OPERATION MANAGEMENT OF DRILLING PROCESSES IN SURFACE MINING

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CONTRIBUTION OF AUTHORS

The author of this thesis is the primary author for all manuscripts contained within. Professor Mustafa Kumral is the supervisor of the Ph.D. candidate and included as a co-author for each of these manuscripts.

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ABSTRACT

In recent years, the profit margin for mining companies has been declining due to low commodity prices and high operating costs associated with resource degradation and system aging, forcing mining companies to reduce operating costs in order to maintain operations. Cost savings presented by new technologies and computational resources that allow companies to modernize mining equipment are offset by increasing equipment complexity, which can lead to higher operating costs. The drilling operation is one component that can be the focus of cost reduction efforts because it affects all phases of mineral production—from exploration to extraction and mineral processing. Therefore, an efficient drilling operation can help to achieve the desired economic production cycle, but it must be optimized to balance operating performance (measured by the rate of penetration or ROP) with longer drill bit life. The ROP depends on various controllable (i.e., rotation speed, weight on the bit, and bailing air pressure) and uncontrollable (i.e., physical and mechanical properties of the rock formation, bit type, bit material, operator expertise, and drilling machine condition) parameters. The ROP and controllable parameters are directly related: when the controllable parameters increase, ROP also increases and operating costs decrease consequently. However, high controllable parameters shorten bit life and enhance bit consumption through wear. Thus, there is a trade-off between bit consumption and operating cost. The relationship between ROP and the bit life must be optimized to minimize the total cost of the operation for mine management. Identifying an optimum set of operational parameters helps to ensure the minimum cost per drill bit, which represents a considerable portion of the total operating cost of the machine. Hence, it is crucial to estimate the optimum bit replacement time while considering ROP. Another important factor that directly affects drilling performance and the cost is the condition of the drilling equipment, which is getting larger due to economies of scale.

Unexpected failures severely affect the production schedule; thus, equipment reliability is required for satisfactory performance. Statistical tools and simulation techniques are the best methods to determine bit replacement time, whereas reliability and maintenance analysis are the best tools to ensure operational performance. These tools help to forecast future failure of repairable and non-repairable system components, prevent unexpected stoppages, and improve the quality of the maintenance. This thesis focuses on 1) optimizing drilling operation parameters using design of experiment tolls, cost minimization with evolutionary algorithms, machine performance assessment, and risk quantification using reliability analysis and stochastic modeling techniques (Markov Chain Monte Carlo and Mean Reverting); 2) determining optimum replacement time of drill bits based on historical data using discrete event simulation and minimizing replacement costs by using an evolutionary algorithm and Monte-Carlo Simulation.

ABRÉGÉ

Ces dernières années, la marge bénéficiaire des sociétés minières a diminué en raison des prix bas des mineraux et des coûts d'exploitation élevés liés à la dégradation des ressources naturelles et au vieillissement du système, forçant les sociétés minières à réduire leurs coûts d'exploitation pour maintenir leurs activités. Les épargnes présentées par les nouvelles technologies et les ressources informatiques qui permettent aux entreprises de moderniser leurs équipements d'extraction minière sont compensées par une complexité croissante des équipements qui peut entraîner des coûts d'exploitation plus élevés. Les opérations de forage sont l'un des éléments sur lesquels peuvent porter les efforts de réduction des coûts car elles touchent toutes les phases de la production minérale, de l'exploration à l'extraction en passant par le traitement des minéraux. Par conséquent, une opération de forage efficace peut contribuer à atteindre le cycle de production économique souhaité, mais elle doit être optimisée pour équilibrer les performances opérationnelles (mesurées par le taux de pénétration ou ROP) avec une durée de vie prolongée du foret. La ROP dépend de diverses conditions contrôlables (vitesse de rotation, poids sur le trépan et pression de gonflage) et incontrôlables (propriétés physiques et mécaniques de la formation rocheuse, type de trépan, matériau du trépan, experience de l'opérateur et état de la machine de forage). Les paramètres ROP et contrôlables sont directement liés: lorsque les paramètres contrôlables augmentent, les ROP augmentent également et les coûts d'exploitation diminuent en conséquence. Cependant, des paramètres contrôlables élevés raccourcissent la durée de vie du trépan et augmentent sa consommation par l'usure. Il y a donc un compromis entre la consommation de bits et les coûts d'exploitation. La relation entre le ROP et la durée de vie du trépan doit être optimisée afin de minimiser le coût total de l'opération pour la gestion de la mine. L'identification d'un ensemble optimal de paramètres opérationnels permet de garantir un coût

minimum par trépan, qui représente une partie considérable du coût total d'exploitation de la machine. Par conséquent, il est crucial d’estimer le temps optimal de remplacement des bits tout en tenant compte de la ROP. Un autre facteur important qui affecte directement les performances de forage et le coût est l'état des équipements de forage, qui s'agrandit en raison d'économies d'échelle. Les défaillances inattendues affectent gravement le calendrier de production; ainsi, la fiabilité de l'équipement est requise pour des performances satisfaisantes. Les outils statistiques et les techniques de simulation sont les meilleures méthodes pour déterminer le temps de remplacement des bits, tandis que les analyses de fiabilité et de entretien sont les meilleurs outils pour garantir les performances opérationnelles. Ces outils aident à prévoir les pannes futures des composants système réparables et non réparables, à prévenir les arrêts imprévus et à améliorer la qualité de l’entretien. Cette thèse porte sur 1) l'optimisation des paramètres des opérations de forage à l'aide de la conception de droits d'expérience, la minimisation des coûts avec des algorithmes génétiques, l'évaluation des performances de la machine et la quantification des risques à l'aide d'analyses de fiabilité et de techniques de modélisation stochastiques (Markov chain Monte Carlo et mean reverting); 2) déterminer le temps de remplacement optimal des bits de forage sur la base de données historiques à l'aide de la simulation d'événements discrets, et minimiser les coûts de remplacement à l'aide d'un algorithme génétique et de la simulation de Monte-Carlo.

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CHAPTER 1

1. INTRODUCTION

1.1 Overview

Open-pit mining is among the most commonly used surface mining techniques. The production cycle of an open-pit mining operation includes fragmentation, loading, hauling, comminution, and concentration. The most widely used and economical fragmentation technique is drilling and blasting. Given that fragmentation is the first process of this cycle, the issues in this stage propagate the successive activities easily. As such, drilling and blasting have special importance. Drilling is used for many purposes such as exploration, creating a blast hole, grouting and soil stabilization, drainage, and ground support [1]. Among these purposes, blast hole drilling, which creates arrays of holes with an adequate geometry into a rock mass for blasting operation in the mineral industries, is the most widely used application [2].

Horizontal layers, called benches, are created by drilling and blasting with particular explosives. The height of the benches depends on the production rates, selectivity requirement, loss and dilution, safety concerns, slope stability requirement, and the equipment size. The blast-holes are drilled in patterns that depend on the rock characterization. After the holes are loaded with the explosives, blasting operation, the most economical method of primary rock fragmentation, is implemented on the bench. The fragmented material is loaded and hauled to its destination [3].

The drilling and blasting program affects successive stages of the production cycle. The particle size of the rock fragments has a considerable impact on the loading, hauling, primary crushing, and mineral processing. Thus, the cost of transportation, crushing, and grinding can be significantly reduced if rock fragment size is optimized [4] by conducting drilling systematically with an appropriate blasting pattern.

The physical and the mechanical properties of the rock mass (especially compressive strength) have an important role in determining the blasting pattern and drill hole diameters and depths [5, 6] (Figure 1-1). The vertical (burden) and horizontal (spacing) distances between the blast-holes to the bench edge are functions of the hole diameter [3]. Drill holes must be deeper than the height of the bench to avoid bench floor problems. This height difference is called sub-drill. Stemming in Figure 1-1 refers to material placed in the blast-hole to contain the explosive energy within the hole and thus enhance fragmentation of the rock mass without generating fly rock. The line parallel to the crest of a bench formed by drill holes is called a row. There are 3–8 rows of drill holes on a given actual bench [3].

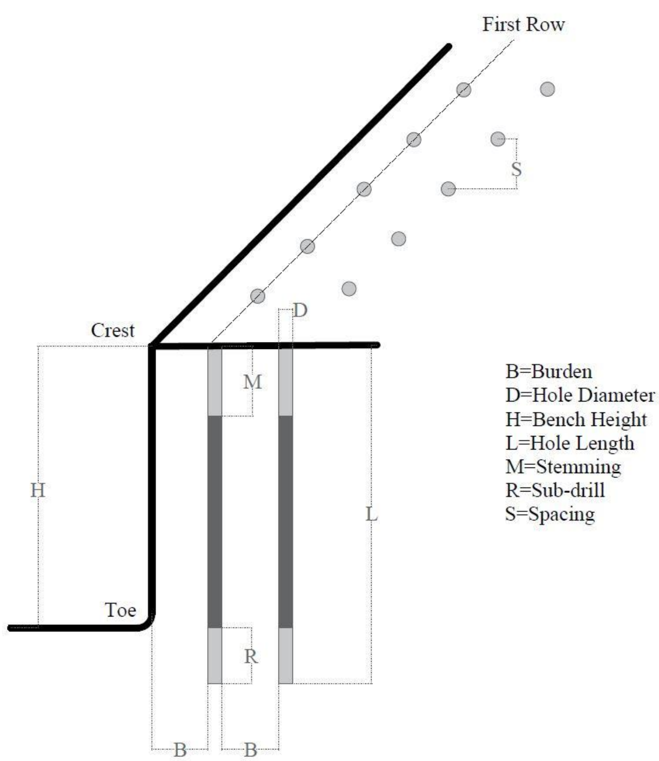

Figure 1-1: Illustration of a bench showing drill hole parameters

The most commonly applied mechanical drilling methods are rotary-percussive and rotary drilling [1]. The former is generally applied to hard rock formations [7], and the energy required to create cracks is generated by a drill based on the impact of hammer blows [8]. Rotary-percussive drilling is classified as top hammer or down the hole hammer, depending on the location of the hammer on the rig. In rotary drilling, drill bits are pushed into the rock mass by rotations of a drill, which forces the rock to develop cracks. Unlike rotary-percussive drilling, which has a low feed force with percussive blows, rotary drilling has a high feed force without percussive blows. Three types of drill bits are available from many manufacturers for rotary drilling, namely three-cone bits (standard steel tooth bits, tungsten carbide insert bits or TCBs), polycrystalline diamond compact bits, and diamond bits (surface set bits and impregnated bits). TCBs dominate rotary drilling applications because they can be used for rock types ranging from soft to very hard rocks, they are resistant to wear, and they are easier to handle in difficult situations [9, 10]. This research mainly focuses on rotary drilling with TCBs.

