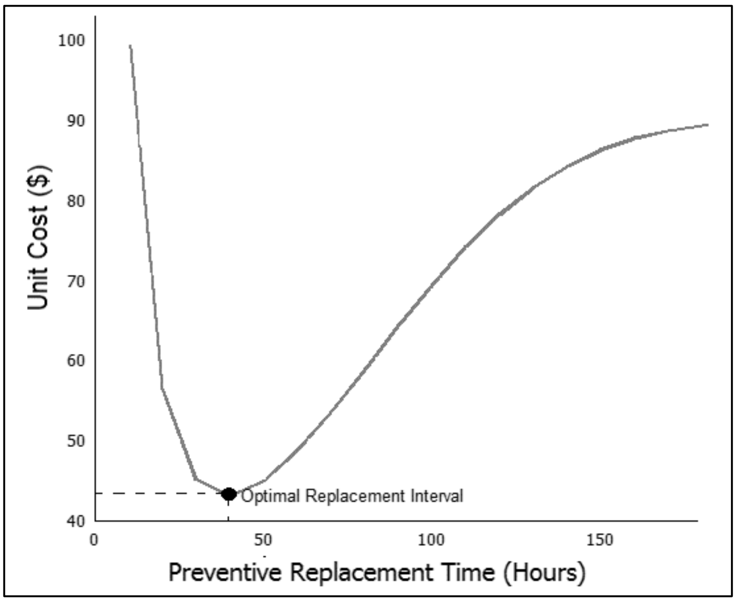


Figure 5.4 Sample Curve of Positive Replacement Decision

Applicability of preventive replacements for the dragline components stated in Table 5.5 was evaluated. Two representative graph of unit cost minimization curves can be viewed in Figures 5.5-5.6. The graphs for the other components can be examined in Appendix A, Figures A1- A11.

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $1337
Cost for unplanned replacement: $1879

Time Units	Cost/Unit Time
500	2.81982
1000	1.52275
1500	1.09212
2000	0.87569
2500	0.74461
3000	0.65624
3500	0.59234
4000	0.54382
4500	0.50560
5000	0.47464
5500	0.44900
6000	0.42738
6500	0.40888
7000	0.39284
7500	0.37879
8000	0.36637
8500	0.35530
9000	0.34537
9500	0.33639
10000	0.32824
10500	0.32080

NO OPTIMUM REPLACEMENT TIME

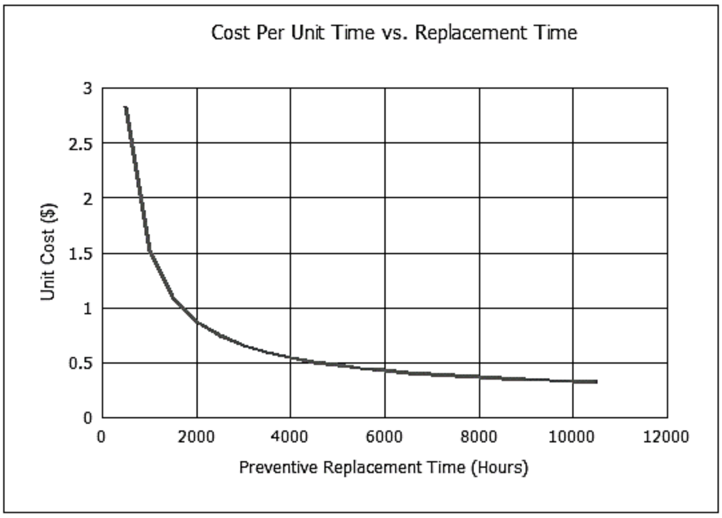


Figure 5.5 Preventive Replacement Interval Curve for Marion Dragging Socket

Chart Start Time: 75
Increment by: 75

Cost for planned replacement: $195
Cost for unplanned replacement: $509

Time Units	Cost/Unit Time
75	2.63192
150	1.45408
225	1.11363
300	0.97030
375	0.90082
450	0.86542
525	0.84764
600	0.83956
675	**0.83695**
750	0.83741
825	0.83954
900	0.84245
975	0.84562
1050	0.84875
1125	0.85165
1200	0.85422
1275	0.85645
1350	0.85832
1425	0.85987
1500	0.86112
1575	0.86211

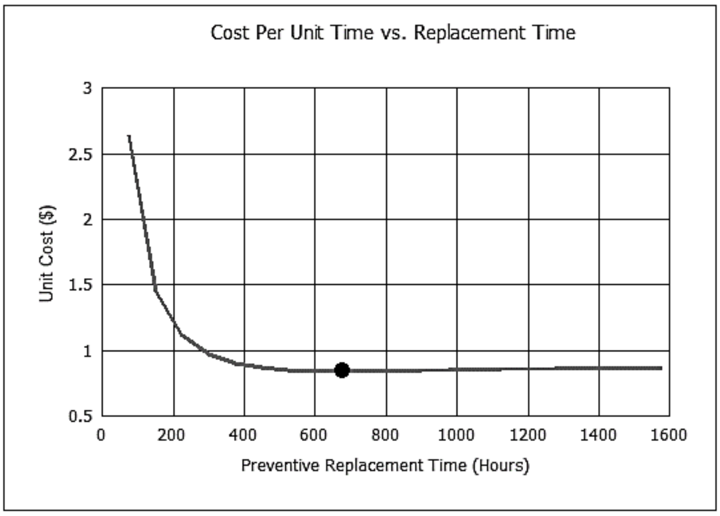


Figure 5.6 Preventive Replacement Interval Curve for Page Rigging Rope-Mode01

Figure 5.5 shows that unit cost decreases consistently even if preventive time interval continues to rise. It proves that there is not any optimum time interval for preventive replacement of Marion dragging socket. In Figure 5.6, the curve points to a minimization point although it does not exhibit exact behavior in Figure 5.4. It is a cost-balance point rather than an optimization point. However, this interval can be selected as a candidate replacement point to minimize hidden negative effects of corrective replacement. In order to validate applicability of this candidate point, condition that this interval is less than the component lifetime should be checked. Mean lifetimes of wear-out components and their candidate replacement intervals were given in Table 5.7. For Page rigging component in Figure 5.6, the replacement interval (675 hours) is not less than mean lifetime (588 hours). Therefore, it is not meaningful to apply preventive replacement for this component. It can be realized from Table 5.7 that all global minimum points, i.e. candidate replacement intervals, exceeds expected lifetimes of the components. Under this circumstances, it is not feasible to apply preventive replacement policy for the components.

Table 5.7 Age-Replacement Intervals for the Wear-Out Components

Wear-Out Components	Mean Lifetime (Hours)	Global Minimum Points at the Curves (Hours)
Marion Dragging - Ringbolt	859	7,200
Marion Dragging - RopeMode01	1,248	5,250
Marion Dragging - Socket	12,686	No Minimum Point
Marion Hoisting - RopeMode01	2,852	9,750
Marion Rigging - RopeMode01	489	No Minimum Point
Marion Rigging - PulleyMode01	3,765	12,000
Page Dragging - Ringbolt	1,011	7,200
Page Dragging - RopeMode01	2,521	No Minimum Point
Page Hoisting - RopeMode01	1,848	No Minimum Point
Page Hoisting - Brake	6,642	No Minimum Point
Page Rigging - RopeMode01	588	675
Page Rigging - PulleyMode01	14,902	No Minimum Point
Page Rigging - Socket	2,363	No Minimum Point

Wearing levels of components and ratio between preventive and corrective replacement costs are the main determinants of replacement intervals. Although current data utilized in the analyses points to infeasibility of replacement policy for the components, it may be beneficial to learn about the relationship between corrective/preventive cost ratio and preventive replacement intervals. By this way, decision maker in dragline maintenance can quickly update replacement decisions considering changeable cost ratios. Figures 5.7-5.8 illustrate the applicable replacement intervals and required corrective/preventive cost ratios for the wear-out components. Each point on the curves was estimated using equations in Table 5.6.

The curves in Figures 5.7-5.8 start from minimum applicable cost ratios and their resultant replacement intervals. For instance, minimum ratio for Marion dragging rope-mode01 should be 3.39 in order to implement preventive replacement with 1,248 hours intervals. In some circumstances, corrective maintenance cost can increase dramatically if there are logistic or supply problems for spare parts or if failure of components starts to cause catastrophic damages and longer repair durations. At that time, replacement interval reduces due to increase in the cost ratio. Numerical values of the graphs in Figures 5.7-5.8 and unit cost change can be examined in Appendix B, Tables B.1-B.2.

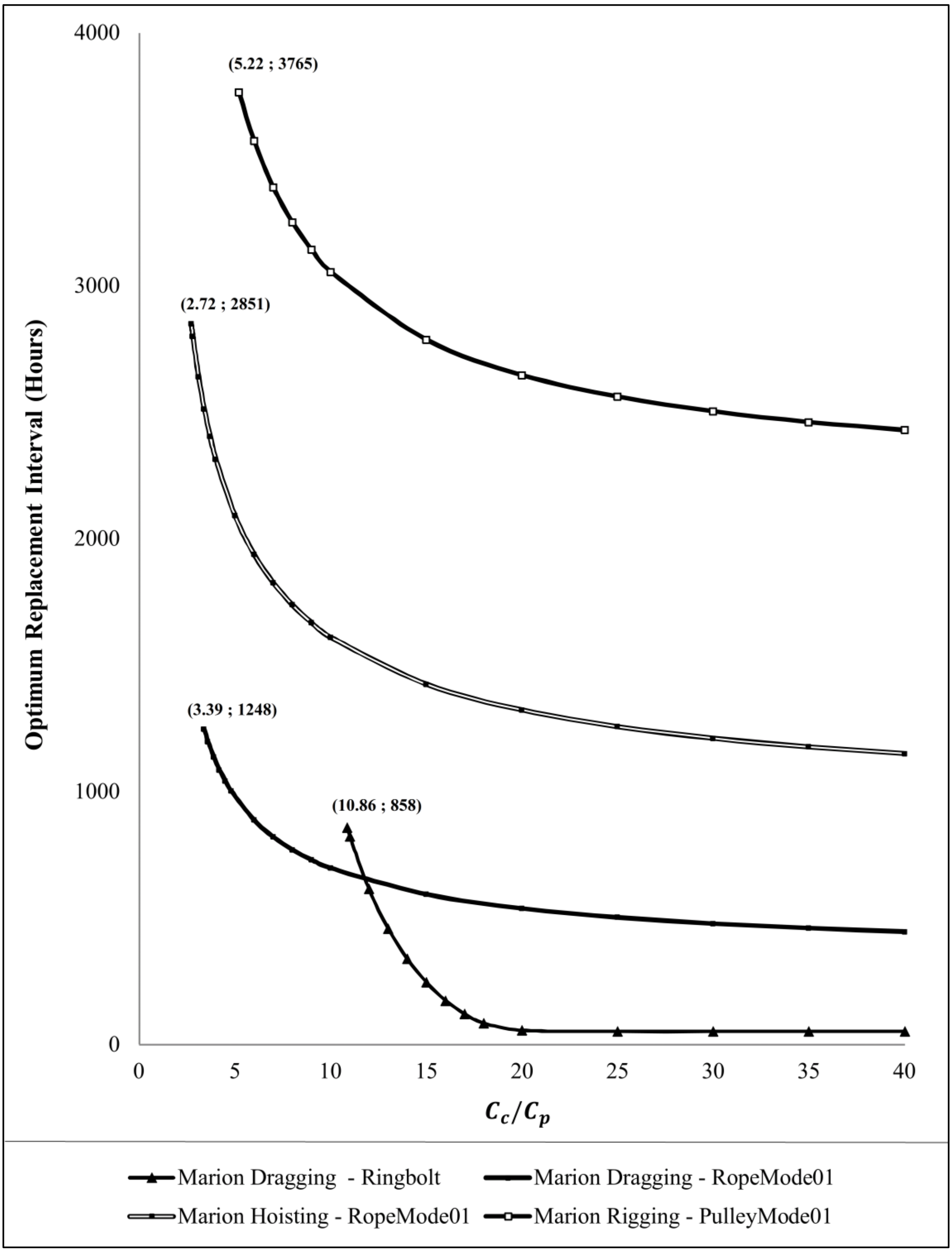


Figure 5.7 Optimum Replacement Intervals of Marion Wear-out Components for Different Ratios of Corrective (C_c) and Preventive (C_p) Replacement Costs