The rotary drilling operation (Figure 1-2) is based on the rotation system and the pulldown system. The rotation system provides movement to turn the bit into the rock. There is an optimum rotation speed (RPM) for each type of rock [8]. The pulldown force depends on the compressive strength of the rock and the desired drill hole diameter [11]. In addition, to break a fresh portion of the rock in rotary drilling, rock cuttings formed by the interaction between the bit and the rock formation must be moved away from the bottom to the top by means of a circulating fluid or compressed air (Figure 1-2) [12]. This also helps to limit bit wear (thermic wear) due to high temperature [13]. Most of the time, compressive air is used as the circulating fluid because it is more efficient than water or other types of drilling fluids [12]. Further, it is able to eject larger rock cuttings from blast-holes, and it keeps the hole dry; therefore, explosives can be filled without additional operations such as dewatering [14].

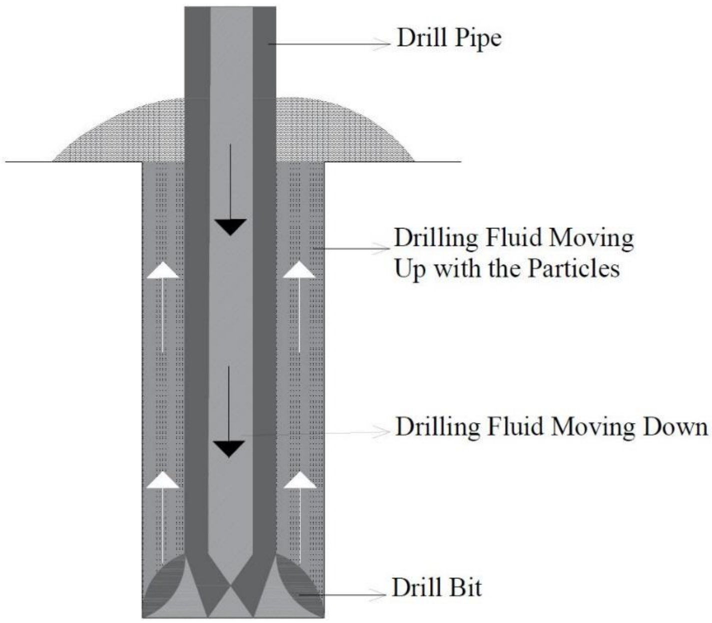

Figure 1-2: Schematic illustration of a rotary drilling operation

Rotary drilling consists of four main activities: moving (2–3 min), leveling (1 min), drilling, and pipe handling 1–2 min). Moving begins when the drill is ready to move to the next blast-hole. Leveling begins with lowering the leveling jacks once the drill is positioned precisely on the drill hole location. Leveling is required to have a firm base. The collaring phase of drilling operation starts with lower feed force, slower rotary speed and less compressed air than the required amount to drill and drill into the first 2 m of the hole. Full-fledged drilling begins after collaring. If the height of the intended blast-hole is longer than the height of the drill pipe, the drilling operation is paused to add a new drill pipe. These activities are repeated to obtain the required number of blast-holes [15].

1.2 Research Motivation

Mining companies face many challenges in recent years, including environmental pressure, high operating costs, and low commodity prices. To remain in business within this atmosphere, they have been forced to explore effective cost management strategies to rationalize and improve operations and enhance the viability of the mining operation. Increasing bench drilling efficiency and performance in open-pit mines must be a priority, because the drilling operation affects the blasted quantity, particle size distribution of fragmented material, fill factor of shovel and truck, and input size of the crusher.

In terms of the industrial aspect, one of the reasons for the excessive drilling cost is drill bit consumption associated with the interaction with the rock. Drill bit condition significantly affects the cost of the drilling operation and drilling performance. Bits are generally used until they are worn, which negatively affected the ROP - a key criterion to measure drilling performance. If the bit is changed while still effective, the company will lose money because of the high bit consumption. Therefore, drill bit condition monitoring is crucial for cost management, but it is generally overlooked.

Equipment condition monitoring and performance prediction are key to cost management strategies because the equipment is one of the most significant assets of a mining company. Efficient equipment utilization has strong potential to reduce costs and generate considerable savings because system aging and resource degradation are two main reasons for increasing operating costs in mining activities. Performance prediction of drilling equipment is related to drilling operation efficiency: it is necessary to schedule the equipment availability in order to reach the intended economic level of mineral production. Therefore, reliability analysis, which is an effective method to investigate equipment condition, is needed to design a realistic production schedule and achieve the desired operation.

Over the past two decades, many studies have examined the importance of rotary drilling operation parameters to optimize drilling performance and lower operating costs. In particular, studies have aimed to predict drilling performance and extend bit life while improving the ROP. However, the performance prediction and the determination of optimum operating parameters for different working conditions have not been firmly established. Published studies are limited to small-scale drilling operations in the field or laboratory experiments. Index values and some regression analyses have been able to explain the drilling mechanism, but these are insufficient to describe the whole process. The current knowledge of the drilling operation is theoretical; more studies are needed to fill the gap between theory and practice.

1.3 Research Objectives

Drilling operations require advanced technical expertise and technology to lower costs. Therefore, this thesis proposes approaches to increase the performance and efficiency of bench drilling through modeling, simulation, and optimization tools. A variety of methods, including multiple regression modeling, stochastic processes, discrete event simulation (DES), and evolutionary algorithms are used to elucidate the dynamics behind bench drilling, variables affecting drilling, and their effects on ROP. Specific objectives are to:

1. monitor wear in drill bits to determine their optimal replacement time;
2. model the relationship between the reliability of drilling machine and drilling performance;
3. minimize drilling operating costs through optimizing drilling variables;

4. quantify the effect of uncertainties in drilling operations on mine production scheduling; and
5. assess risks associated with drill bit consumption for a given period.

This thesis explores cost minimization elements and decision-making mechanisms in open-pit mining production drilling, which is currently missing in academia and industry literature.

1.4 Original Contribution

This research proposes new modeling, simulation, and optimization approaches to bench drilling operations that have the potential to add value to an open-pit mining operation. Specific contributions are as follows:

1- established a model between energy cost and rotary drilling operation parameters (e.g., RPM, weight on the bit and bailing air pressure);

2- developed a risk quantification approach associated with production rate and mine management;

3- proposed an uncertainty management strategy that considers drill bit changing time, maintenance time, drilling time, available equipment, the required number of drill bits, and the number of intended drill holes;

4- quantified the evolution of drill bit wear over the time using time series regression analysis;

5- modeled the drilling operation to assist production scheduling and asset management;

6- simulated physical activities in bench drilling through DES to help determine the feasibility of production plans;

7- established a relationship between bit replacement time and the related cost and

8- proposed a practical approach to determine optimum drill bit replacement time based on the minimization of total expected replacement cost.

1.5 Outline of the Thesis

This thesis is organized according to the following chapters.

Chapter 1 provides a general background regarding the drilling operation, research motivation, research objectives, and original contributions.

Chapter 2 presents a literature review of topics related to this research, including (1) monitoring and optimizing drilling operations by predicting ROP and wear, (2) mining equipment reliability, and (3) simulation techniques associated with risk management and spare part management.

Chapter 3 provides a detailed review of, and the requirements for, rotary drilling operations. The effects of controllable variables including RPM, weight on the bit, and bailing air pressure on drilling performance were quantified by an experimental design. The optimum replacement time of drill bits based on a cost minimization problem was formulated by an evolutionary algorithm. The cost optimization was applied and the trade-off problem between energy cost and drill bit consumption was solved.

Chapter 4 discusses reliability analysis for both repairable and non-repairable systems and risk assessment. Reliability and the performance of the equipment were quantified. The probable realizations of the drilling operation were generated by Markov Chain Monte Carlo and Mean Reverting simulation techniques in order to assess the risk.

Chapter 5 proposes a drill bit replacement strategy based on reliability analysis of drilling machines and bits. The optimum replacement time of drill bits was determined by DES. The mineral production capacity was formulated based on historical data.

Chapter 6 examines a drill bit replacement strategy based on minimizing replacement cost. A cost minimization problem based on the replacement cost was formulated to estimate the optimum replacement time by using evolutionary algorithms. A regression model is fitted for the relationship between the drill bit replacement time and the total expected replacement cost.

Chapter 7 draws conclusions based on the research and provides a framework for future work.

CHAPTER 2

2. LITERATURE REVIEW

In this chapter, an extensive literature survey is presented on the concept of rotary blast-hole drilling.

2.1 Rotary Drilling Monitoring and Optimization

Among the many systems of drilling available (e.g., percussion, high-frequency vibration, and dissolution), rotary drilling has the most applicability to in open pit mines [11]. Rotary drilling transmits mechanical energy into the rock mass by rotations of a drill, which forces the rock to develop cracks. It can be used for rock types ranging from soft to hard rocks. Therefore, rotary drilling has been the subject of many research projects for decades.

Recently, interest has grown in monitoring rotary drilling for both open-pit and underground mining activities in order to evaluate performance. Most studies have been based on controllable parameters, namely rotation speed (RPM), weight on the bit (WOB), bailing air pressure (BAP), and instantaneous rate of penetration (ROP) and uncontrollable parameters such as the physical and mechanical properties of the rock formation and drilling vibration. Quantifying the effect of both controllable and uncontrollable parameters on the rotary drilling operation and establishing the relationship between ROP and geological conditions have been the main goals.

Several authors have investigated relationships between mechanical energy during drilling operations and various rock and operational parameters. Teale [16] introduced a mathematical model to quantify the mechanical energy (i.e. specific energy = thrust + torque) needed to break a unit volume of rock during rotary drilling. He considered pulldown force, RPM, drill-hole diameter, rotation torque, and ROP as parameters for the model. The author asserted that the model could indicate some parameters of rock strength during the drilling process. Scoble, Peck [17] evaluated the effects of controllable parameters on rotary drilling into different rock types. The authors contended that the nature of the rock drives variations in the ROP during drilling through its effect on pulldown force, not RPM. Similar to Teale [16], the authors used specific energy to measure mechanical performance while changing the parameters and determined that rock strength can be monitored by variations in the specific energy. Liu and Karen Yin [18] defined a new concept called the specific surface energy, namely the specific energy per specific surface area (surface area per unit volume). They claimed that the specific surface energy is related to RPM, pulldown force, and rock hardness. The functional relationship among drilling parameters was also investigated to measure drilling performance. The authors evaluated several parameters such as the rock properties of the formation and operating conditions to monitor the drilling performance.