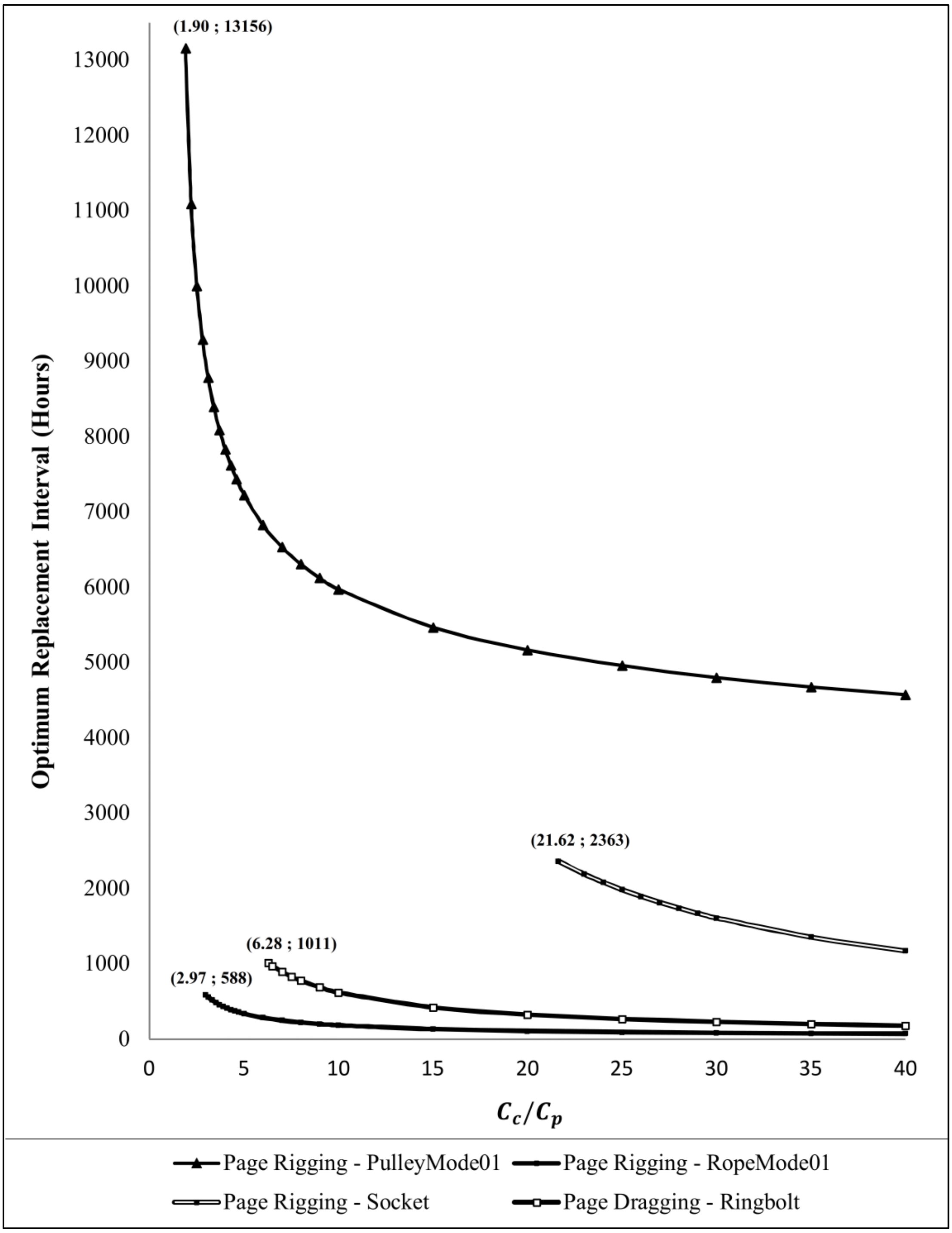


Figure 5.8 Optimum Replacement Intervals of Page Wear-out Components for Different Ratios of Corrective (C_c) and Preventive (C_p) Replacement Costs

5.3.2 Development of an Optimization Algorithm for Inspection Intervals

Inspections are generally carried out at regular intervals to detect deficiencies in the systems and to maintain components preventively against the potential failures. Scope of an inspections is specified in advance and answers the questions of who, how, and how long to perform the activities effectively during implementation period. In this sense, the scope should specify i) components which should be concentrated on during the period, ii) which strategy should be applied for correct maintenance decision of individual components, and iii) the thresholds to initiate repairing or replacement activities. Inspection works can be modified according to different operation conditions and changing failure profiles of systems. Draglines in Tunçbilek coal mine are inspected at 160 hours intervals with 8 hours durations. Common activities of inspections for the draglines are listed as:

<u>Dragging Unit</u>

- In case of wear-out in normal level, damaged zones on drag chains are welded. If wear-out is in excessive level or irrecoverable fracture takes place on the component, it is replaced with an identical one.
- In case of wear-out in normal level, damaged zones on drag ringbolt are welded. If wear-out is in excessive level or irrecoverable fracture takes place on the component, it is replaced with an identical one. The component is also lubricated against friction.
- Tips of the drag ropes in the socket is controlled. If rope tips are scotched, these parts are cut and fixed again with the ringbolt. Wire fractures and wear-out condition are controlled along the whole rope. If there is ruptures on the components, it is replaced with the identical one. This replacement can be out of the regular inspection hours.
- In drag control part, transmission boxes, gears, bearings, felts, lubrication leakages, valves, brake linings, limit switches, hoist drums, hoist drum gears, and couplings are controlled. If there is short-period repair requirement, this repair is carried out. In case of long-time repairing requirement, a maintenance plan is developed with a planned system shutdown.

Hoisting Unit

- Tips of the hoist ropes in the socket is controlled. If rope tips are scotched, these parts are cut and fixed again with the ringbolt. Wire fractures and wear-out condition are controlled along the whole rope. If there is ruptures on the components, it is replaced with the identical one. This replacement can be out of the regular inspection hours.
- In hoist control part, transmission boxes, gears, bearings, felts, lubrication leakages, valves, brake linings, limit switches, hoist drums, hoist drum gears, and couplings are controlled. If there is short-period repair requirement, this repair is carried out. In case of long-time repairing requirement, a maintenance with a planned system shutdown plan is developed.

Rigging Unit

- Wire fractures and wear-outs on rigging rope and breaks, fractures and wear-out on rigging sockets and rigging pulleys are controlled. Repair activities on these components are not recommended. Instead, they are replaced with an identical ones in case of any problem. In obligatory cases, some minor repairs can be performed for these components.

Bucket Unit

- Bucket teeth, chains, and ringbolts are repaired if required.
- Some partial repairs can also be made on bucket main body. For general maintenance of bucket, bucket body can be replaced with its spare without interrupting dragline production.

Boom Unit

- Welding of chord connections and condition of chords against buckling, fracture and any other deficiencies are controlled. Maintenance on boom must be performed with a scheduled and planned program.

Movement Unit

- In rotation mechanism, gears of transmission box, bearings, felts, operating status of lubrication pumps, lubrication leakages at the felts of main rotation axle, pinion gears at the tips of main rotation axle, pulleys of turret traversing mechanism, rails, flanges, and wear-out condition at any of these components are controlled. Failures at this mechanism are repaired with a prescribed program or failed components are replaced with an identical one.

- In walking mechanism, gears of transmission box, bearings, felts, lubrication lines and their injectors, walking axle, journal bearing, bushing of walking feet and their pins, steel construction of walking feet are controlled against any deformation. The anomalies that can be fixed in place are maintained with a planned program.
- In warning mechanism, connection couplings, warning generator brushes, and condition of whether there is any arc at armature or not are controlled. If the brushes are eroded, they are replaced with a new one. Brush dust is removed with compressed air against probability of dust to initiate any short circuit due to arc. If any arc is initiated at armatures, these arc are removed via grinding armatures with a portable grinding machine or turning lathe.

Machinery House

- Generators are connected to each other with coupled sliding bearing system. Coupling settings, wear-outs at the sliding bearing, and cleanness of liquid mineral oil which maintain the bearings are controlled. Generator armature brushes and occurrence condition of arc at the armatures are controlled. If the brushes are eroded it is replaced with a new one. Brush dust is removed with compressed air against probability of dust to initiate any short circuit due to arc. If any arc is initiated at armatures, this arc are removed via grinding armatures with a portable grinding machine or turning lathe. Electrical connections at generators are controlled.
- Mechanical and electrical connections, armatures, brushes, bearings, and lubrication feedings of all motors are controlled. If there is any failure that can be recovered in-place, it is fixed. Critical failures are fixed at the workshop.
- Lubrication requirement of dragline components are met with two type of automatic lubrication systems. Injectors at lubrication line, valves, oil stock is the mechanism, pumps, air compressors, valves of the air system, and timing mechanism are controlled. The parts in malfunctioning state are repaired immediately.

Time between inspections, i.e. inspection intervals, highly effect annual maintenance cost of draglines. If the interval is shortened too much in order to take more preventive precautions, it causes halt of the machinery with high frequency. Therefore, production loss rises to a level that cannot be compensated with benefits of these preventive inspections. On the other hand, if the intervals are extended too much, this condition induces failure of components with higher frequency. In this situation, machine is halted frequently due to corrective maintenance of components and wear-out problems at machinery parts become problematic. Therefore, inspection intervals should be determined so that cost of direct and indirect consequences of overall halts should be minimized. In inspection optimization, characterization of system components and effects of failures on system functionality should be specified precisely. In this study, a real-time algorithm was created to find out optimum inspection intervals of draglines via taking maintenance decisions of dragline components at different time points and minimizing overall annual maintenance cost of these decisions. Behavior of a sample system with two-components can be examined in Figure 5.9, to be familiar to the algorithm in advance.

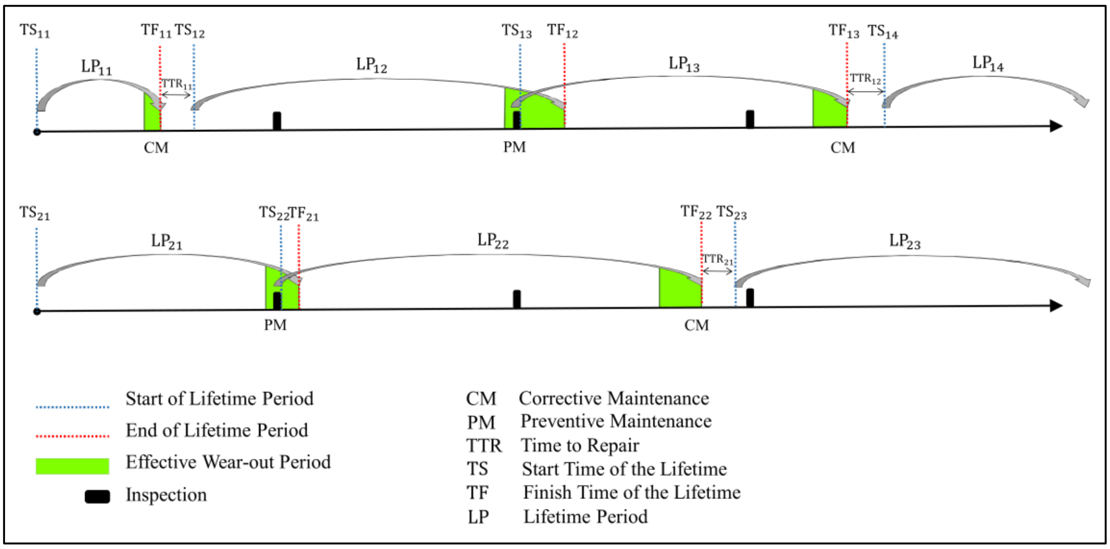


Figure 5.9 Maintenance Behavior of a Two-Components System according to the Algorithm

As seen in Figure 5.9, the algorithm basically specifies start (TS) and finish (TF) points for successive lifetime periods (LP) of each component and determines maintenance type and resultant cost at each TF point. At the initial time, the components are started to operate simultaneously. Immediately after, random time between failures, i.e. TBF, values are assigned to the component according to their characterization. Length of each LP changes according to the assigned TBF and other system halts. For instance, LP_{21} in Figure 5.9 includes random TBF of component-2, system halts due to inspections, legal work breaks in shifts, and repairing activity of component-1 (TTR_{11}). At the end of each lifetime, algorithm makes a decision on the type of maintenance as corrective and preventive. This decision is based on wear-out detection probabilities of components in inspections. In Figure 5.9, wear-out detectability period is highlighted with green color. This period can be determined with failure detection threshold (FTD) value. FTD is in terms of percentage and identifies effective utilization time of components. For instance, if TBF of a component is 200 hours and FTD is 95% and then, the last 10 hours (remaining 5% of lifetime) give an indication for the approaching failure. It specifies the time length of the green-colored zone in Figure 5.9. When each LP is realized to be finished, algorithm checks the length of this detectability period. If the detectability period starts before any inspection, then the defect is detected at the inspection prior to failure. At this condition, preventive maintenance is performed for the component and a new random TBF is assigned. Since inspection durations are constant, finish time of the inspection becomes start time (TS) of the new lifetime. In Figure 5.9, TS_{22} is an example of this situation. If the defect cannot be caught during any inspection, component is failed at the end of its normal lifetime period and a corrective maintenance is performed. For instance, LP_{11} in Figure 5.9 ends without giving any alarm during inspections. At that time, a random repairing time (TTR) is assigned to the component for corrective maintenance. Therefore, starting point of the new lifetime is sum of the last TF and this random TTR value.

The algorithm creates an active time which raises with small increments in each loop. After each increment, active time is updated and algorithm evaluates surviving/failure condition of each component for this updated time. If maintenance decisions are given, random cost values including direct and indirect cost are accumulated under system maintenance cost item. The simulation is ended when active time is equal to target time. The algorithm optimizes inspection intervals via changing interval lengths and minimizing system maintenance cost with repetitive simulation runs (Figure 5.1). Flowchart of the algorithm is stated in Figure 5.10.

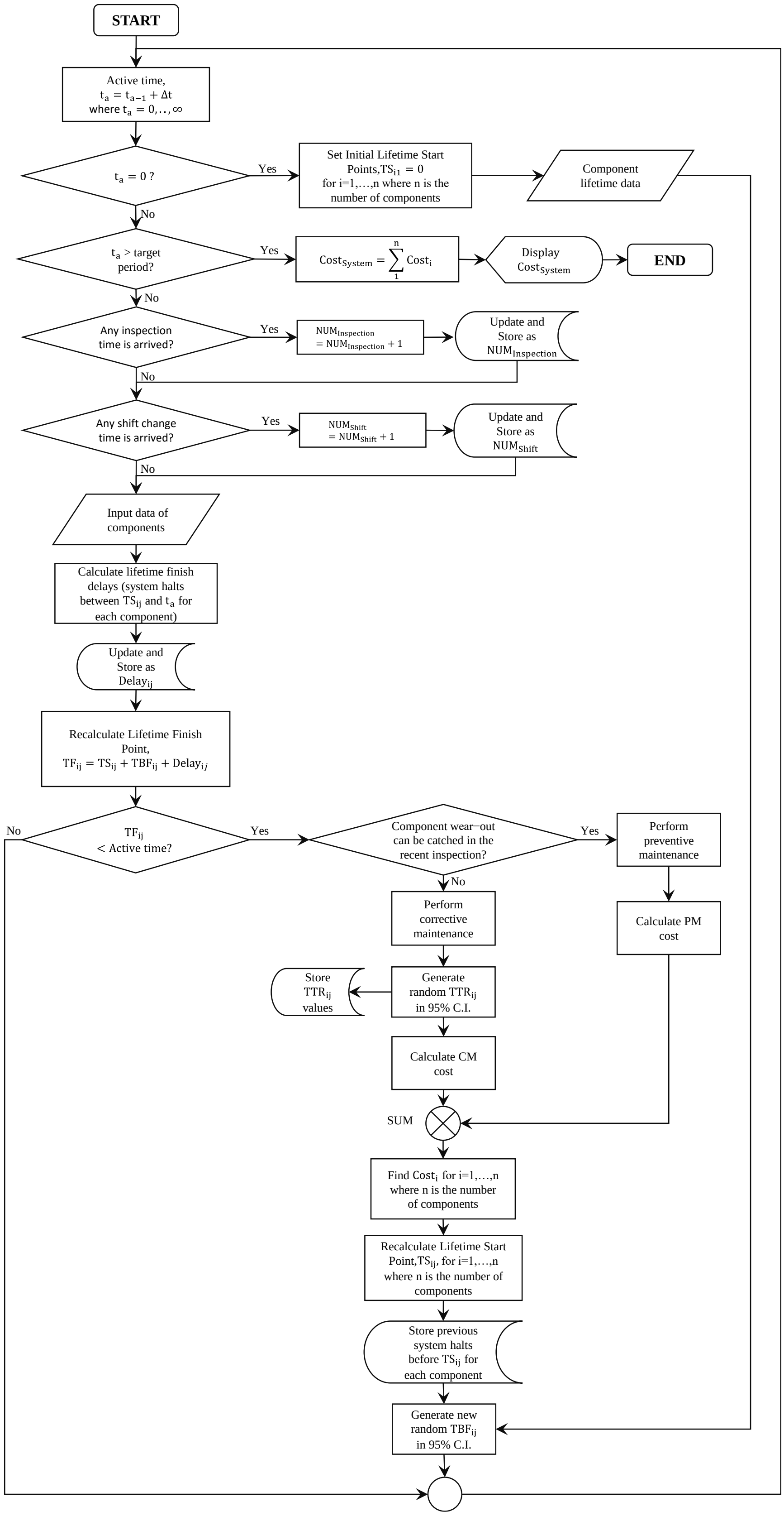


Figure 5.10 Flowchart of Inspection Algorithm with Constant Inspection Interval

Summary of algorithm stages and main assumptions can be investigated as follows:

- Algorithm computes five dependent sub-events in each loop: Time counting, estimation of lifetime period length, maintenance decision-making, assignment of a start point for new lifetime, and cost estimation.

  Time Counting:
- Algorithm starts with t_0=0. It increases with unit time increments and creates an updated active times at the start of each loop.
- When the updated active time reaches to any shift or inspection time, it counts and updates the total number of shift or inspection from the beginning. By this way, scheduled system halts are stored.

  Estimation of Lifetime Period Lengths:
- At t_0=0, system components are initiated to operate simultaneously with random survival times, i.e. TBF, according to their lifetime characteristics.
- The algorithm estimates length of lifetime (LP) where component is operable via assigning start (TS) and finish (TF) points to individual lifetimes. In addition to component's survival time, updated system halts due to inspections, shifts, and corrective maintenance of other system components are also added to find out updated TF points. This condition does not affect survival times of components, only shifts TF points on the timeline.

  Decision of Maintenance Type:
- When active time arrives to TF of any component, the algorithm analyzes probability of component wear-out to be detected at the previous inspection.
- The algorithm assumes that the anomaly at component can be detected during this inspection if wear-out period starts before the inspection. In this condition, a preventive maintenance takes place for the component.
- If there is a sudden or hidden failure for component without any indication or wear-out period does not initiate before the previous inspection, the component is assumed to be failed during operation and a corrective maintenance is performed.

  Assignment of a Start Point for New Lifetime:
- After each maintenance activity, a new random TBF is assigned to the maintained component. Starting point of new lifetime is estimated with one of the following assumptions: i) Summation of the last TF and random time-to-repair (TTR) value

after corrective maintenance or ii) finish time of the last inspection time after preventive maintenance. TTR values for corrective maintenance are assigned randomly considering repair time distributions of components.

Maintenance Cost Estimator:

- Maintenance costs of individual components are stored as preventive and corrective maintenance costs cumulatively. Since preventive maintenance takes place only in regular inspections, production loss due to the maintenance is ignored in cost estimation of preventive maintenance. In corrective maintenance, indirect cost is estimated considering assigned random TTR in each activity. Corrective maintenance cost is also determined randomly.
- Maintenance cost of each component is accumulated in system maintenance cost item until active time reached to the target analysis time and then simulation is ended.
- Overall maintenance cost of system is evaluated for changing inspection intervals with repetitive simulation runs. The interval which minimizes the overall cost is obtained as optimal interval.

The algorithm utilized following variables: i) Component lifetime characteristics, ii) time-to-repair distributions of components, iii) failure detection thresholds (FTD), iv) corrective costs of components in case of failures, v) preventive cost of components when maintained in inspections, vi) unit production losses in system halts, and vii) planned system halts during shifts and inspection. In the algorithm, random TBFs of components was provided from lifetime characteristics obtained in Section 4.2. Random repair durations (TTR) were assigned from distributions in Table 5.2. Failure detection threshold (FTD) values were determined according to the opinions of dragline maintenance experts (Table 5.8).Corrective costs after each failure covered indirect and direct cost values. Constant direct cost values were taken from Table 5.3. On the other hand, indirect cost values were designated randomly due to random TTR values, using Equation 5.2. Preventive costs included only direct inspection costs of components since inspections were carried out in constant durations. These values are up-to-date values of year 2015 as given in Table 5.8. In addition, unit production losses for both draglines were stated in Table 5.1. Planned system halts in each shift and inspection were taken as 30 minutes and 8 hours, respectively.

Table 5.8 Preventive Inspection Costs and FTD Values of Dragline Components

UNITS	COMPONENTS	PAGE		MARION	
		Preventive Inspection Cost ($)	**Failure Detection Threshold (%)**	**Preventive Inspection Cost ($)**	**Failure Detection Threshold (%)**
Dragging	Dragging Chain	65	90	98	95
	Dragging Ringbolt	16	85	16	90
	Dragging Rope-Mode01	-	-	-	-
	Dragging Rope-Mode02	-	-	-	-
	Dragging Control	196	85	295	90
	Dragging Rope Socket	65	95	65	95
Hoisting	Hoisting Rope-Mode01	-	-	-	-
	Hoisting Rope-Mode02	-	-	-	-
	Hoisting Brake	33	80	65	85
	Hoisting Control	123	90	164	95
	Hoisting Rope Socket	65	95	-	-
Rigging	Rigging Rope-Mode01	-	-	-	-
	Rigging Rope-Mode02	-	-	-	-
	Rigging Rope Socket	16	95	16	95
	Rigging Pulley-Mode01	22	98	33	95
	Rigging Pulley-Mode02	-	-	-	-
	Rigging Ringbolt	109	90	131	90
Bucket	Teeth	65	95	65	95
	Bucket Pin Set	98	90	98	90
	Bucket Chain Assembly	196	90	229	90
	Bucket Ringbolts	245	90	245	90
	Bucket Body	262	95	327	95
Movement	Rotation Mechanism	327	98	589	95
	Walking Mechanism	491	95	785	90
	Warning Mechanism	196	90	393	90
Machinery House	Generators	164	95	295	90
	Motors	44	98	87	95
	Lubrication Mechanism	49	75	49	80

As discussed at the beginning of section, rope components are not replaced at the inspections. Therefore, rope-mode01 components are excluded in preventive inspection as stated in Table 5.8. Moreover, mode02 failure modes for both rope and pulley components are expected to occur during operations. Therefore, they were also excluded in Table 5.8. Considering these cost assumptions and the methodology in

Figure 5.10, the algorithm was simulated using Reliasoft Reno software. Inspection optimization curves and numerical results obtained in the simulation can be viewed in Figure 5.11 and Table 5.9, respectively.

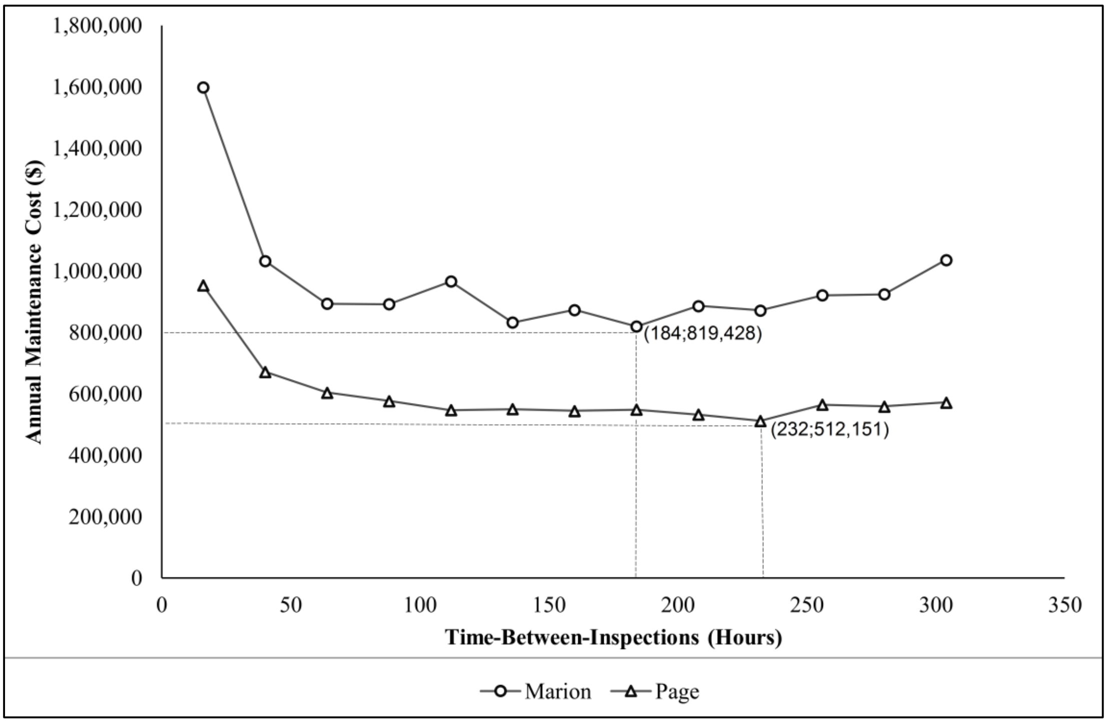


Figure 5.11 Inspection Optimization Curves for the Draglines

Table 5.9 Variation of Total Maintenance Costs According to Inspection Intervals

Inspection Interval (hours)	MARION		PAGE	
	Total Cost ($)	**Cost Change (%)**	**Total Cost ($)**	**Cost Change (%)**
16	1,599,547	+83.0	953,511	+75.2
40	1,033,099	+18.2	672,219	+23.5
64	893,757	+2.3	604,655	+11.1
88	892,107	+2.1	577,143	+6.0
112	966,352	+10.6	547,009	+0.5
136	832,068	-4.8	550,133	+1.1
160	873,946	0.0	544,219	0.0
184	819,428	-6.2	548,292	+0.7
208	886,724	+1.5	532,885	-2.1
232	871,997	-0.2	512,151	-5.9
256	921,108	+5.4	564,688	+3.8
280	924,187	+5.7	558,785	+2.7
304	1,036,597	+18.6	572,038	+5.1

Figure 5.11 revealed that overall maintenance cost which covers direct and indirect economic consequences of maintenance activities minimize at 184th and 232th inspection interval for Marion and Page, respectively. It means that these intervals have better capability to catch candidate failures and decrease failures during operations. Therefore, current inspection interval of 160 hours may be extended for both draglines. Compared to the current inspection interval of 160 hours, the optimized inspection intervals can reduce total maintenance cost with 6.2% and 5.9% for Marion and Page, respectively (Table 5.9). Moreover, corrective and preventive maintenance cost variations according to inspection intervals changes were also discussed. Log-scale charts for annual corrective costs of Marion and Page subsystems for changing inspection intervals can be viewed in Figures 5.12-5.13. It should be noted that these values cover overall direct and indirect economic consequences of component failures.