With the development of technology, research has been carried out to monitor drilling operations with technological tools. Peck [19] determined the relationship between operating parameters and geo-mechanical and structural properties of rocks. Field tests showed that physical and mechanical properties of rocks can be determined by operating parameters recorded using an automated drill monitoring system, reducing the number of laboratory tests required. Further, drilling monitoring can provide significant information about optimum operating parameters and bit condition. Peck [20] also carried out comprehensive research to establish the relationship between geological formation and operating parameters in order to estimate rock strength properties and facilitate geological exploration, mine planning, bit selection, bit wear evaluation, and drill automation and control. Results showed that bit wear reduced the ability to define drilling performance variations under different rock conditions. The study also showed that automation of drilling operation can be achieved by continuous monitoring of operating performance. Hence, critical operating parameters can be optimized, and the approach could aid bit selection.

Aboujaoude [15] introduced an approach to control RPM during drilling and thus dampen vibrations before they reach a significant level. Laboratory tests showed that rock type, the position of the rotary head, and backlash between the rotary head and the mast are key factors affecting the prediction of vibration frequencies. Field tests were conducted to identify the machine dynamics for RPM, then a software simulator was implemented to analyze the test results. The simulation and the field tests results showed that the RPM controller is viable and can be used under all drilling conditions. Furthermore, Hatherly, Leung [21] proposed an approach called monitoring-while-drilling (MWD) and compared MWD data to geological data. They concluded that the best geological information can be provided by blast-hole drilling with MWD equipment when RPM and WOB are constant.

Unlike previous researchers, Ghosh, Schunnesson [22] suggested a method to evaluate the performance of rotary drilling with tri-cone bits and monitor bit wear with MWD data. The authors investigated the trend of ROP versus the operating lifetime of the drill-bits to identify bit replacement time. Bit wear was highly correlated with ROP degradation. Principal component analysis showed that the magnitude of the operating parameters must be reduced to extend the operating life of the bits.

Ataei, KaKaie [23] developed a model to that was able to predict ROP from rock mass properties (texture, uniaxial compressive strength (UCS), and joint spacing, aperture, filling, and inclination) and drillability index, instead of operating parameters. Based on the relationship, rock drillability index was defined and rock mass was classified. To provide a better estimate, the authors also presented a new ROP model that considered both drillability index and operating parameters such as RPM, WOB, and BAP. The authors asserted that drillability index can successfully predict ROP and assist mine production planning. In addition, Kricak, Miljanovic [10] developed a fuzzy logic model to predict the ROP of tri-cone rotary blast-hole drilling in open-pit mines based on field data from rocks of differing UCS. The model had five input variables (hole length, drilling time, pulldown force, RPM and UCS). A highly accurate prediction was obtained, despite variations in rock formation within the same drilling bench, probably due to the high volume of input data.

Ergin, Kuzu [24] optimized roller-cone bit selection and rotary blast-hole drilling operations in order to achieve high ROP and prolonged bit life with the lowest total cost. Representative field samples were used in laboratory tests to investigate the geotechnical parameters of the rock formation. Full-scale drilling tests with four bit types were performed to optimize operating parameters. The ROP, torque, and power draw were measured to determine operating costs. After the laboratory experiments, the operating parameters were optimized by systematically changing the settings, and field tests were carried out to verify the model. Al-Chalabi, Lundberg [25] performed a case study to a model the economic lifetime of drilling machines. Operating and maintenance costs, purchase price, and machine resale value were considered to optimize the replacement time of a drilling machine. The proposed approach was based on financial data instead of reliability or failure data. Results showed that increasing the purchase price and decreasing the operating and maintenance costs significantly increased the optimal replacement time. Moreover, a regression analysis showed that maintenance cost has the largest impact on the optimal replacement time.

McGill University has a long history of drilling operation related researches. Apart from the researches of Aboujaoude [15], Peck [19] and Peck [20] which previously mentioned, there are also ongoing researches which address different aspects of rotary drilling operations in surface mining. Lucifora [26] has been working on an advanced drill control system to supervise the operation cycle of production drills and exploring the effect of drill bit design on drilling performance. Moreover, Rafezi [27] has been working on developing a wear monitoring system through the rotary motor current and vertical vibration signals in order to assist in failure prediction. Bit vibration fault frequencies, signal features from wavelet decomposed vibration and statistical features from rotary motor current have been used to investigate failure behavior of rotary drill bits.

2.2 Reliability Analysis of Drilling Equipment

Reliability analysis is the most significant system characterization method for both repairable and non-repairable systems. It is essential to measure the performance of systems [28] and assists in production scheduling, maintenance scheduling, and spare part management. Thus, many studies have investigated the importance of reliability analysis on the mining cycle to optimize individual operations. Interest has grown in using reliability analysis for drilling equipment to achieve the desired production target. For example, Barabadi, Barabady [29] estimated the number of spare parts required to prevent unexpected stoppages for a drilling machine using reliability analysis of field datasets. After creating scenarios based on reliability models, field tests were performed and showed that the hazard rate is approximately two times higher in ore rock than in waste rock under similar conditions. The authors concluded that the reliability characteristics and the number of required drill bits are strongly related to the type of drill bit and the length of the drill-hole. Similarly, Ghodrati and Kumar [30] forecast the required non-repairable inventory based on environmental factors. To analyze the behavior of the non-repairable items, a reliability analysis was conducted. According to the reliability model, two replacement strategies were developed and compared one considered environmental factors and one ignored environmental factors. Results showed that environmental factors must be taken into consideration for accurate inventory management. The authors concluded that the operating environment has a considerable impact on system performance, and reliability analysis is the best way to characterize inventory behavior.

Reliability analysis has a key place in maintenance management. Rahimdel, Ataei [28] modeled the reliability of four rotary drilling machines with the aim of improving machine reliability using reliability centered maintenance and creating a strategy to optimize preventive maintenance based on safety, operational, and economic criteria. The preventive maintenance intervals were defined for each machine based on the critical level of reliability, which was calculated by the reliability models of the machines. The authors asserted that the proposed model can improve the reliability of the rotary drilling machines after the maintenance activity. The maintenance cost is highly related to the reliability of the equipment. Balaraju, Govinda Raj [31] presented a reliability analysis of load-haul-dump machines in order to improve the equipment life while minimizing maintenance costs. Reliability-based preventive maintenance time intervals were estimated and scheduled based on minimizing total operating cost. The power law process—the most suitable tool to model the reliability problems of repairable systems—was applied to machines and the parameters were estimated. The authors asserted that preventive maintenance and additional failure costs are the key factors to estimate preventive maintenance intervals. Javanmard and Koraeizadeh [32] also predicted preventive maintenance intervals based on equipment cost and reliability. They introduced a new optimization procedure that uses a flexible interval technique aimed at planning preventive maintenance intervals at the lowest cost and highest reliability. The findings can be applied to all kinds of equipment. The authors advised precisely recording operating and maintenance time information for better scheduling.

2.3 Simulation Techniques

Improving technology has led to the development of decision-making tools. Simulation techniques are commonly used to evaluate the performance of various operational scenarios during mine design and operating phases. Discrete event simulation (DES), a stochastic modeling tool, facilitates modeling mining systems that consist of several discrete sequences of the events to optimize operation [33]. It is an invaluable tool to analyze system dynamics and performance [34]. For example, Dindarloo and Osanloo [35] applied DES to model material transport in a large open-pit mine for a three month period. Findings demonstrated that mineral production could be improved, and costs could be reduced using this simulation technique. A case study verified the proposed model. In addition, Botín, Campbell [36] proposed an approach to optimize the size and performance of a mine development system using DES to assign unit operation activity to six types of mining equipment: drilling, blast loading, roof scaling, ore transport, roof bolting, and concreting. A case study validated the proposed approach. The authors concluded that the DES model could support management decisions in short-term mine planning and equipment dispatching systems.

Although the process of the modeling needs extensive experience and knowledge, replacement analysis with DES is a practical tool to evaluate the effect of failures on mining equipment [37]. Yuriy and Vayenas [37] developed a model to analyze maintenance activity by developing a combination of reliability assessment based on evolutionary algorithms and DES. The authors assessed two simulation tools for the same mining problem. The aim of the study was to analyze the effect of a single component of the equipment failure on the entire operating cycle. The authors generated random scenarios to model a sublevel-stopping underground hard rock mine by DES and reliability assessment based on evolutionary algorithms. Mechanical availability and equipment utilization were analyzed by both simulation tools. The authors concluded that both tools produced corresponding results.

Mining operations include several random events, which are poorly predicted by deterministic models [38]. DES provides probabilistic solutions that are viable for mining operations. Kaba, Temeng [39] developed a model to forecast mine production using DES to model the random behavior of excavators and trucks. Comparing stochastic results, deterministic results, and actual results showed a stronger fit between the stochastic model and actual results than the deterministic model.

Some researchers contend that DES should be replaced by other modeling techniques. Yarmuch, Epstein [40] presented a methodology to decide the location of a crusher considering minimum capital and operating costs in an open-pit mine using Markov chains. The randomness of the failures was modeled by the Markov chain and DES to determine the productivity of the crusher system. Comparison of the two model results showed that Markov chain model could be used in place of a simulation model for mineral productivity calculations because the Markov chain model was able to generate relationships between variables that DES could not.

In the next four chapters are presented the papers accompanying this thesis.

CHAPTER 3

3. COST OPTIMIZATION OF DRILLING OPERATIONS IN OPEN-PIT MINES THROUGH PARAMETER TUNING

3.1 Abstract

Low commodity prices have forced many mining companies to suspend or cease operations. To remain in business, some mine managers are exploring strategies to reduce operating costs. Given its importance as a cost element, increasing bench drilling efficiency and performance in open pit mines has the potential to generate considerable savings. Efficiency and performance gains can be realized by monitoring the drilling operation, analyzing monitoring data with statistical tools and optimizing operational variables. Finding the best configuration of controllable drilling parameters (e.g., rotation speed, pulldown force and bailing air pressure) would assist to increase penetration rate and optimize drilling operation cost. In this part of the thesis, after the effects of controllable variables on drilling performance are quantified by the experimental design, a cost minimization problem is formulated to determine replacement time of drill bits by an evolutionary algorithm (EA). Results show that the proposed approach could be used to determine the optimal drilling parameters and minimize the energy cost in open pit mines.