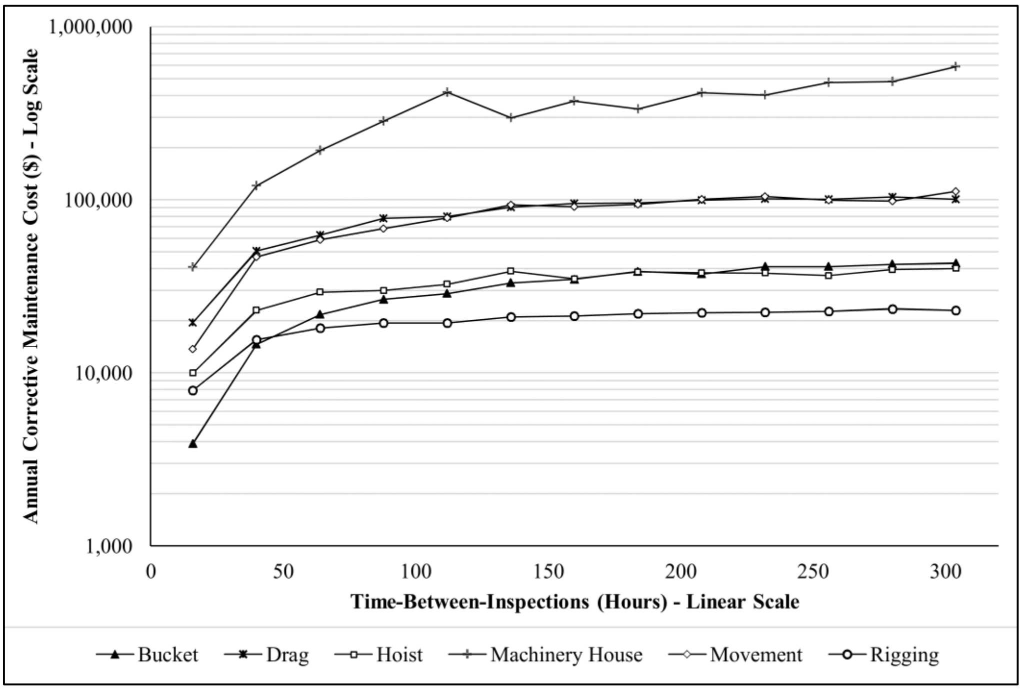


Figure 5.12 Annual Corrective Maintenance Costs of Marion Units for Changing Inspection Intervals

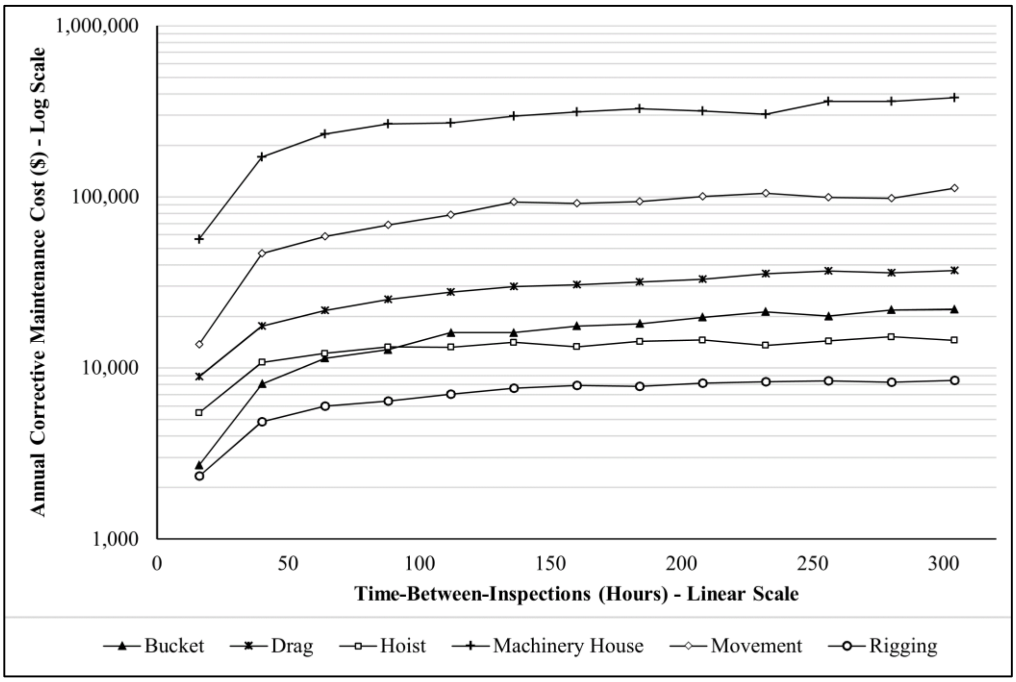


Figure 5.13 Annual Corrective Maintenance Costs of Page Units for Changing Inspection Intervals

It was observed from Figures 5.12-5.13 that machinery houses have the major effect on corrective maintenance costs of the draglines. For Marion, movement and drag units followed similar curves and had secondary great effects on maintenance costs following machinery house. It was seen from Figure 5.13, subsystems of Page exhibited almost the same rate for increasing inspection interval. Movement is the second most influential unit contributing corrective cost of the system.

Variation of preventive maintenance cost for the subsystems can also be viewed in Figures 5.14-5.15. The values on the curves are direct costs of preventive maintenance activities. Indirect cost was excluded since the inspections are carried out in constant durations. Therefore, production loss due to inspections were included separately as indirect preventive maintenance cost in Figures 5.14-5.15. Production loss due to inspections is one of the main determinants in optimization. Redundant inspections with high frequency decrease corrective costs but dramatically increase production losses. In this sense, optimal points in Figure 5.11 established a sensitive balance to achieve correct inspection interval.

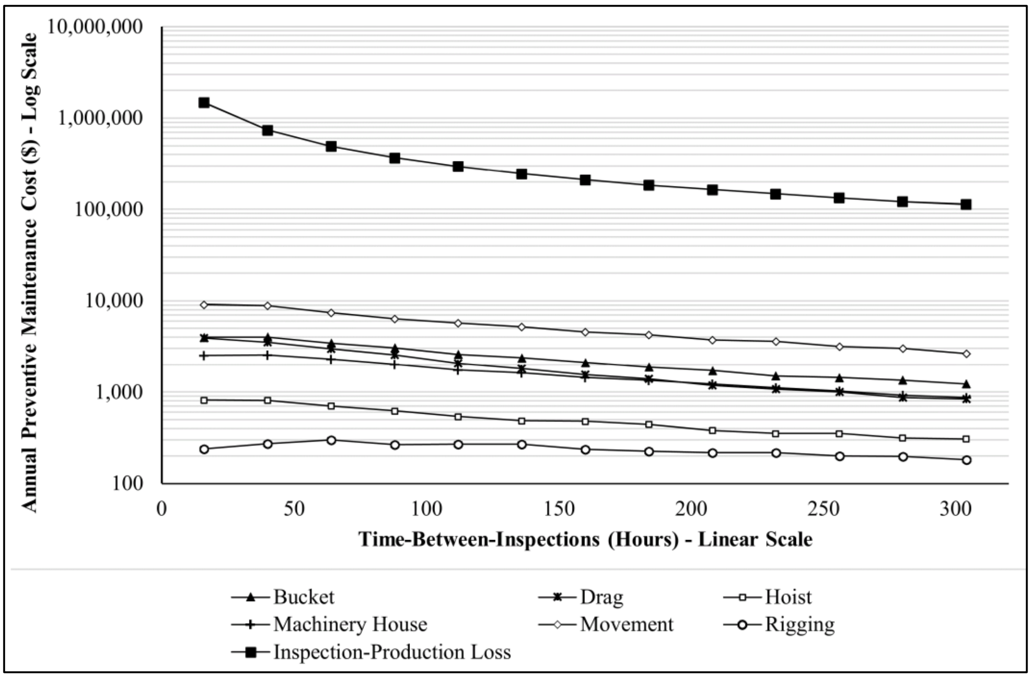


Figure 5.14 Annual Preventive Maintenance Costs of Marion Units for Changing Inspection Intervals

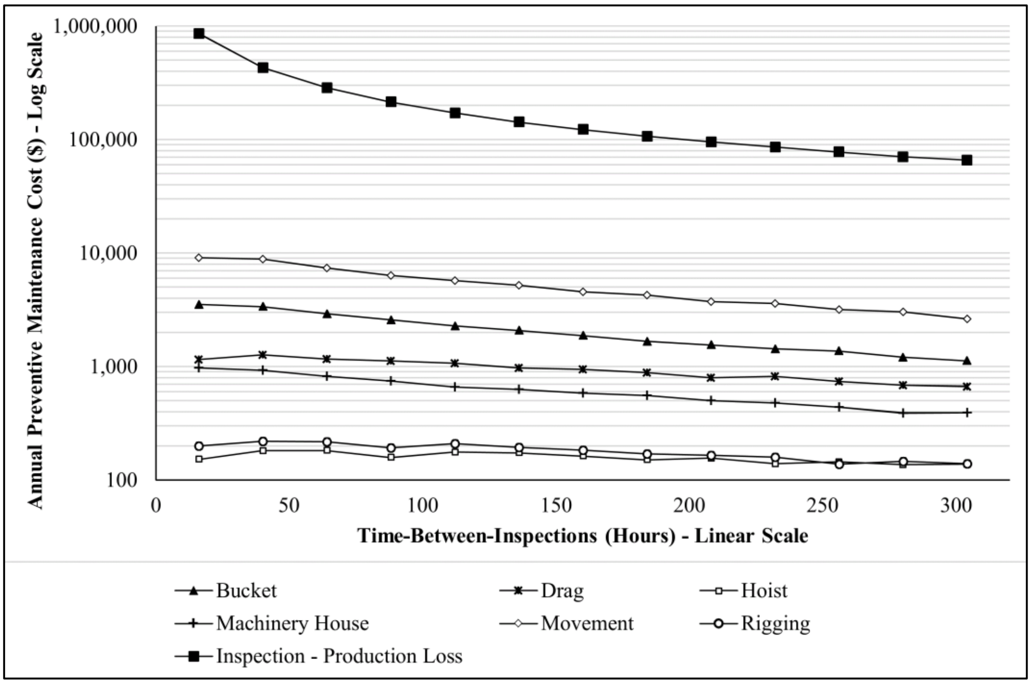


Figure 5.15 Annual Preventive Maintenance Costs of Page Units for Changing Inspection Intervals

In Figures 5.14-5.15, movement and bucket units for both draglines were observed to be maintained preventively with the highest total costs compared to the other units. On the other hand, rigging and hoisting are the units leading the least preventive maintenance cost.