3.2 Introduction

Drilling is among the most significant processes in open-pit mining operations; the success of rock fragmentation strongly depends on drilling design and performance. New optimization and computer tools present opportunities to minimize the energy cost of drilling operations, as well as initiate new drilling technologies [41].

Rotary drilling is the most extensively used technique for drilling operations, ranging from surface blast hole mining to deep drilling. Rotary drilling with tri-cone tungsten carbide bits has broad applicability because drilling parameters can be adapted to hard and soft rock formations [10]. For example, a slower rotation speed (RPM) is effective for hard rock formations because it provides sufficient time to create stress on the rock, whereas a higher RPM is effective for soft rock conditions. Tungsten carbide bits are mainly used for hard and abrasive rock formations [10].

The rotary drilling technique is based on two distinct motions—axial thrust and rotational torque—provided by a hydraulic or electric rotary head. Axial thrust is needed to push the bit into the rock to break one-unit volume of rock. Rotational torque is a force acting on a drill rig to rotate a drill bit through the rock formation. The tri-cone bits use the thrust and torque to spall the rock [42]. Sufficient weight on the drill bit is necessary to accomplish the drilling operation. Weight on the bit includes the dead weight of the drilling rig (i.e., the rotary head, drill rods, and cables) and the pull-down force (PDF). A feed system that generates adequate PDF is used to move the rotary head up and down [43].

Drill holes must also be cleaned during drilling by removing cuttings between the wall of the hole and drill rod with compressed air [42]. The air is also used for cooling to protect the bearings. Insufficient air pressure is among the primary reasons for drill bit wear and shorter bearing life. On the other hand, excessive air causes dust and noise problems, shortens bit life and increases energy costs [44]. Therefore, the operation parameters of a drilling machine such as RPM, PDF and bailing air pressure (BAP) have a profound effect on rock fragmentation success.

The Rate of Penetration (ROP) is accepted as a key performance criterion of a drilling operation because it directly indicates the production capacity [10]. Knowledge of the drilling rate based on operation parameters and the rock formation also helps to predict physical and mechanical properties of the rock formation [45]. Although the ROP is heavily influenced by the physical and mechanical properties of the rock formation, it is difficult to model the precise association between ROP and rock properties for the following reasons [46]. First, operation parameters are adjusted for rock characteristics in order to increase the ROP. For example, increasing the bit weight when drilling in soft rock formations only slightly increases the ROP because the bit teeth will bury into the formation and increase the torque [47]. For hard rock formations, heavier weight on the bit is crucial to increase the ROP, but the bit life is reduced above a given weight, which affects the drilling rate directly [47]. Further, the complexity of a drilling operation increases depending on the geological condition [21]. In modeling, the drilling environment is often assumed to be homogenous. Therefore, it is not feasible to develop a model that takes into account all parameters that directly affect the drilling rate [46].

Cutting tools are considered the most expensive tools during a drilling operation [13], accounting for an estimated 21% of total drilling costs [48]. Therefore, for more than two decades—in addition to improving the ROP—studies have focused on extending drill bit life and understanding bit deterioration and failure. Optimization of operation parameters minimizes energy costs of the operations while maximizing the sustainability of drill bits [49, 50]. The main reason for tool consumption is bit deterioration associated with the interaction between the rock and the bit. The mechanism of drill bit wear depends on rock characteristics and equipment reliability [45]. Excessive pulldown force can over-stress drill bits and even break bit teeth. Excessive rotation speed and incorrect bailing pressure also contribute to bit wear [17, 20]. A worn bit has a low ROP [19] but on the other hand, replacing a bit prior to the end of its beneficial life increases drilling cost unnecessarily [48]. Thus, there is a trade-off between bit wear and drilling energy cost.

Energy consumption is an important cost element of drilling activity. It is calculated from the specific energy—the energy required to drill a unit volume of rock [16]. The specific energy is determined from the RPM, PDF, rotational torque (T), ROP and the area of the hole [22]. Specific energy is considered an indicator of rock condition: drilling hard rock requires more specific energy [18].

This chapter focuses on determining ideal drilling operation parameters for a given drilling operation and minimizing the number of bits consumed for a given bench. First, prior to data gathering in the minefield, a face-centered central composite design (FCCCD), as one of the experimental design methods in response surface methodology (RSM), was developed on the basis of the specified variables and levels. Based on this design, the testing procedure was conducted on an open-pit mine, analyzed, evaluated and optimized by design of experiment tools to quantify the relationship between operating parameters and ROP. Finally, an evolutionary algorithm (EA) was applied to determine optimum drilling operation parameters and drill bit replacement time while minimizing the energy cost of the operation, calculated from the specific energy. Field data were chosen over laboratory data because they were considered to be most representative of operational conditions [42]. The originality of the research rests on modeling parameters affecting bench drilling (e.g., machine parameters, drill bit replacement time and the effect of the bit wear), formulating the problem as an optimization problem and solving the problem with the design of experiment tools and the EA.

3.3 Model Development

Data collection is the first step to develop an appropriate cost minimization model (Figure 3-1). To determine the drilling time for each drill-hole, FCCCD was chosen because it minimizes the cost of obtaining usable datasets and requires less time, effort and resources. The FCCCD was used to analyze the relationship between dependent (rate of penetration, vibration, and torque) and independent (RPM, PDF and BAP) variables, and optimization procedure of drilling parameters was applied. After optimum drilling time for every time interval was calculated based on optimized parameters, the drilling time was set as a target value to investigate the out-of-working range parameters to optimize energy cost. When out-of-range parameters were determined, the required drilling energy was then calculated for each drill hole by using the specific energy formulation. The drilling time and the level of combinations were used to calculate the required drilling energy. The last step was to determine the optimum drill bit replacement time. The objective function was formulated as the minimization of cost under the constraints of minimum drilling time, required drilling length, level of parameters and a total number of available drill bits. The tradeoff problem between energy cost and drill bit consumption was solved by the EA.

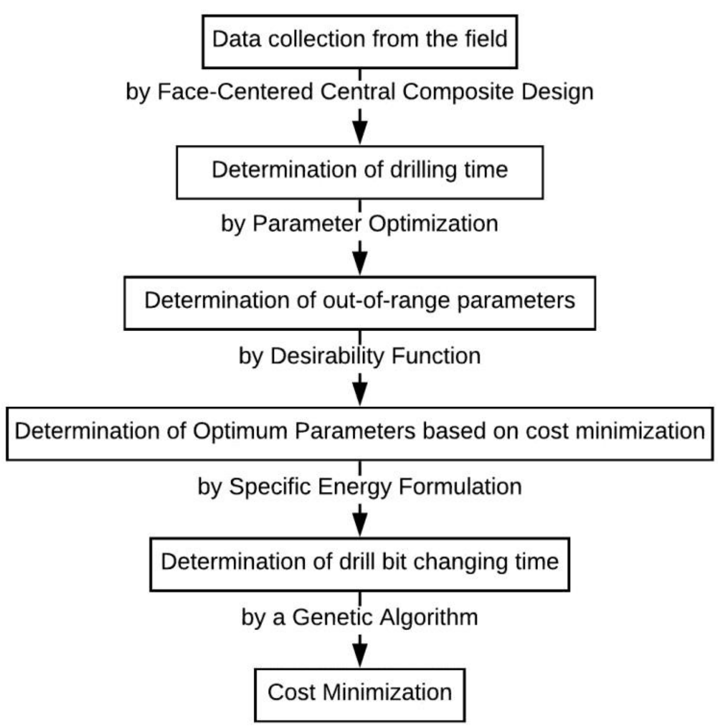

Figure 3-1: Model development steps

3.3.1 Data Collection

In engineering research, the dataset should be large enough to represent the entire population; on the other hand, data collection should be cost-effective [51]. Therefore, experimental design methods should be used to create data collection patterns. They allow the researcher to plan experiments so as to generate quantitative data. Moreover, they help to minimize the cost of data collection [52].

RSM design methods are used to observe the most influential factors in response among the factors whose levels are fixed before the study in order to maximize or minimize the response[53]. FCCCD is a second order multivariate technique includes all possible combinations for all factors. In FCCCD design, the number of trails (*N*) that are needed to collect data is shown by Eq. 3-1 [51].

$$N = 2^k + 2k + n_c \tag{3-1}$$

where k is the number of factors, 2^k is the number of 2-level factorial runs, $2k$ is the axial runs and n_c is the center point runs. A typical second-order model can be expressed by Eq. 3-2 [51].

$$y = \alpha + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j \tag{3-2}$$

where y is the response, x_i and x_j are the variables. α is the intercept; β_i and β_{ii} are the linear and quadratic effect of the ith variable, respectively. β_{ij} represents the interaction effect of two variables [51].

The three controllable factors (RPM, PDF, and BAP) were analyzed at two levels. An FCCCD is displayed graphically in Figure 3-2 as a cube showing 15 combinations.

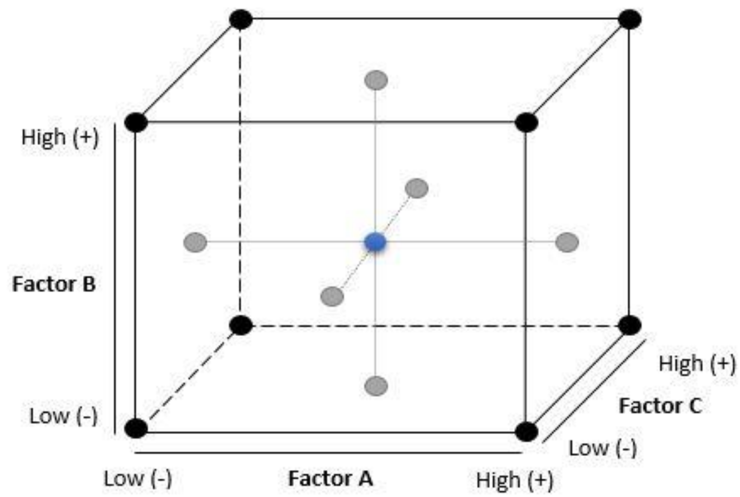

Figure 3-2: Face centered central composite design for three variables (FCCCD)

The operation parameters and their levels were selected by considering the real drilling operational conditions at the mine site. Table 3-1 shows the required combinations with coded values and the level of the factors. (To protect the confidentiality of the company, more details about the mine cannot be provided.).

After creating the design pattern, drilling time was recorded for each drill hole for 15 different combinations (plus one additional central point which is needed for optimization) during the specified time (Each drill hole length is 20m and drill bit diameter is around 35 cm).

Table 3-1: FCCCD with three factors

Combinations	RPM	PDF	BAP	Drilling Time (min/20m)
1	-	-	-	.
2	-	-	+	.
3	-	+	-	.
4	-	+	+	.
5	-	0	0	.
6	0	0	-	.
7	0	-	0	.
8	0	0	0	.
9	0	0	0	.
10	0	0	+	.
11	0	+	0	.
12	+	0	0	.
13	+	-	-	.
14	+	-	+	.
15	+	+	-	.
16	+	+	+	.

Factors	Levels		
	-	0	+
RPM (rev/min)	40	60	80
PDF (kN)	200	250	300
BAP (MPa)	1	1.3	1.6

3.3.2 Determination of Drilling Time

FCCCD can be used to optimize the independent variable to obtain a desirable level of the dependent variable. Eq. 3-3 is a model with three predictor variables (a, b and c) affecting the dependent variable (Y). α is the intercept and β denotes the coefficient that is the change in the dependent variable corresponding to a unit change of a predictor variable when other variables are constant [52]. In other words, β allows the dependent variable to be predicted from changes to the independent variable. The most influential independent variable can be determined. In addition, Eq. 3-3 is used to calculate drilling time for each drill hole according to the level of independent variables. The equation is created from parameter estimation results which were calculated by JMP statistical analysis software.

$$Y = \alpha + \beta_1 a + \beta_{11} a^2 + \beta_2 b + \beta_{22} b^2 + \beta_3 c + \beta_{33} c^2 + \beta_{12} ab + \beta_{13} ac + \beta_{23} bc + \beta_{123} abc \qquad (3\text{-}3)$$

3.3.3 Parameter Optimization and Desirability Function

Design of experiment (DOE) methods provide an effective and efficient way to investigate the relationship between independent and dependent variables. It is neither cost-effective nor efficient to carry out experiments with every factorial combination because of a large number of trails needed. To exclude unnecessary trails and optimize the process, RSM can be used. The objective of RSM, which is a mathematical and statistical technique, is to determine an optimum condition or a region for a dependent variable which is influenced by various independent variables [54]. To determine the structure of the relationship between variables, the first step is to approximate the model function by low order polynomials to minimize the sum of squares of the errors (first or second order). Once, an appropriate model is obtained, the solution is tested by goodness-of-fit tests whether it is satisfactory or not. A detailed description of the design of experiments theory can be found in Box and Draper [54], Myers [51] and Montgomery [52], among many others.

The desirability function approach is a conclusively proved technique to determine the optimum level of the dependent variable. It is used to find the optimum experimental conditions in order to reach satisfactory results. This approach has two steps; finding the optimum level of independent variables to obtain the most acceptable responses on the dependent variable and maximizing the overall desirability of the responses in the range of the independent variables [55]. Desirability varies between 0 and 1 which are an undesirable response and an ideal response, respectively.

Depending on the desired criteria, the different individual desirability functions can be established. If the response must be maximized, Eq. 3-4 can be used to describe $d_i(y_i)$ [56].

$$d_i(\hat{y}_i(x)) = \begin{bmatrix} 1 & if\ \hat{y}_i(x) > T_i \\ \left(\frac{\hat{y}_i(x) - L_i}{T_i - L_i}\right)^{w_u} & if\ L_i \leq \hat{y}_i(x) \leq T_i \\ 0 & if\ \hat{y}_i(x) < L_i \end{bmatrix} \quad (3\text{-}4)$$

where U_i is the upper limit value, L_i is the lower limit value, T_i is the target value and w_u is the weight which shows the importance of being close to the maximum. Following equation shows if it must be minimized (Eq. 3-5) [56].

$$d_i(\hat{y}_i(x)) = \begin{bmatrix} 1 & if\ \hat{y}_i(x) < T_i \\ \left(\frac{\hat{y}_i(x) - U_i}{T_i - U_i}\right)^{w_l} & if\ T_i \leq \hat{y}_i(x) \leq U_i \\ 0 & if\ \hat{y}_i(x) > U_i \end{bmatrix} \quad (3\text{-}5)$$

where w_l is the weight which shows the importance of being close to the minimum. If a particular value (target value) is the most desirable response, then the function can be described by Eq. 3-6 [56].

$$d_i(\hat{y}_i(x)) = \begin{bmatrix} 0 & if\ U_i < \hat{y}_i(x) \\ \left(\frac{\hat{y}_i\,(x) - L_i}{T_i - L_i}\right)^{w_u} & if\ T_i < \hat{y}_i(x) < U_i \\ 1 & if\ \hat{y}_i(x) = T_i \\ \left(\frac{\hat{y}_i\,(x) - L_i}{T_i - L_i}\right)^{w_u} & if\ L_i < \hat{y}_i(x) < T_i \\ 0 & if\ \hat{y}_i(x) < L_i \end{bmatrix} \tag{3-6}$$

Once the desirability functions are used to transform variables individually, they are then combined using the geometric mean, which gives the overall desirability *(D)* (Eq. 3-7) [55].

$$D = (d_1(y_1)d_2(y_2) \ldots d_k(y_k))^{1/k} \tag{3-7}$$

where k is the number of responses. If any response is undesirable, overall desirability will be zero. Therefore, the quality of the model in the optimization process is crucial for the success of the desirability function [56].

3.3.4 Calculation of Drilling Energy

The calculation of energy consumption is required for different combinations of drilling parameters. Specific energy is the total work (axial force plus rotational torque) per unit time [22]. It is as an indicator of the mechanical efficiency of a drilling process and is calculated by Eq. 3-8 [16].

$$e_s = \left(\frac{F}{A}\right) + \left(\frac{2\pi}{A}\right)\left(\frac{NT}{ROP}\right)\ in\text{-}lb/in^3 \tag{3-8}$$

where e_s is the specific energy (*in-lb/in*^{3}), *F* is the PDF (*lb*), *A* is the area of the borehole (*in*^{2}), *N* is the RPM (*rpm*), *T* is the rotational torque (*lb-in*), and *ROP* is the rate of penetration (*in/min*).

The original equation above is in imperial units, but for this research, variables were converted to SI units.

Liu and Yin [18] defined the specific surface energy in rotary drilling as the energy required to create a new unit of surface area. They incorporated into the calculation of the effects of vibration, which is inversely proportional to specific energy. Eq. 3-9 presents the specific surface energy formulation.

$$E_a A_s = E_v = \left(\frac{F}{A_e}\right) + \left(\frac{2\pi NT}{A_e u}\right) - \left(\frac{V_{vib}}{A_e u}\right) N/m^2 \tag{3-9}$$

where E_a is the specific surface energy *(N/m)*, A_s is the specific surface area *(m^2/m^3)*, E_v is the specific energy *(N/m^2)*, F is the PDF *(N)*, A_e is the excavation area *(m^2)*, N is the RPM *(rps)*, T is the torque *(N-m)*, u is the ROP *(m/s)* and V_{vib} is the total vibration *(N-m/s)*. The last term of the equation shows the calculation of the vibration effect, which is generally ignored because of its relatively small magnitude. Therefore, this equation can be rewritten as Eq. 3-10.

$$E_a = \left(\frac{1}{A_s A_e}\right) \left(F + \frac{2\pi NT}{u}\right) N/m^2 \tag{3-10}$$

According to Ghosh et al. [22], cleaning the boreholes with compressed air is a key component that is missing from the specific energy calculation. It is as important as other two operation parameters. Hence, BAP is the missing part to fill the gap due to determine a reliable specific energy calculation. The energy consumption of BAP was obtained from the field and added to the specific energy calculations for all combinations, then the results were converted as kWh to determine the cost of unit energy (c_e) using Eq. 3-11.

$$c_e = e_s \times P_u \tag{3-11}$$

3.3.5 Cost Minimization

This research was extended to determine the optimal drilling parameters under the constraint of completing bench drilling in a specified time period. The goal is to minimize the energy cost by the objective function and determine how many drill bits are required. All variables needed to develop the optimization model were calculated from Eq. 3-3 to Eq. 3-11. The model is given below.

- Decision variables

x represents the number of bits.

t represents the total time required to complete drilling on the bench which is calculated at the second step of model development.

- Model parameters

c_b is the cost of a bit.

MT is the maximum allowable time to complete the task.

TB is the total number of available bits.

- Objective Function

$$\text{Minimize } c_b + c_e t \tag{3-12}$$

Subject to

$$t \leq MT \text{ and } t > 0 \tag{3-13}$$

$$x \leq TB \tag{3-14}$$

$$x > 0 \text{ and } x \in N^{+} \tag{3-15}$$

To solve the problem, the EA approach provided in the Solver MS Office tool was used. The GA can be an appropriate technique when the objective function is discontinuous, NP-hard or non-smooth [57]. The problem in this research is non-smooth because the objective function is non-differentiable. Therefore, EA can generate a good approximation for problems that cannot be solved through exact methods. EA is expressed by a binary string representation of the candidate solutions. As a meta-heuristic, EA mimics the mechanism of biological evolution through the processes of mutation, crossover, and reproduction [57]. Meta-heuristics have been widely used to solve various mining problems [58-61].

In the EA approach, several initial solutions (chromosomes) are randomly produced. A set of chromosomes is generated at random to create a population. The number of chromosomes in the population is the population size. A new population is created by the selection process using various sampling mechanisms. The production of a new solution through an iteration is called a generation. All chromosomes are updated by the reproduction, crossover and mutation operators in each new generation. The revised chromosomes are termed offspring.

Although a binary vector is generally used, integer or floating vectors can also be used as the representation structure in EA-based meta-heuristics. A chromosome is represented as $Y=(y_1(l_1), y_2(l_2) \ldots, ym(l_m))$, where m is the population size. Since the problem is a cost minimization problem, the randomly generated chromosomes are ranked in ascending order. The selected chromosome is perturbed through crossover and mutation operators. It is important to note that good solutions always have less chance to be perturbed. This mechanism keeps good solutions with higher probability. Thus, as the process advances, low-cost solutions survive. If the procedure is continued for sufficient iterations, it converges in optimality or near-optimality.