5.3.3 Risk-Based Reliability Allocation of the Dragline Components for Effective Maintenance

As discussed in Sections 5.3.1 and 5.3.2, determination of preventive replacement decisions and optimal inspection intervals help optimization of maintenance policies via minimizing economic consequences of maintenance. Another issue in maintenance optimization is reliability allocation of system elements. Each component in a system holds different lifetime and maintenance breakdown in varying lengths. Time restrictions during maintenance activities force maintenance crew to perform repairing or inspection activities in short periods. In this sense, it is required to be aware of contribution of individual components to system performance in order to perform maintenance activities more effectively. In this basis, component criticalities can be estimated to develop a reliability allocation model. Reliability allocation basically investigates optimal reliability improvement requirements of individual component to keep overall mechanism reliability in prescribed levels effectively.

In the study, criticality of individual component was estimated using risk priority numbers (RPN). This values provide a decision measure about which components necessitate maintenance with priority to minimize overall consequences of failures. It is common in the literature to acquire RPNs using three indicative parameters: Severity (S), occurrence (O), and detectability (D) as given in Equation 5.3. These parameters take values between 1 and 10 in order to measure significance of failure modes (severity), their occurrence frequency (occurrence), and their probabilities to be detected (detectability).

$$RPN = S \times O \times D \tag{5.3}$$

Severity is generally assigned subjectively. According to the study scope, this parameter can be determined considering various factors such as, safety risks, environmental hazards, production interruptions, damage on company image, social pressure, and economic consequences of events. Since economic consequences of failure offers highly rational measure to identify severity factors, indirect and direct cost of each failure modes were taken into consideration to quantify this parameter in this study. In this sense, failure costs in Table 5.3 was utilized in the severity estimation. On the other side, occurrence factor in RPN was determined considering mean survival times, i.e. time between failures, of individual components. Expected lifetime durations of the components determined in Section 4.2 were used to identify the occurrence factors according to the ranking criterion in Table 5.10. The third parameter, detectability, was excluded in this study since detectability is already included in severity factor in mission-critical systems (The USA Department of Army, 2006).

Table 5.10 RPN Occurrence Factor (The USA Department of Army, 2006)

Ranking	**Expected Failure Rates**	**Rate Conditions**
10	1/10+	Very high failure rate
9	1/20	Very high failure rate
8	1/50	High failure rate
7	1/100	High failure rate
6	1/200	Moderate to high failure rate
5	1/500	Moderate failure rate
4	1/1,000	Occasional failure rate
3	1/2,000	Low failure rate

Estimated RPN numbers of the dragline components are given in Table 5.11. It should be noticed that there is no any hard failure record for the boom component. Although there was only preventive boom maintenance data, its severity was assigned as 10 since hard failure of boom may induce catastrophic consequences for overall system. RPN scores reveal that generator and motors have the greatest priority in reliability improvement of the draglines.

Reliability of each component decreases in time with different rates according to their lifetime characterization. For instance, after 24 hours operating period, some components can be at reliability limits between 60-70% while others can be between 95-100%. Performance improvement of lower-reliability component cannot always give the expected results in minimization of overall system cost. Although higher-reliability components seem to require lower maintenance effort compared to the other ones, breakdown of these components may induce excessive system halts and high amount of production loss. Therefore, both reliability and failure risks of components should be evaluated when deciding maintenance criticalities of components in the system halts. In this basis, the scores stated in Table 5.11 were utilized to allocate reliabilities to components to keep system reliability at target amounts while minimizing overall negative consequences of failures effectively.

Table 5.11 Risk Priority Numbers of Dragline Components

Unit	Component	Page			Marion		
		S	**O**	**RPN**	**S**	**O**	**RPN**
Dragging	Chain Assembly	3	4	12	3	5	15
	Ringbolt	2	4	8	1	4	4
	Rope-mode01	3	3	9	5	4	20
	Rope-mode02	1	4	4	1	4	4
	Control	3	3	9	4	5	20
	Sockets	1	2	2	1	1	1
Hoisting	Brake	1	2	2	2	3	6
	Rope-mode01	6	3	18	7	3	21
	Rope-mode02	1	2	2	1	1	1
	Sockets	5	1	5	1	1	1
	Control	4	1	4	4	4	16
Bucket	Bucket Body	2	4	8	4	4	16
	Chain Assembly	2	1	2	4	1	4
	Digging Teeth	2	4	8	1	4	4
	Pins	1	4	4	1	5	5
	Ringbolt	2	4	8	2	4	8
Rigging	Socket	1	3	3	1	2	2
	Ringbolt	1	2	2	1	2	2
	Rope-Mode01	1	5	5	1	5	5
	Rope-Mode02	1	1	1	1	3	3
	Pulley-Mode01	2	1	2	3	2	6
	Pulley-Mode02	2	3	6	2	3	6
Machinery House	Generators	10	3	30	10	4	40
	Motors	10	4	40	10	4	40
	Lubrication	1	4	4	3	5	15
	Air Conditioning	1	2	2	1	1	1
Movement	Rotation	5	4	20	5	4	20
	Walking	5	4	20	8	4	32
	Warning	8	3	24	5	2	10
Boom	Boom Chords	10	1	10	10	1	10

It is a requirement to make a sensitive balance between time-dependent component reliability and its criticality to decide maintenance priorities for individual components. In the study, risk-based reliability allocation was achieved using Equations 5.4-5.7 (Mettas, 2000).

$$\text{Minimize } \sum_{i=1}^{n} c_i(R_i) \tag{5.4}$$

Subject to

$$R_s > R_G \tag{5.5}$$

$$R_{i,min} < R_i < R_{i,max} \tag{5.6}$$

$$c_i(R_i : f_i, R_{i,min}, R_{i,max}) = e^{\left[(1-f_i)\frac{R_i - R_{i,min}}{R_{i,max} - R_i}\right]} \tag{5.7}$$

Objective function in Equation 5.4 minimizes improvement cost of individual system component to ensure target reliability of overall system. Cost measure, $c_i(R_i)$, is a dimensionless parameter and rates the difficulty to raise component reliability from its current value to R_i. Equations 5.5-5.7 in the algorithm specify system reliability (R_s), target system reliability (R_G), minimum ($R_{i,min}$) and maximum ($R_{i,max}$) feasible reliability values for components. Minimum reliability of component is the typical reliability value of component for the goal operating time. For instance, if it is aimed to improve reliability of a system at the end of 24-hours operating time and the reliability of the system component is 80% at 24th hour, its minimum reliability will be 80%. The algorithm assigns the components reliability values with equal or greater amount of their minimum reliabilities after reliability allocation process. Cost functions of individual components in Equation 5.7 are determined considering $R_{i,min}$, $R_{i,max}$, and feasibility factor. With using max and min reliability values, the algorithm restricts the unit improvement of higher-reliability components compared to the lower-reliability. This is a realistic case since it is harder to improve higher-reliability component compared to the lower ones. Feasibility factor (f_i) in Equation 5.7 means the convenience of reliability improvement and takes a comparative value between

0.01 and 0.99. It can be quantified according to the scope of reliability allocation. For instance, if it is required to regard economic consequences of components, it can be assigned higher feasibility values for these components. If the scope is about structural convenience of components for maintenance after failure, repair and inspection duration can be regarded. Briefly, this parameter builds a comparative priority level between the components. In the study, these factors were calculated via ratio of component RPNs and the highest RPN in the system. For example, Page motors have the highest RPN value with score of 40. Feasibility number of 0.99 was assigned to this component. Page generators hold RPN number of 30 and then this component has feasibility number of 0.74.

A sample case for both dragline can be investigated in Tables 5.12 and 5.13. In the example, Page and Marion draglines are detected to have reliability with 43% and 44% at the end of 24-hours operating time, respectively. It is aimed to improve system reliability to 60% and 80% at the target time using the algorithm in Equations 5.4-5.7. The feasibility factors in Table 5.12 and 5.13 are constant for all cases. However, $\mathrm{R_{i,min}}$ values are the current component reliabilities at the target time (24 hours for this case). $\mathrm{R_i}$ values are the required reliability values of component allocated considering their risk factors. For instance, in order to improve system reliability to 60%, Page rotation is the component which have the greatest effect on reliability improvement of system where it is for pulley-mode1 in Marion dragline. For target system reliability, maintenance-critical component and their improvement requirements can differ. For instance, reliability growth requirement of Page rotation changes from 9% to 13.9% when target Page reliability is increased from 60% to 80%.

Decision maker in the dragline maintenance can utilize the reliability allocation methodology discussed in this section and modify the parameter values considering the mine site conditions. By this way, realistic and applicable maintenance criticality models can be developed to improve system reliability in a cost-effective manner.

Table 5.12 Reliability Allocation of Page Components for Target Reliabilities

Units	Components	f_i	$R_{i,min}$ (%)	$R_G = 60\%$		$R_G = 80\%$	
				R_i (%)	Growth (%)	R_i (%)	Growth (%)
Dragging	Chain Assembly	0.30	98.58	98.58	0.00	99.35	0.78
	Ringbolt	0.20	99.15	99.15	0.00	99.52	0.37
	Rope-mode01	0.22	99.96	99.96	0.00	99.96	0.00
	Rope-mode02	0.10	95.39	95.76	0.39	98.22	2.97
	Control	0.22	98.25	98.25	0.00	99.20	0.97
	Sockets	0.05	99.49	99.49	0.00	99.64	0.15
Hoisting	Brake	0.05	96.71	96.71	0.00	98.59	1.94
	Rope-mode01	0.45	100.00	100.00	0.00	100.00	0.00
	Rope-mode02	0.05	99.98	99.98	0.00	99.98	0.00
	Sockets	0.12	99.49	99.49	0.00	99.65	0.16
	Control	0.10	100.00	100.00	0.00	100.00	0.00
Bucket	Bucket Body	0.20	92.23	94.29	2.23	97.52	5.74
	Chain Assembly	0.05	97.57	97.57	0.00	98.87	1.33
	Digging Teeth	0.20	94.04	95.20	1.23	97.98	4.19
	Pins	0.10	100.00	100.00	0.00	100.00	0.00
	Ringbolt	0.20	96.00	96.30	0.31	98.51	2.61
Rigging	Socket	0.07	99.26	99.26	0.00	99.53	0.27
	Ringbolt	0.05	98.10	98.10	0.00	99.07	0.99
	Rope-Mode01	0.12	100.00	100.00	0.00	100.00	0.00
	Rope-Mode02	0.02	100.00	100.00	0.00	100.00	0.00
	Pulley-Mode01	0.05	100.00	100.00	0.00	100.00	0.00
	Pulley-Mode02	0.15	92.19	94.13	2.10	97.42	5.67
Machinery House	Generators	0.74	95.89	97.69	1.88	99.23	3.48
	Motors	0.99	91.75	99.38	8.32	99.84	8.82
	Lubrication	0.10	98.83	98.83	0.00	99.36	0.54
	Air Conditioning	0.05	100.00	100.00	0.00	100.00	0.00
Movement	Rotation	0.50	85.12	92.85	9.08	96.92	13.86
	Walking	0.50	99.12	99.12	0.00	99.61	0.49
	Warning	0.59	99.91	99.91	0.00	99.93	0.02
Boom	Boom Chords	0.01	100.00	100.00	0.00	100.00	0.00

Table 5.13 Reliability Allocation of Marion Components for Target Reliabilities

Units	Components	f_i	$R_{i,min}$ (%)	$R_G = 60\%$		$R_G = 80\%$	
				R_i (%)	Growth (%)	R_i (%)	Growth (%)
Dragging	Chain Assembly	0.37	94.83	96.24	1.49	98.41	3.78
	Ringbolt	0.10	100.00	100.00	0.00	100.00	0.00
	Rope-mode01	0.50	96.27	97.21	0.98	98.90	2.73
	Rope-mode02	0.10	99.47	99.47	0.00	99.63	0.16
	Control	0.50	96.31	97.22	0.94	98.91	2.70
	Sockets	0.02	99.98	99.98	0.00	99.98	0.00
Hoisting	Brake	0.15	93.26	94.94	1.80	97.68	4.74
	Rope-mode01	0.52	95.76	97.05	1.35	98.84	3.22
	Rope-mode02	0.02	100.00	100.00	0.00	100.00	0.00
	Sockets	0.02	100.00	100.00	0.00	100.00	0.00
	Control	0.40	93.46	95.72	2.42	98.15	5.02
Bucket	Bucket Body	0.40	99.35	99.35	0.00	99.65	0.30
	Chain Assembly	0.10	100.00	100.00	0.00	100.00	0.00
	Digging Teeth	0.10	95.30	95.93	0.66	98.19	3.03
	Pins	0.12	96.89	96.91	0.02	98.69	1.86
	Ringbolt	0.20	100.00	100.00	0.00	100.00	0.00
Rigging	Socket	0.05	98.97	98.97	0.00	99.40	0.43
	Ringbolt	0.05	99.01	99.01	0.00	99.42	0.41
	Rope-Mode01	0.12	99.54	99.54	0.00	99.67	0.13
	Rope-Mode02	0.07	97.43	97.43	0.00	98.83	1.44
	Pulley-Mode01	0.15	89.73	93.27	3.95	96.79	7.87
	Pulley-Mode02	0.15	100.00	100.00	0.00	100.00	0.00
Machinery House	Generators	0.99	96.43	99.63	3.32	99.90	3.60
	Motors	0.99	99.72	99.90	0.18	99.98	0.26
	Lubrication	0.37	98.13	98.13	0.00	99.25	1.14
	Air Conditioning	0.02	100.00	100.00	0.00	100.00	0.00
Movement	Rotation	0.50	93.61	96.08	2.64	98.37	5.08
	Walking	0.79	95.38	97.91	2.65	99.26	4.07
	Warning	0.25	100.00	100.00	0.00	100.00	0.00
Boom	Boom Chords	0.01	100	100	0.00	100	0.00

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Dragline is a massive earthmover that performs overburden stripping by itself via successive cycles of dragging and hoisting bucket, swinging machinery house to spoil area and dumping full bucket. Operational status of draglines raises the importance of performance awareness for individual components in the mechanism. This situation requires deductive evaluation of component characterization and understanding of component effects on system performance. Underestimating root-causes of system halts and preventive measures in maintenance policies can induce rapid degradation of system elements and frequent system breakdowns. Draglines may suffer from insufficient and poor maintenance policies which may reduce stripping productivity. In this sense, sustainability of dragline operations can be improved via developing of reliability-based maintenance optimization methods.