3.4 Case Study

To evaluate the performance of the proposed approach, a case study was carried out in an open pit mine. Bit replacement time was collected from 15 different combinations of operating parameters based on FCCCD pattern to estimate the mean operational lifetime of drill bits. The tests were replicated during the specified time and the means were used. The ROP was recorded in every 10 hours for all combinations until it reached the 50. hour. Operational characteristics were regressed to quantify the relationship between operating parameters and ROP for all combinations. Interaction effects were ignored because their p-values were higher (p= 0.1-0.9) than alpha (p=0.05). Therefore, interaction effects were extracted from the equations. Parameter estimation results which were obtained from FCCCD by JMP Software can be seen at Table 3-2 with coded values and ANOVA results are shown in Table 3-3. The most influential parameter for rotary drilling operation is RPM when the bit is new. Over time, because of bit wear, the effect of RPM and ROP decrease dramatically.

Table 3-2: Parameter Estimation

10.Hour	Estimate	St. Error	t-Ratio	p-Value	Pareto Chart
Intercept	12.71	0.06	133.92	<.0001*	
RPM	**-1.59**	**0.04**	**-39.30**	**<.0001***	
PDF	**-0.41**	**0.04**	**-10.13**	**<.0001***	
BAP	**-0.25**	**0.04**	**-6.18**	**0.0008***	
RS*PDF	0.09	0.05	1.93	0.1012	
RS*BAP	0.09	0.05	1.93	0.1012	
RS*RS	-0.09	0.08	-1.18	0.2821	
PDF*BAP	-0.01	0.05	-0.28	0.7916	
PDF*PDF	0.01	0.08	0.09	0.9331	
BAP*BAP	0.01	0.08	0.09	0.9331	
20.Hour	**Estimate**	**St. Error**	**t-Ratio**	**p-Value**	**Pareto Chart**
Intercept	19.62	0.07	119.43	<.0001*	
RPM	**-1.73**	**0.05**	**-35.90**	**<.0001***	
PDF	**-0.35**	**0.05**	**-7.26**	**0.0003***	
BAP	**-0.31**	**0.05**	**-6.43**	**0.0007***	
PDF*BAP	0.08	0.05	1.39	0.2133	
RS*PDF	0.05	0.05	0.93	0.3892	
RS*BAP	0.05	0.05	0.93	0.3892	
RS*RS	-0.05	0.09	-0.51	0.6254	
PDF*PDF	-0.05	0.09	-0.51	0.6254	
BAP*BAP	-0.05	0.09	-0.51	0.6254	
30.Hour	**Estimate**	**St. Error**	**t-Ratio**	**p-Value**	**Pareto Chart**
Intercept	31.50	0.13	91.99	<.0001*	
RPM	**-1.46**	**0.08**	**-17.48**	**<.0001***	
PDF	**-0.37**	**0.08**	**-4.43**	**0.0044***	
BAP	**-0.35**	**0.08**	**-4.19**	**0.0057***	
RS*PDF	0.18	0.09	1.87	0.1100	
PDF*PDF	-0.23	0.16	-1.40	0.2112	
RS*RS	0.22	0.16	1.37	0.2205	
PDF*BAP	-0.08	0.09	-0.80	0.4525	
BAP*BAP	-0.13	0.16	-0.78	0.4626	
RS*BAP	-0.05	0.09	-0.54	0.6116	
40.Hour	**Estimate**	**St. Error**	**t-Ratio**	**p-Value**	**Pareto Chart**
Intercept	46.81	0.12	208.52	<.0001*	
RPM	**-1.66**	**0.08**	**-20.08**	**<.0001***	
PDF	**-1.33**	**0.08**	**-16.09**	**<.0001***	
BAP	**-0.43**	**0.08**	**-5.20**	**0.0020***	

RS*BAP	0.18	0.09	1.89	0.1072	
RS*RS	-0.27	0.16	-1.65	0.1503	
RS*PDF	0.10	0.09	1.08	0.3209	
PDF*PDF	-0.12	0.16	-0.72	0.5001	
PDF*BAP	0.03	0.09	0.27	0.7959	
BAP*BAP	-0.02	0.16	-0.10	0.9264	
50.Hour	**Estimate**	**St. Error**	**t-Ratio**	**p-Value**	**Pareto Chart**
Intercept	114.17	1.77	64.40	<.0001*	
PDF	**-20.13**	**1.18**	**-17.00**	**<.0001***	
BAP	**-5.82**	**1.18**	**-4.92**	**0.0027***	
PDF*BAP	**5.26**	**1.32**	**3.98**	**0.0073***	
PDF*PDF	-3.90	2.31	-1.69	0.1419	
BAP*BAP	-2.75	2.31	-1.19	0.2783	
RS*RS	2.20	2.31	0.95	0.3766	
RPM	-0.75	1.18	-0.63	0.5498	
RS*PDF	0.61	1.32	0.46	0.6599	
RS*BAP	-0.39	1.32	-0.29	0.7796	

Table 3-3: Summarized ANOVA for regression models

Time Interval	F-Value	p-Value	R^2 (%)
10 Hours	188.29	<.0001*	89.65
20 Hours	154.34	<.0001*	85.59
30 Hours	39.01	<.0001*	83.19
40 Hours	77.81	<.0001*	81.51
50 Hours	37.35	<.0001*	78.25

The R^2 values in Table 3-3 were relatively low because the mining site was assumed as homogeneous; however, the rock formation has many fractures and different minerals are present that directly affect the ROP. Moreover, the effect of bit wear can be seen with time and it affects the linearity of the model.

According to the parameter estimation results described above, ROP was calculated for every 20 m, which is the length of a drill hole of the open pit mine for every 10-hour interval.

The results were used to find optimum parameter combinations in the range of working conditions to minimize the average required time to drill a hole for every time interval. FCCCD was applied to obtain optimum parameters based on desirability level (ideal response). The optimum parameter combinations were created and the 3 of the 50 results for every interval with the optimum drilling time can be seen in Table 3-4.

Table 3-4: Optimum parameter combinations in the range of working condition with 100% desirability

Time Intervals (hour)	RPM	PDF	BAP	Time (min)
0-10	80	275	1.6	10.5
	80	300	1.3	
	75	300	1.6	
10-20	80	280	1.0	17.0
	77	295	1.3	
	75	300	1.6	
20-30	80	270	1.3	26.0
	80	260	1.6	
	75	300	1.3	
30-40	80	300	1.0	43.0
	80	295	1.6	
	77	300	1.3	
40-50	80	290	1.6	86.5
	77	295	1.6	
	58	300	1.6	

Table 3-4 shows that when the drill bit is new, the ROP is strongly affected by RPM, thus the higher level of RPM causes a higher ROP. Moreover, some certain amount of PDF and BAP are enough for the desired operation. If the PDF and BAP are more than a certain amount, they accelerate the bit deterioration, otherwise, the ROP decreases. In other words, the key factor of drilling operation is RPM. On the other hand, when the bit is getting worn, RPM is losing its importance and PDF is the most important parameter to drill a hole.

Once the optimum drilling time of every interval was determined by minimization criteria of FCCCD, different combinations can be created depends on the range of machine limits which can be seen in Table 3-5. Therefore, drilling time was set as a target value and best combinations based on desirability level and max.-min criteria were calculated.

Table 3-5: Drilling machine working limits

Parameters	**Max.**	**Min.**
RPM (rev/min)	30	100
PDF (kN)	150	500
BAP (MPa)	0.7	2.0
T (kNm)	5	25

FCCCD was used to set the optimum drilling time as the target value and the parameters were optimized in the new range (Table 3-6).

The impact of bit wear on drilling time can be seen clearly after the 30th hour. After this hour, the effect of RPM is decreasing, and PDF becomes the key parameter for the drilling operation.

After optimizing the drilling parameters, cost minimization procedure was applied. The energy consumption of drilling operation was calculated for every combination of every interval by specific energy formulation and it is multiplied by the unit price of the energy consumption (P_u) which was C$0.05/kWh. Energy calculation formulation can be seen in Eq. 3-16.

Table 3-6: Examples of optimized-drilling-parameters based on desirability level

Interval	RPM (rev/min)	PDF (kN)	BAP (MPa)	Desirability (%)	Time (min)
0-10	100	160	0.7	97	10.5
	77	400	0.7	86	
	80	235	2.0	84	
10-20	100	150	1.0	97	17.0
	70	500	0.7	90	
	72	450	1.0	80	
20-30	100	190	1.0	90	26.0
	70	500	0.7	90	
	100	150	1.3	87	
30-40	30	480	0.7	95	43.0
	40	440	0.7	90	
	45	425	0.7	86	
40-50	60	350	2.0	75	86.5

$$E_d = \left(\frac{PDF}{A} + \frac{2\pi \times RPM \times T}{A \times ROP}\right) \times V + BAP \quad (3\text{-}16)$$

where E_d is required energy for drilling (kWh), PDF is pull down force (kN), A is drill hole area (m^2), RPM is rotation speed (r/min), T is rotation torque (kNm), ROP is rate of penetration (m/min), V is the volume of the drill hole (m^3) and BAP is bailing air pressure (kWh). (1000 kNm = 0.278 kWh). The energy requirement of BAP is selected from manufacturer catalog.

The drilling cost of selected parameter combination associated with drilling operation can be seen in Table 3-7 (The combinations were selected according to desirability which must be more than

75%). The results show that RPM is the key factor for energy consumption. Moreover, the cost to drill a hole is increasing by time because of the drill bit wear which affects ROP immensely.