This study integrated system reliability modelling and maintenance optimization in order to generate optimal maintenance policies for draglines. Using machinery catalogues, expert opinions, and information in datasets, dragline system was decomposed into subsystems and components considering functional and structural dependencies in the system. Various statistical and graphical methods were used to analyze behavior of individual datasets of components and to validate goodness of data. Reliability modelling of subsystems were generated using the lifetime datasets of components. Understanding of subsystem behavior allowed constitution of overall system reliability model. In reliability analyses, failure modes of each component and frequent maintenance strategy on them were also examined in detail. Evaluation of time-varying component reliability and root-causes of system halts provided a basis to criticize and build up maintenance optimization criteria for the draglines. In the study, maintenance optimization issue was handled considering i) applicability of preventive component replacements, ii) cost-effective inspection interval optimization, and iii) risk-based reliability allocation of the components.

Following key conclusions can be drawn from this research study:

- Data values for individual component should be checked for data anomalies such as, clustering, oscillation, mixture, and trend. Any unexpected data gathering or fluctuation can be indicator of deficiency in data collection or missing data. Run charts offer useful analysis to detect potential data anomalies and their causes. In addition, potential outlier values should also be controlled considering their distribution characteristics. Although box plots can be utilized as a non-parametric method, they can induce misleading inference for heavily-tailed distributions. Therefore, decision on outliers can be made subjectively also regarding box plots and distribution shape.
- Although Crow-AMSAA is highly robust test, trend decisions on this type of datasets should be interpreted using both qualitative and other quantitative methods. Results of quantitative test can differs where hypothesis testing values are slightly above or below the limit values. In this case, interpretation of data behavior subjectively via considering recent periods instead of whole observation period can be beneficial in trend decisions.
- Reliability evaluation using reliability block diagrams analyzes the root-causes for system failures effectively. Deductive structure of the method allows to investigate contribution of individual components on system performance and to detect weakest links in system productivity.
- Extending/shortening lifetime duration points to lifetime trend and this condition can be detected using trend tests. Reliability of this type of components is required to be estimated using stochastic model which can measure lifetime deterioration/growth. General Renewal Process is a flexible and effective method to characterize trend-component in any level between as good as new and as bad as old. Hoisting rope-mode02, hoisting control, bucket main body, bucket teeth, bucket ringbolt, rigging pulley-mode02, generators, motors, rotation, and warning

mechanisms for Page dragline, dragging chain, hoisting brake, rigging socket, and rotation mechanisms for Marion dragline were processed using General Renewal Process. Reliability of other non-repairable and also non-trend repairable components were estimated using best-fit distributions. Especially, Weibull distribution was best-fitted in majority of the components.

- Reliability assessment without analyzing failure modes and their maintenance types can cause misinformation about the resultant reliability values. Common failure modes and their repair activities were listed in the study to clear how reliability improvement could be provided with which maintenance activities. Dragging, hoisting, and rigging ropes are non-repairable components which fails due to rupture and maintained with replacement. Although some other components such as, chain, socket, and teeth are generally non-repairable, they are individual members of the sets. Therefore, they were assumed as repairable mechanisms with non-repairable subcomponents. Replacement of individual parts and welding are common maintenance activities for the mechanical repairable components of dragline. On the other hand, more complicated mechanisms, such as, motor, generator, rotation, walking are maintained via repairing failed electrical and mechanical subcomponents and also lubrication activities.
- Resultant reliability values revealed that dragging and bucket subsystems have the shortest lifetimes. Dragging unit is expected to survive for 210 and 170 hours for Page and Marion draglines, respectively. It is 188 and 200 hours for the bucket units. Boom is the least breakdown inducing unit for both draglines. Any failure in this unit causes catastrophic failure and leads to long-period system halts. The records on boom is only about preventive welding against fractures. Expected intervals for preventive welding requirement of booms are 7,391 and 11,502 hours for Page and Marion draglines, respectively. Reliability of overall system showed that Page and Marion are expected to operate continuously for 35.6 and 34.0 hours, respectively.
- Although maintenance studies in the literature have generally considered availability or reliability factors alone in optimization process, cost is the main factor to develop more realistic and applicable policies. Availability factor can also be included in cost parameter via considering economic consequences of

downtimes. This study evaluates cost of individual failure modes combining direct and indirect cost values. Direct cost is the expected physical value of failure consequences where indirect cost is production loss of downtimes. Estimation of indirect cost is very important since indirect cost generally overtakes direct cost in production industries. Unit production cost in the study for Marion and Page was calculated as 9.03 and 5.23 $/min, respectively. It regarded the unit time revenue from overburden excavation considering swell and fill factors, cycle time, bucket capacity, and operator efficiency. On the other hand, direct costs are specific to the components, obtained via questionnaires filled by dragline maintenance experts. Regarding repair costs and production losses, motors and generators are expected to induce the most destructive failure consequences, since their repair times are comparatively larger than other components. On the other hand, mechanical components such as, socket, teeth, ringbolt, and pin are generally recovered in shorter periods and then they are expected to induce less economic consequences in each failure.

- The study used age-replacement policy to detect applicability of preventive replacements for wear-out components. Dragging ringbolt, dragging rope-mode01, dragging socket, hoisting rope-mode01, rigging rope-mode01, and rigging pulley-mode01 for Marion dragline and dragging ringbolt, dragging rope-mode01, hoisting rope-mode01, hoisting brake, rigging rope-mode01, rigging pulley-mode01, rigging socket for Page dragline were determined as candidate wear-out components for preventive replacement. Using age replacement equations, it was decided that there is no applicability of age-replacements for the components in current conditions. However, replacement interval graphs were plotted to evaluate and update the decisions according to changeable ratios between corrective and preventive replacement costs.
- Risk analysis showed that machinery house and movement units are the subsystems with the highest failure risk. Reliability allocation algorithm using risk factors revealed that improvements in rotation and motor components offer the highest contribution on dragline reliability in economical manner.
- An original time counter algorithm was generated to obtain optimum inspection intervals for draglines. The algorithm aimed to minimize overall annual

maintenance costs of draglines via changing inspection intervals. Random lifetime behavior of all components, contributions of random failures and scheduled breaks to system halts, and decisions on preventive/corrective maintenance for the components were included in the algorithm. Cost values in maintenance decisions of individual components were estimated randomly due to changing production losses. The simulation showed that 184 and 232 hours intervals are optimal to carry out inspections for Page and Marion, respectively. These optimal values are expected to yield an economic savings with 6.2% for Page and 5.9% for Marion compared to current inspection conditions at the mine site.

- Maintenance and reliability assessment methodologies in the study and the developed algorithm for inspection interval optimization offer an holistic view on maintenance evaluation of all machinery systems as well as draglines. Decision makers can utilize these methodologies to discuss maintenance and operational performances of their systems.

6.2 Recommendations

Although the study is expected to make significant contribution to development of maintenance strategies for draglines, various areas can be improved in future studies. Recommendations on these areas are given as follows:

- For healthy and detailed analysis of draglines, standards on maintenance recording can be established and utilized at mine sites. A training can also be performed for maintenance crew about how to standardize maintenance recording. Detailed expression on causes and results of failures, statistics about required crew number per failure, and detectability (delay time) condition before failures can be asked in maintenance sheets. Failed components, existing failure modes, and repairing types can be expressed using unique codes.
- Constitution of a web-based maintenance platform for mining industry can be beneficial for academic and industrial evaluation of maintenance efficiency for mining machineries.

- Dynamic maintenance policies can be developed regarding inflation rate, production rate considering demand/supply amounts, changes in ore prices, operator efficiency, effectiveness of maintenance crew, and convenience of weather conditions for operations.
- Spare part optimization is a challenging issue in maintenance optimization. Reliability-based stock and demand plan for spare parts can be studied for mining machineries as a future study.
- Opportunistic maintenance and crew number optimization can be included in maintenance policies of mining machineries.
- There is not any record on delay-time maintenance of mining machinery component for preventive replacement policies. A long-period maintenance recording plan can be formed in mine sites to identify failure-alert periods of individual components. According to failure modes, various field test can be applied to detect wear-out rates.
- Studies on inspection optimization generally aims to find out inspection intervals. However, optimality of inspection duration is underestimated. Therefore, efficient implementation duration for planned regular inspections can be detected considering work packages in each inspection.

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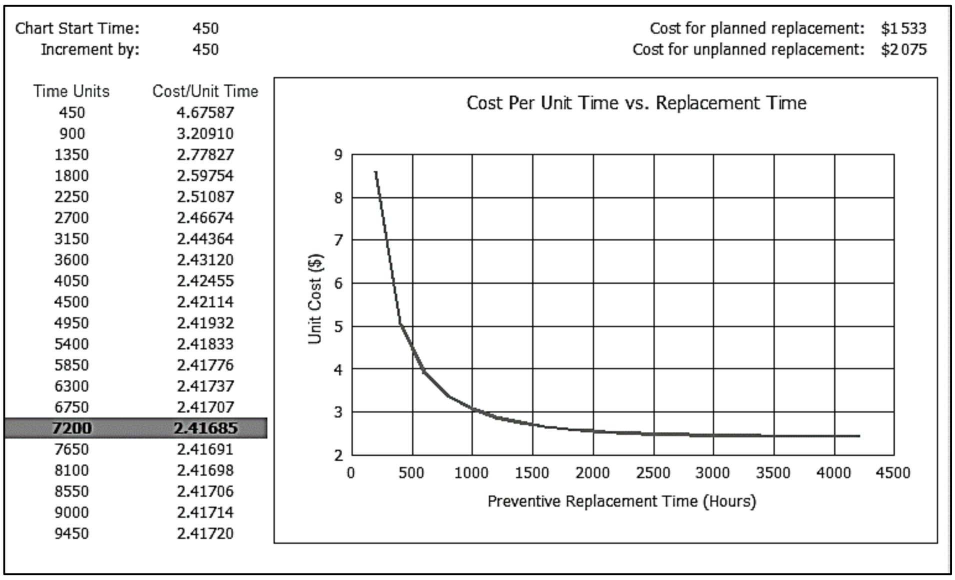
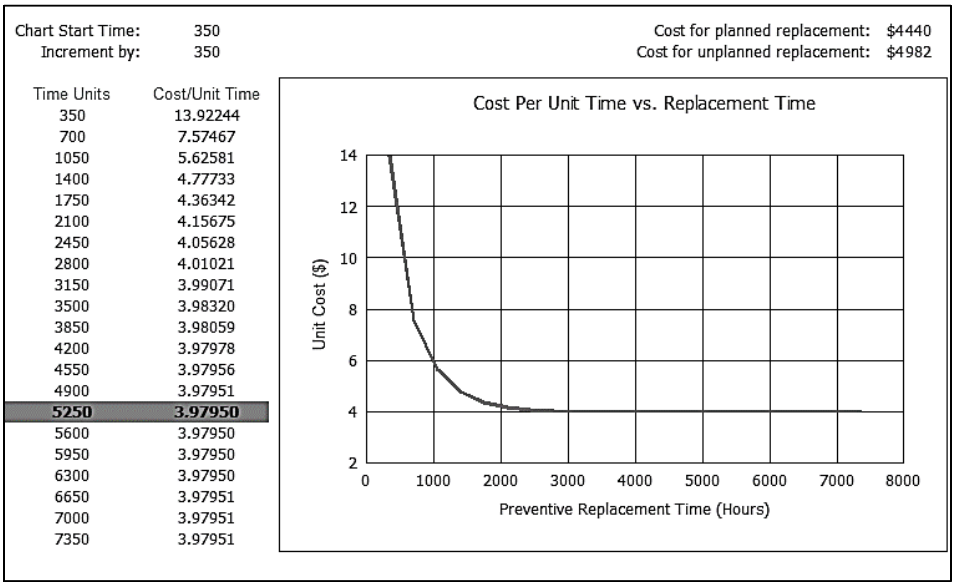
APPENDIX A

PREVENTIVE REPLACEMENT INTERVAL CURVES



Time Units	Cost/Unit Time
450	4.67587
900	3.20910
1350	2.77827
1800	2.59754
2250	2.51087
2700	2.46674
3150	2.44364
3600	2.43120
4050	2.42455
4500	2.42114
4950	2.41932
5400	2.41833
5850	2.41776
6300	2.41737
6750	2.41707
7200	2.41685
7650	2.41691
8100	2.41698
8550	2.41706
9000	2.41714
9450	2.41720

Figure A.1 Age-Replacement Curve of Marion Dragging Ringbolt



Time Units	Cost/Unit Time
350	13.92244
700	7.57467
1050	5.62581
1400	4.77733
1750	4.36342
2100	4.15675
2450	4.05628
2800	4.01021
3150	3.99071
3500	3.98320
3850	3.98059
4200	3.97978
4550	3.97956
4900	3.97951
5250	3.97950
5600	3.97950
5950	3.97950
6300	3.97950
6650	3.97951
7000	3.97951
7350	3.97951

Figure A.2 Age-Replacement Curve of Marion Dragging Rope-Mode01

Chart Start Time: 750
Increment by: 750

Cost for planned replacement: $8250
Cost for unplanned replacement: $8792

Time Units	Cost/Unit Time
750	11.87076
1500	6.24778
2250	4.49100
3000	3.71987
3750	3.34921
4500	3.17361
5250	3.09679
6000	3.06716
6750	3.05739
7500	3.05470
8250	3.05409
9000	3.05397
9750	**3.05396**
10500	3.05396
11250	3.05396
12000	3.05396
12750	3.05396
13500	3.05396
14250	3.05397
15000	3.05397
15750	3.05397

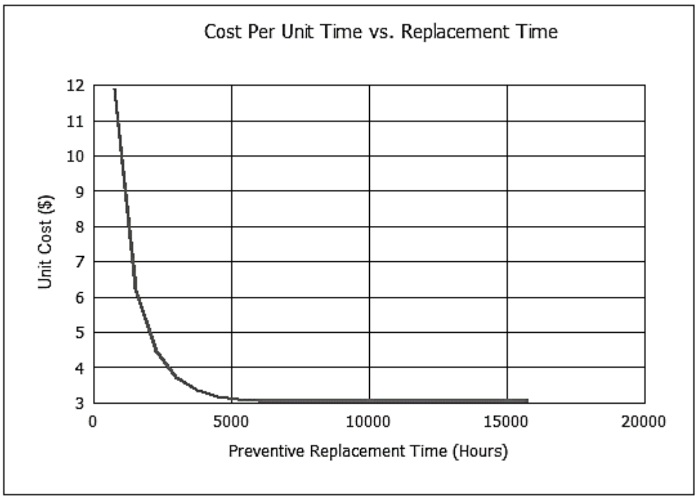


Figure A.3 Age-Replacement Curve of Marion Hoisting Rope-Mode01

Chart Start Time: 750
Increment by: 750

Cost for planned replacement: $1703
Cost for unplanned replacement: $2245

Time Units	Cost/Unit Time
750	2.72569
1500	1.44052
2250	1.02663
3000	0.83175
3750	0.72506
4500	0.66255
5250	0.62501
6000	0.60251
6750	0.58933
7500	0.58190
8250	0.57794
9000	0.57597
9750	0.57508
10500	0.57472
11250	0.57460
12000	**0.57458**
12750	0.57458
13500	0.57459
14250	0.57460
15000	0.57460
15750	0.57460

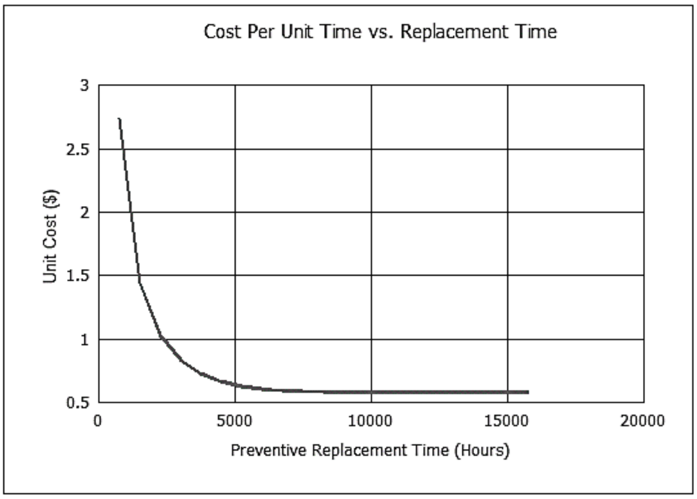


Figure A.4 Age-Replacement Curve of Marion Rigging Pulley-Mode01

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $547
Cost for unplanned replacement: $1089

Time Units	Cost/Unit Time
500	2.89464
1000	2.58586
1500	2.46894
2000	2.40785
2500	2.37059
3000	2.34561
3500	2.32775
4000	2.31436
4500	2.30397
5000	2.29568
5500	2.28892
6000	2.28330
6500	2.27857
7000	2.27452
7500	2.27102
8000	2.26797
8500	2.26529
9000	2.26291
9500	2.26079
10000	2.25889
10500	2.25717

NO OPTIMUM REPLACEMENT TIME

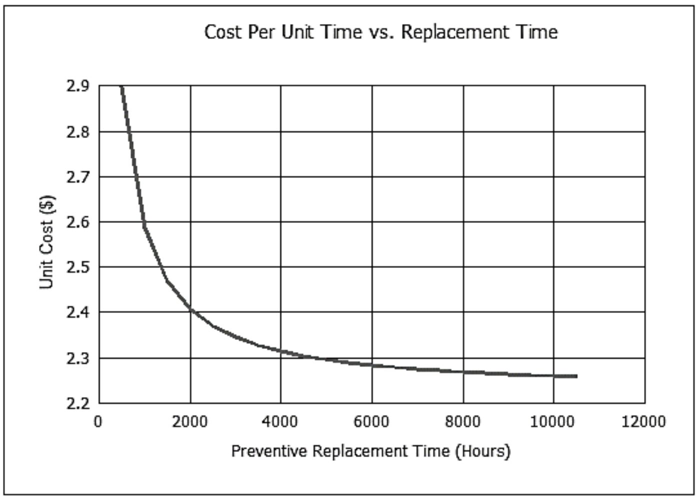


Figure A.5 Age-Replacement Curve of Marion Rigging Rope-Mode01

Chart Start Time: 600
Increment by: 600

Cost for planned replacement: $1179
Cost for unplanned replacement: $1493

Time Units	Cost/Unit Time
600	2.64834
1200	1.81805
1800	1.60148
2400	1.52486
3000	1.49547
3600	1.48408
4200	1.47975
4800	1.47813
5400	1.47755
6000	1.47735
6600	1.47728
7200	**1.47726**
7800	1.47726
8400	1.47726
9000	1.47726
9600	1.47726
10200	1.47726
10800	1.47726
11400	1.47727
12000	1.47727
12600	1.47727

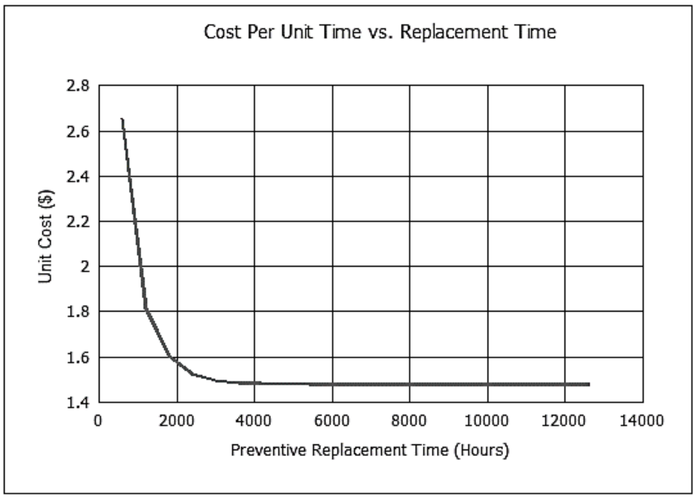


Figure A.6 Age-Replacement Curve of Page Dragging Ringbolt

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $1762
Cost for unplanned replacement: $2076

Time Units	Cost/Unit Time
500	4.03331
1000	2.65247
1500	2.27927
2000	2.11486
2500	2.02416
3000	1.96732
3500	1.92865
4000	1.90076
4500	1.87979
5000	1.86349
5500	1.85049
6000	1.83989
6500	1.83110
7000	1.82371
7500	1.81741
8000	1.81198
8500	1.80726
9000	1.80312
9500	1.79947
10000	1.79621
10500	1.79330

NO OPTIMUM REPLACEMENT TIME

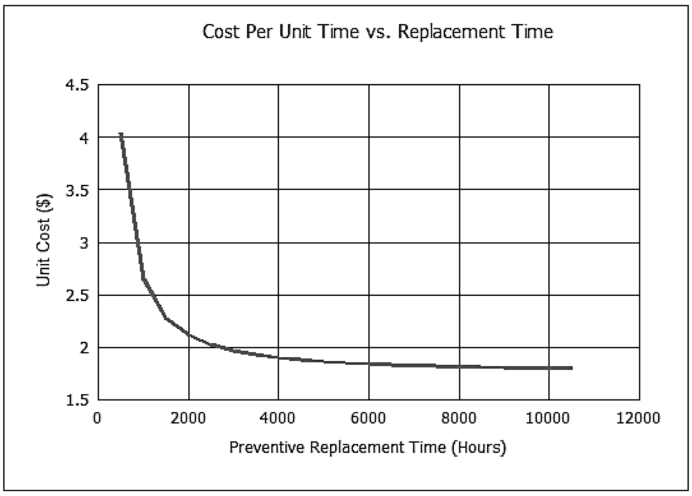


Figure A.7 Age-Replacement Curve of Page Dragging Rope-Mode01

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $1607
Cost for unplanned replacement: $1921

Time Units	Cost/Unit Time
500	4.50594
1000	2.69684
1500	2.04679
2000	1.70238
2500	1.48555
3000	1.33490
3500	1.22329
4000	1.13681
4500	1.06753
5000	1.01058
5500	0.96280
6000	0.92204
6500	0.88680
7000	0.85597
7500	0.82872
8000	0.80445
8500	0.78266
9000	0.76296
9500	0.74507
10000	0.72871
10500	0.71370

NO OPTIMUM REPLACEMENT TIME

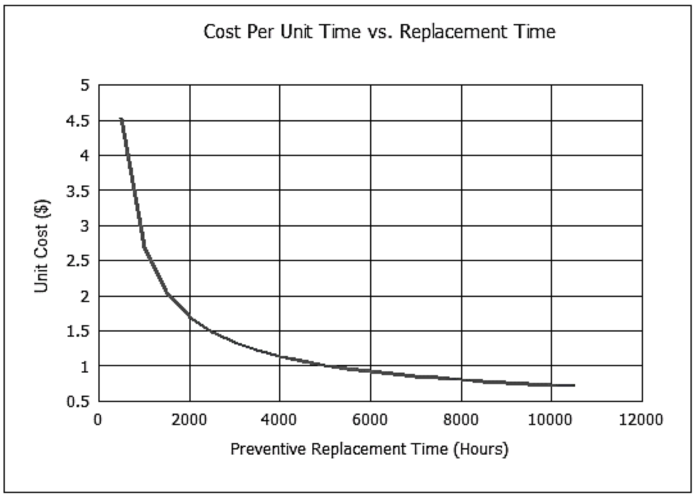


Figure A.8 Age-Replacement Curve of Page Hoisting Brake

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $3701
Cost for unplanned replacement: $4015

Time Units	Cost/Unit Time
500	7.41134
1000	3.79465
1500	2.77524
2000	2.42992
2500	2.29997
3000	2.24324
3500	2.21514
4000	2.19982
4500	2.19083
5000	2.18525
5500	2.18161
6000	2.17915
6500	2.17743
7000	2.17620
7500	2.17529
8000	2.17461
8500	2.17410
9000	2.17369
9500	2.17338
10000	2.17313
10500	2.17293