Table 3-7: The summary of drilling cost

Time Interval	RPM (rev/m)	PDF (kN)	BAP (MPa)	Total Cost (per h)	Cost/Hole
0-10	100	160	0.7	14.85	2.60
	77	400	0.7	9.80	1.71
	80	235	2.0	12.75	2.23
	90	235	1.0	13.21	2.31
	61	480	1.3	8.07	1.41
	80	275	1.6	11.92	2.09
	80	300	1.3	11.66	2.04
	75	300	1.6	10.65	1.86
10-20	100	150	1.0	15.24	4.32
	70	500	0.7	8.22	2.33
	73	450	1.0	9.32	2.64
	75	245	2.0	11.31	3.20
	65	480	1.6	8.40	2.38
	80	280	1.0	10.65	3.02
	77	295	1.3	10.75	3.05
	75	300	1.6	10.47	2.97
20-30	100	190	0.9	15.12	6.55
	70	500	0.7	8.05	3.49
	100	150	1.1	15.29	6.63
	65	490	1.3	6.97	3.02
	75	450	2.0	11.36	4.92
	80	270	1.3	11.35	4.92
	80	260	1.6	11.65	5.05
	75	300	1.3	10.06	4.36

30-40	40	480	0.7	5.47	3.92
	50	440	1.0	7.53	5.40
	55	425	1.3	8.54	6.52
	60	365	2.0	8.54	6.12
	90	220	0.7	12.43	8.91
	80	300	1.0	10.50	7.52
	80	295	1.6	11.59	8.31
	77	300	1.3	10.58	7.58
40-50	60	350	2.0	8.47	12.21
	80	290	1.6	11.54	16.63
	77	295	1.6	10.82	15.60
	58	300	1.6	7.11	10.25

The operation parameters were optimized in order to minimize the cost, an optimization model was created. Table 3-8 presents the parameters of the optimization. The cost of the bit was provided by the mining company where the datasets were collected.

Table 3-8: Optimization parameters

Parameter	**Value**
Total Length (m)	8,400
Maximum Time (h)	96
Total Number of Bits	20
Total Bit Cost (C$)	5,000
Drill Length (hole/m)	20

The two of the results of the optimization can be seen in Table 3-9 in order to compare the energy cost. The results show that parameter combination is a key factor for cost minimization. As can be seen from the Table 3-9 that the required time and the required number of drill bits are the same for both cases. However, there is a cost difference between both operations (Operation 1 and

Operation 2 followed the patterns with the combinations which have a minimum drilling energy cost and maximum drilling energy cost in Table 3-7, respectively).

Table 3-9: Cost comparison between optimum combinations

Results	**Operation-1**	**Operation-2**
Drill length (m/ bit)	2,100	2,100
Drilling time (h/bit)	24	24
Total time (h)	95	95
Number of bits	4	4
Bit consumption cost (C$)	20,000	20,000
Energy cost (C$)	**743**	**1,953**
Total cost (C$)	**20,743**	**21,953**

According to the optimization results, parameter optimization is essential for cost minimization. Therefore, it must be taken into consideration due to the required number of bits, energy consumption and operation time which is needed to have a desired drilling operation.

3.5 Conclusions

This part of the thesis proposes FCCCD process and an approach to optimize drilling parameters and determine the optimum time to change drill bits through cost minimization in open pit mines. The results of FCCCD show that RPM was the most influential operation parameter particularly when the drill bit was new, the bit deterioration has a big negative impact on the performance of RPM. On the other hand, when the bit was getting worn, the importance of PDF for the drilling operation was increasing, unlike RPM. The optimum drilling time for a hole was calculated for each time interval by the optimized parameters in the working range. The optimum drilling time then was used to determine the new optimized parameters in the range of drilling machine capability by desirability function. The cost optimization was applied, and the EA was used to solve the trade-off problem between energy cost and drill bit consumption; therefore, energy cost was minimized and the optimum time to change the drill bits was determined. The results of the optimization showed that; although the required time and the required number of drill bits are the same, the energy cost of the operation can be decreased by 67% with the parameter optimization. The results of the case study showed that the proposed approach could be used as a tool for cost minimization associated with bench drilling in open pit mining operations.

3.6 Chapter Conclusion

The effects of controllable parameters were quantified and optimized considering specific time intervals based on cost minimization model in this chapter. To achieve the desired operation, equipment reliability and bit wear quantification should also be taken into account. Thus, the effect of uncontrollable parameters into drill bit can be quantified more accurately. Therefore, equipment reliability which has a direct impact on drilling performance will be considered in the following chapter. Equipment condition will be monitored using historical data through reliability analysis. The relationship between the equipment condition and the performance will be established. The stochastic environment of drilling operation will be simulated.

CHAPTER 4

4. RELIABILITY-BASED PERFORMANCE ANALYSIS OF MINING DRILLING OPERATIONS THROUGH MARKOV-CHAIN MONTE-CARLO AND MEAN REVERTING PROCESS SIMULATIONS

4.1 Abstract

In recent years, commodity prices have swiftly decreased, narrowing the profit margin for many mining operations and forcing them to find effective cost management strategies to respond to low prices. Given that equipment is one of the most significant assets of a mining company, efficient equipment utilization has strong potential to reduce costs. This chapter focuses on the relationship between the number of available drilling machines based on reliability analysis and the number of holes to be created on a bench of an open pit mining operation. Since equipment availability is random in nature, a range of holes to be drilled corresponding to a specified probability level was determined. To assess the performance of the proposed approach, a case study was carried out using two stochastic modeling techniques. Evolutions of reliabilities of ten rotary drilling machines over a specific time were simulated by Markov Chain Monte Carlo and Mean Reverting processes, using historical data. Multiple simulations were then used for risk quantification. Results show that the proposed approach can be used as a tool to assist in production scheduling and assess the associated risk.

4.2 Introduction

Drilling is one of the primary operations in an open pit mining cycle. It is a complex operation because it is affected by several factors such as geological structure, equipment condition, drilling parameters, and operator experience [62]. Failures in drilling equipment severely affect production schedules because they cause blasting delays and affect the subsequent production process. If limits of operations are known, production plans can be more realistic. Equipment condition is an essential factor to achieve a desirable production rate and to sustain mining operation [63]. Reliability analysis is the best tool to ensure the condition of the equipment. Reliability analysis helps practitioners to forecast future failure of system components and prevent unwanted stoppages [64].

Equipment reliability can be used as a key system performance metric during the equipment lifetime [65, 66]. Field data are required to analyze system reliability and construct reliability models to facilitate decision-making. A non-repairable system is a system in which a repair is expensive or non-feasible. On the other hand, repairable systems are the systems which can be restored after a failure for satisfactory operation [67]. Time between failures and time to repair are primary data types needed to characterize system reliability [68]. Drilling machines are repairable systems that can be restored after failure to perform desired performance.

It is impossible to predict the future availability of drilling equipment in a fleet. Therefore, there is a risk (uncertainty) associated with the number of holes to be drilled. If there are delays due to lack of available equipment, subsequent processes (e.g. blasting, loading, and hauling) will also be delayed such that production targets are not attained. To address the risks arising from available drilling equipment, stochastic modeling is conducted—using past failure and repair data—to simulate the available equipment in the fleet through multiple future scenarios. The stochastic simulations methods are used to calculate a range of production quantities [40].

Mining engineering involves the significant amount of risks due to heterogeneities of geologic and geotechnics phenomena. Mining operations consist of consecutive activities (drilling, blasting, loading, hauling and crushing). Given that the drilling is the first activity, the delays in drilling due to equipment availability or insufficient equipment performance will also result in delays in subsequent activities. Therefore, the production targets may not be attained. To address the risks arising from available drilling equipment, stochastic processes can be used to generate future probable realizations [40, 69]. Markov Chain Monte Carlo (MCMC) simulation and the Mean Reversion (MR) techniques have strong potential to quantify risks associated with drilling operations, which can be significant [40]. MCMC is a mathematical model for stochastic systems describing a series of possible events in a time series, whereby the probability of each event depends only on the condition of the preceding event [70]. MCMC generates probable realizations depending on the current condition. The MR theory states that variables eventually move towards and oscillate around the equilibrium level, which can be calculated from historical data [71]. Thus, MR is used to create possible scenarios depending on the historical average.

MCMC simulation fits well the nature of the problem because the change in available machines in the next time increment does not fluctuate much. In other words, the number of available equipment in drilling operation for next shift depends on the previous shift. Furthermore, due to degradation, equipment availability will decrease over time. This phenomenon can be modeled through MCMC. On the other hand, MR also suits well to simulate the number of available drilling machines. It assumes that random increments are generated from a normal distribution. This is a reasonable assumption because the decrease in equipment availability is governed by the availability of initial time and the long-term of the mean of the process. The biggest issue in MR is to calibrate the parameters. In this research, since information from the previous benches were collected, the calibration is a relatively easy task because there is an opportunity to observe deviations of calibrated parameters from actual realizations. Two different stochastic approaches are used to see if their outcomes agree.

Although both methods simulate equipment availability for a given duration, there are differences between their applications. MCMC uses transition probabilities, and the current state depends upon the previous state. The transition probabilities are computed from the previous experience. This computation is based on a formula. Therefore, the technique is quite fast. In addition, the ability to reduce multidimensional problems to a series of lower-dimensional ones is one of the most important characteristics of MCMC. However, so-called “memoryless” character of MCMC is the biggest drawback. The assumption of the exponential distribution for time to failure is also critical [70, 72]. MCMC should be implemented carefully after the validity of these assumptions. On the other hand, MR is mainly used in finance to simulate long-term future prices. It requires some parameters such as mean reverting factor, long-term mean, and constant volatility factor. These parameters are calibrated from historical data. The values of parameters, to a certain extent, depends on the quality of the maintenance program in the mine and heterogeneity level of rock characteristics. MR assumes that equipment availability tends to be the average availability over the time. This assumption is highly related to the size and quality of maintenance activities. Also, MR is very sensitive to outliers and data noisiness [71].

In recent years, some researchers have focused on performance measurement of drilling machines from different aspects. Ataei et al [23] investigated physical and mechanical properties of rock to measure the penetration rate. Unlike this research, we computed the penetration rate from historical data and, further investigated rock and machine interaction. Basarir et al [73] developed a model to predict the performance of drilling machines by adaptive neuro-fuzzy inference system and multiple regression. However, since the machine condition was ignored, it is difficult to have reliable outcomes. In our research, we linked production scheduling, which focuses on the quantity of material to be extracted for a given set of equipment. Furthermore, Al-Chalabi et al [74] conduct a study for underground mine drilling rig to build a process to simulate the reliability of repairable complex systems based on historical data by Ordinary Monte Carlo simulation. In their research, the previous failures do not affect future events. In other words, it is time-independent. Unlike this research, applying MCMC simulation, time dependency was considered".

In this chapter, the relationship between the reliability of drilling equipment and its performance are quantified. Then, equally probable realizations of the available number of drilling machines over time series are generated through MCMC and MR, based on historical data. These realizations are used to assess the feasibility of targeted production plans. The originality of this chapter lies in proposing a risk quantification approach, which assists mine management to (1) determine production rates (mine production scheduling) based on drilling performance and (2) develop drilling equipment maintenance plans (preventive maintenance and spare part management).