NO OPTIMUM REPLACEMENT TIME

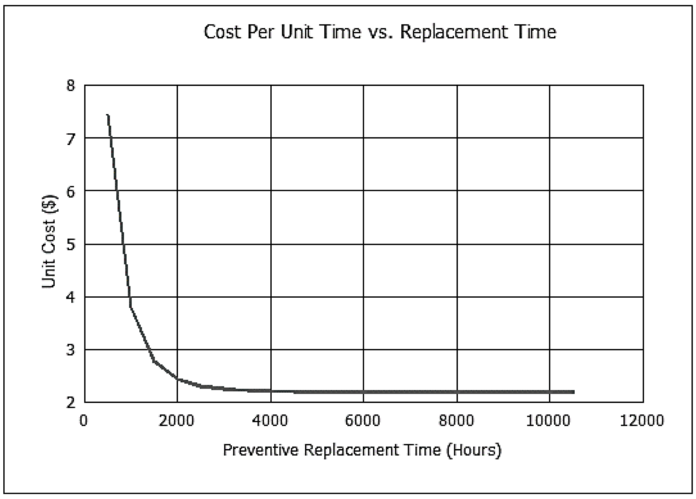


Figure A.9 Age-Replacement Curve of Page Hoisting Rope-Mode01

Chart Start Time: 500
Increment by: 500

Cost for planned replacement: $1050
Cost for unplanned replacement: $1364

Time Units	Cost/Unit Time
500	2.10001
1000	1.05001
1500	0.70000
2000	0.52500
2500	0.42001
3000	0.35002
3500	0.30006
4000	0.26267
4500	0.23369
5000	0.21068
5500	0.19207
6000	0.17681
6500	0.16417
7000	0.15364
7500	0.14481
8000	0.13737
8500	0.13108
9000	0.12575
9500	0.12121
10000	0.11735
10500	0.11405

NO OPTIMUM REPLACEMENT TIME

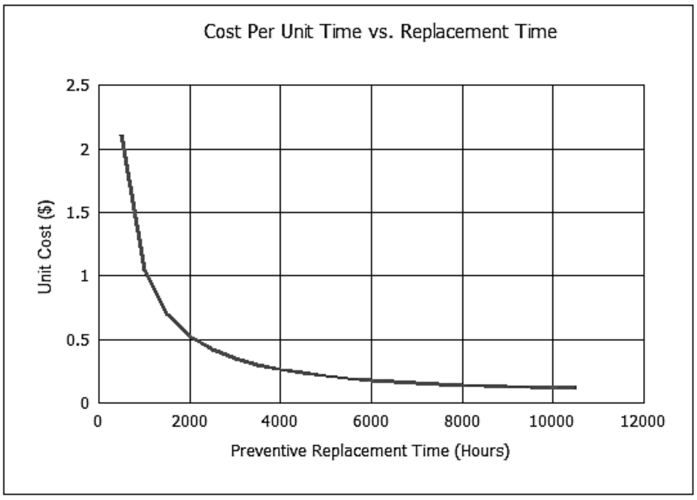


Figure A.10 Age-Replacement Curve of Page Rigging Pulley-Mode01

Chart Start Time:	500	Cost for planned replacement:	$374
Increment by:	500	Cost for unplanned replacement:	$688

Time Units	Cost/Unit Time
500	0.93537
1000	0.57138
1500	0.45360
2000	0.39684
2500	0.36426
3000	0.34363
3500	0.32975
4000	0.32001
4500	0.31298
5000	0.30780
5500	0.30393
6000	0.30099
6500	0.29875
7000	0.29703
7500	0.29570
8000	0.29467
8500	0.29387
9000	0.29325
9500	0.29277
10000	0.29239
10500	0.29209

NO OPTIMUM REPLACEMENT TIME

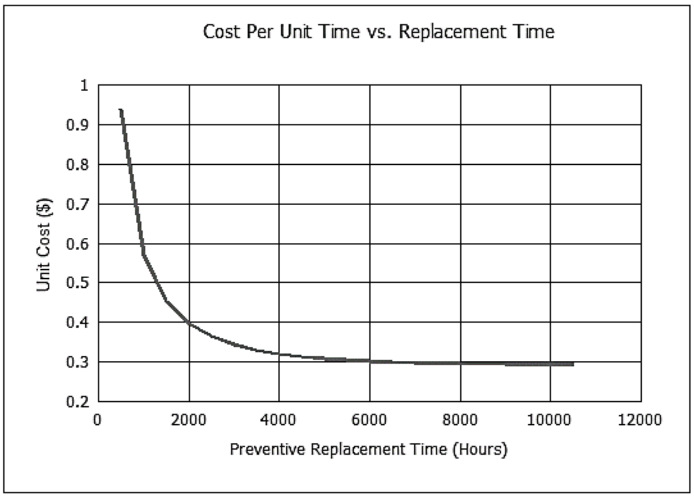


Figure A.11 Age-Replacement Curve of Page Rigging Socket

APPENDIX B

AGE-REPLACEMENT INTERVALS OF DRAGLINE COMPONENTS

Table B.1 Age-Replacement Intervals of Marion Wear-out Components

Marion Dragging - Ringbolt			**Marion Dragging - RopeMode01**			**Marion Hoisting - RopeMode01**			**Marion Rigging - PulleyMode01**		
Cost Ratio	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**
6.0	6,696.5	7	1.4	3,443.8	1.1	1.3	6,308.5	0.5	1.3	12,604.9	0.3
6.3	5,428.2	7.3	1.6	2,650.1	1.3	1.6	4,441.5	0.5	1.6	8,442.9	0.4
6.6	4,493.4	7.7	1.8	2,229.9	1.4	1.9	3,709.1	0.6	1.9	6,902.9	0.5
6.9	3,786.0	8	2	1,963.5	1.6	2.2	3,289.4	0.7	2.2	6,055.9	0.5
7.2	3,237.8	8.4	2.2	1,776.4	1.7	2.5	3,007.7	0.8	2.5	5,504.2	0.6
7.5	2,803.8	8.7	2.4	1,636.1	1.8	2.7	2,851.0	0.8	2.8	5,109.5	0.7
7.8	2,453.4	9.1	2.6	1,526.0	2	2.8	2,801.2	0.9	3.1	4,809.8	0.7
8.1	2,165.6	9.4	2.8	1,436.8	2.1	3.1	2,641.1	0.9	3.4	4,572.9	0.8
8.4	1,925.4	9.8	3	1,362.6	2.2	3.4	2,512.3	1	3.7	4,379.7	0.9
8.7	1,722.3	10.1	3.3	1,271.6	2.4	3.7	2,405.6	1	4.0	4,218.7	0.9
9.0	1,548.5	10.5	3.4	1,248.0	2.4	4.0	2,315.3	1.1	5.0	3,829.7	1.1
9.3	1,398.0	10.8	3.6	1,198.2	2.6	5.0	2,091.5	1.3	5.2	3,765.0	1.1
9.6	1,266.7	11.1	3.9	1,137.4	2.7	6.0	1,938.7	1.5	6.0	3,573.7	1.3
9.9	1,151	11.5	4.2	1,086.0	2.9	7.0	1,826.0	1.6	7.0	3,390.5	1.5
10.9	859.0	12.5	4.5	1,041.8	3.1	8.0	1,738.7	1.8	8.0	3,252.3	1.6
11.0	824.1	12.7	4.8	1,003.3	3.2	9.0	1,668.6	2	9.0	3,143.8	1.8
12.0	615.4	13.8	6.0	888.1	3.8	10.0	1,610.8	2.1	10.0	3,056.2	2
13.0	459.4	14.8	7.0	821.5	4.3	15.0	1,425.2	2.9	15.0	2,787.2	2.8
14.0	339.6	15.8	8.0	770.7	4.8	20.0	1,322.9	3.6	20.0	2,647.8	3.7
15.0	246.5	16.7	9.0	730.4	5.2	25.0	1,257.2	4.4	25.0	2,562.1	4.5
16.0	174.5	17.5	10.0	697.6	5.7	30.0	1,211.1	5.1	30.0	2,504.0	5.4
17.0	121.0	18.2	15.0	594.3	7.8	35.0	1,177.0	5.8	35.0	2,461.9	6.2
18.0	85.1	18.7	20.0	538.6	9.9	40.0	1,150.5	6.5	40.0	2,430.0	7.1
20.0	56.6	19.2	25.0	503.3	12.0						
25.0	52.0	19.2	30.0	478.7	14.0						
30.0	52.0	19.2	35.0	460.5	16.0						
35.0	52.0	19.2	40.0	446.6	18.0						
40.0	52.0	19.2									

Table B.2 Age-Replacement Intervals of Page Wear-out Components

Page Dragging - Ringbolt			**Page Rigging - RopeMode01**			**Page Rigging - PulleyMode01**			**Page Rigging - Socket**		
Cost Ratio	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**	**Cost Ratio**	**Time (Hours)**	**Unit Cost ($)**
2.3	5,823.8	2.3	1.5	2,283.9	2.5	1.9	13,156.5	0.1	6.6	19,245.1	2.8
2.6	4,139.1	2.6	1.7	1,539.7	2.9	2.2	11,092.7	0.1	6.9	16,977.0	2.9
2.9	3,213.5	2.9	1.9	1,184	3.2	2.5	9,998.9	0.1	7.2	15,145.8	3.0
3.2	2,637.3	3.2	2.1	975.8	3.5	2.8	9,291.3	0.1	7.5	13,644.7	3.2
3.5	2,245.9	3.5	2.3	838.1	3.8	3.1	8,784.3	0.2	7.8	12,397.5	3.3
3.8	1,962.8	3.7	2.5	739.4	4.1	3.4	8,397.2	0.2	8.0	11,679	3.4
4.1	1,748.2	4	2.7	664.8	4.4	3.7	8,088.6	0.2	9.0	9,026.6	3.8
4.4	1,579.6	4.3	2.9	606.1	4.7	4.0	7,834.7	0.2	10.0	7,343.3	4.2
4.7	1,443.5	4.6	3.0	588.0	4.8	4.3	7,620.7	0.2	15.0	3,819.5	6.3
5.0	1,331.1	4.8	3.1	558.4	4.9	4.6	7,437.1	0.2	20.0	2,603.4	8.4
5.5	1,181.4	5.3	3.3	518.9	5.2	5.0	7,228.0	0.2	21.6	2,363.0	9.0
6.0	1,064.9	5.7	3.5	485.5	5.4	6.0	6,826.8	0.2	23.0	2,191.8	9.6
6.3	1,011	6	3.7	456.8	5.6	7.0	6,534.4	0.2	24.0	2,082.8	10.0
6.5	971.3	6.2	3.9	431.8	5.9	8.0	6,307.9	0.2	25.0	1,984.4	10.4
7.0	894.4	6.6	4.1	409.9	6.1	9.0	6,125.1	0.2	26.0	1,895.2	10.8
7.5	830.0	7	4.3	390.4	6.3	10.0	5,973.1	0.2	27.0	1,813.8	11.2
8.0	775.1	7.4	4.5	373.0	6.5	15.0	5,467.8	0.2	28.0	1,739.4	11.6
9.0	686.5	8.2	4.7	357.4	6.7	20.0	5,167.3	0.2	29.0	1,671.0	12.0
10.0	617.8	9	5.0	336.6	7	25.0	4,959.0	0.2	30.0	1,607.9	12.4
15.0	420.6	12.7	6.0	283.9	7.8	30.0	4,802.1	0.2	35.0	1,354.1	14.4
20.0	324.7	16.2	7.0	247.3	8.6	35.0	4,677.6	0.2	40.0	1,171.1	16.4
25.0	267.1	19.5	8.0	220.2	9.3	40.0	4,575.2	0.3			
30.0	228.4	22.6	9.0	199.3	9.9						
35.0	200.3	25.7	10.0	182.6	10.4						
40.0	179.0	28.7	15.0	132.5	12.6						
			20.0	107.6	14.1						
			25.0	92.8	15.2						
			30.0	83.3	16						
			35.0	76.7	16.5						
			40.0	72.0	17						

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EDUCATION

Degree	**Institution**	**Year of Graduation**
MS	METU Mining Engineering	2011
BS	METU Mining Engineering	2007
High School	Aliağa Super High School, İzmir	2002

WORK EXPERIENCE

Year	**Place**	**Enrollment**
2009-Present	METU Mining Engineering	Research Assistant
2009	MechSoft Software Solutions	CAD Engineer
2008	GÜRSAN Construction Machines Co.	Sales Engineer

FOREIGN LANGUAGES

Advanced English

PUBLICATIONS

1. Gölbaşı, O. and Demirel, N. (2015). Stress Investigation in an Earthmover Bucket Using Finite Element Analysis: A Generic Model for Dragline. *Journal of South African Institute of Mining and Metallurgy, 115*, 623-628.
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