4.3 Research Methods

After collecting field data over one year, a power law model was applied for each drilling machine. The power law method, also known as Crow – AMSAA, was used to analyze repairable complex systems. The power law model parameters were calculated by Reliasoft© RGA software. To investigate the trend of the time-between-failure datasets, the Laplace trend test was used to show if the system behavior was improving or deteriorating. Historical data were also used to investigate the relationship between machine reliability and machine performance by JMP© statistical software. In addition, the number of available drilling machines for each shift was simulated separately by MCMC (100 simulations in ModelRisk© software) and MR (100 simulations in Microsoft Excel©) for a three-month period. Finally, the range of drillable holes was generated according to the number of available drilling machines.

4.3.1 Reliability Analysis

Reliability analysis helps to deal with the uncertainty and to make an informed decision. The general expression for the function of reliability is given by Eq. 4-1[66].

$$R(t) = \Pr\{T \geq t\} \tag{4-1}$$

where *R(t)* is the reliability at time t, T is the time to failure of the system or item and R(t) ≥ 0, R (0) = 1. Other expressions of the reliability function are presented by Eq.4-2 and Eq. 4-3 [67].

$$R(t) = 1 - F(t) = 1 - \int_0^t f(x)dx \tag{4-2}$$

$$R(t) = e^{-\int_0^t \lambda(t)dt} \tag{4-3}$$

where *F(t)* is cumulative failure distribution function, *f(x)* is the failure probability density function and *λ(t)* is the hazard rate.

The reliability expressions given above are used to determine the reliability of a system or an item which the times to failure is characterized by statistical distributions such as exponential, normal or Weibull if the system behaves "as good as new" after the repair [74]. The failure process is called renewal process. This basic model is called Homogenous Poisson Process (HPP) [74]. The reliability function for 3-Parameter Weibull distribution is given by Eq. 4-4 [65] where the three defining parameters of the Weibull distribution are shape parameter (β) also known as Weibull slope, scale parameter (η) and location parameter (γ) also known as shift parameter. These systems are known as independent and identically distributed (i.i.d.) when there is not any trend at the dataset. However, for the complex systems such as trucks, loaders and drilling machines the failures are dependent based on the current age of remaining components. Therefore, the most cases the complex systems are between "as good as new" and "as bad as old" conditions after the repair and the deterioration trend can be seen. This process is called non-renewable process. To characterize the reliability of drilling machines, Non-Homogenous Poisson Process (NHPP), which is a generalization of the Poisson process, can be used instead of distributions. It has a wide applicability to model repairable systems [74, 75].

$$R(t) = e^{-(\frac{t-\gamma}{\eta})^{\beta}} \tag{4-4}$$

In reliability life data analysis, failure data are needed to calculate the time between failures [65]. A power law model was fitted to the data to analyze the life of each machine for the duration of the operation. The initial transition and steady-state matrices were created to determine the transitions between stages on shifts based on reliability analysis by MC. The last step was to determine the number of available drilling machines and the expected number of holes that can be drilled. The problem was solved by MCMC and MR.

Complex systems such as trucks, loaders, and drilling machines, the failures depend on the current age of remaining components. Therefore, most complex systems fall between “as good as new” and “as bad as old” conditions after the repair and the deterioration trend can be seen. This process is called a non-renewable process. To characterize the reliability of drilling machines, Non-Homogenous Poisson Process (NHPP)—a generalization of the Poisson process—can be used instead of distributions. It has broad applicability to model repairable systems [75].

Drilling machines can be modeled by Power law method. In terms of an analytical method to investigate the trend of the time between failure datasets, the Laplace trend test is used in this research. It shows the system behavior whether improving or deteriorating.

The power law technique is used to model system failure intensity function to manage each succeeding system failure (Eq. 4-5) for particularly complex repairable systems. β and λ were estimated from Eq. 4-6 and Eq. 4-7 [76].

$$u(t) = \lambda\beta t^{\beta-1}, t > 0 \tag{4-5}$$

$$\hat{\beta} = \frac{\sum_{q=1}^{K} N_q}{\sum_{q=1}^{K}\sum_{i=1}^{N_q} \ln(\frac{T_q}{X_{iq}})} \tag{4-6}$$

$$\hat{\lambda} = \frac{\sum_{q=1}^{K} N_q}{\left(T_1^{\beta}\right) + \left(T_2^{\beta}\right) + \cdots + \left(T_K^{\beta}\right)} \tag{4-7}$$

where K is the number of drilling machines, N_q is the total number of failures for each system, and T is the observation time for each failure dataset. The estimated β value can also indicate the trend. If $\beta = 1$, there is no trend; if $\beta > 1$, the system is degrading; and if $\beta < 1$, the system is improving [75].

The Cramer-Von Mises test is the most suitable goodness of fit test to analyze multiple repairable systems that follow the power law model [77]. If a calculated result is less than critical value from the goodness of fit test table, it fails to reject the NHPP power model. The power law model mean repair function and reliability function, defined as the probability of zero failure from time t to $t+s$, for NHPP, can be seen in Eq. 4-8 and Eq. 4-9, respectively [66].

$$M(t) = \int_0^t \lambda(t)dt \cong \lambda t^{\beta} \tag{4-8}$$

$$R(dt) = e^{-[M(t+dt)-M(t)]} \tag{4-9}$$

4.3.2 Markov Chain (MC)

The mathematical definition of MC can be seen in Eq. 4-10 [78].

$$P\{S_{t+1} = j|S_0 = k_0, S_1 = k_1, \ldots, S_{t-1} = k_{t-1}, S_t = i\} = P\{S_{t+1} = j|S_t = i\} \tag{4-10}$$

where S_t is a stochastic process. For reliability modeling, the probability of being in state *j* in time *t+1(dt)* when it is in state *i* at time *t* can be formulated as in Eq. 4-11 [78].

$$P\{E_{t+1} = j|\ E_t = i\} = \\ \{E1_j(t+1)\big|E1_i(t),\ E2_j(t+1)\ |\ E2_i(t), \ldots, Em_j(t+1)|\ Em_i(t)\} \tag{4-11}$$

where the integers (*1, 2, . . ., m*) represent the number of equipment, and *i* and *j* represent the current and future states, respectively.

Equipment reliability data were used to estimate the number of available drilling machines in a certain period by MC. The power law model tends to represent the life data of the system. It is used to estimate the parameters to make the function fit the data closely [78]. Eq. 4-12 shows the probability of being in operation, after one unit of time (d_t) when equipment is working, and Eq. 4-13 shows the probability of being under repair, after one unit of time (d_t) when equipment is working, based on time-between-failure datasets.

$$P\{E_{t+dt} = j|\ E_t = i\} = \{Em_j(t+dt) = 1\big|Em_i(t) = 1\} = e^{-(\lambda(t^{\beta}))} \tag{4-12}$$

$$P\{E_{t+dt} = j|\ E_t = i\} = \{Em_j(t+dt) = 0\big|Em_i(t) = 1\} = 1 - e^{-(\lambda(t^{\beta}))} \tag{4-13}$$

Similarly, Eq. 4-14 is used to calculate the probability of being in operation, after one unit of time (d_t) when equipment is under the repair condition and Eq. 4-15 is used to calculate the probability of continuing to stay under repair, after one unit of time (d_t) when equipment is under repair the condition based on time-to-repair datasets.

$$P\{E_{t+dt} = j|\ E_t = \ i\} = \left\{ Em_j(t + dt) = 1 \middle| Em_i(t) = 0 \right\} = \ 1 - \ e^{-(\lambda(t^{\beta}))} \tag{4-14}$$

$$P\{E_{t+dt} = j|\ E_t = \ i\} = \left\{ Em_j(t + dt) = 0 \middle| Em_i(t) = 0 \right\} = \ e^{-(\lambda(t^{\beta}))} \tag{4-15}$$

The one-step transition matrix for equipment was formulated from previous equations depending on the states. Multiplication is needed to determine the probability of transitioning one state to another for more than one piece of equipment (Eq. 4-16).

$$P\{E_{t+dt} = j|\ E_t = \ i\} = \left\{ E1_j(t + dt) \middle| E1_i(t) \right\} \times \ldots \times \left\{ Em_j(t + dt) \middle| Em_i(t) \right\} \tag{4-16}$$

After a certain number of transitions, the system will reach a steady state that is independent of the current state and has constant probability. At this state, the transitioning probabilities in a certain state are independent of the probability distribution of the initial state.

More information about developing MC models for repairable systems and mining operations can be found in references [40, 70, 78].

4.3.3 Markov Chain Monte Carlo (MCMC)

MCMC was used to generate samples from complex distributions generated by the MC method. These samples were then used by the Monte Carlo method to quantify estimation and model the risk [18]. There are many algorithms and sampling methods to implement MCMC. The Metropolis-Hastings algorithm is frequently used way to set up MC [79]. It creates random samples from the target distribution to form an MC that conditionally depends only upon the last event [79].

For Ordinary Monte Carlo theory, samples are generated randomly and distributed as independent and identical [79, 80]. However, MCMC is used to create samples that depend only on the previous sample based on MC, which is stationary and reversible. The difference between Ordinary Monte Carlo and MCMC can be seen by the formulation of variance (σ^2) in Eq. 4-17 and Eq. 4-18, respectively [70].

$$\sigma^2 = var\{\, g(X)\} \tag{4-17}$$

$$\sigma^2 = var\{\, g(X)\} + 2\sum_{k=1}^{\infty} cov\{\, g(X_i), g(X_{i+k})\} \tag{4-18}$$

where *g(a)* is a real-valued function on the state space.

The variance of the sample at Eq. 4-17 is independent and identically distributed. That is, the variance of the sample at Eq. 4-18 is the function of the variance of the previous sample.

According to the Metropolis-Hastings algorithm, the probability of a proposed move from *i* to *j* is given by Eq. 4-19 and Eq. 4-20 [70, 79].

$$r\,(i,j) = \frac{h(j)q(j,i)}{h(i)q(i,j)} \tag{4-19}$$

$$a(i,j) = \min(1, r(i,j)) \tag{4-20}$$

where *h* is the un-normalized density, *q* is the conditional probability density, *r* is the Hasting ratio, and *a* is the probability of moving from *i* to *j*.

The choice of the proposal density has a significant impact on the performance of the algorithm. The convergence characteristics of the implemented MCMC will be highly related to the choice of the proposal density. To generate samples, Metropolis sampling is required. In this point, the proposal distribution $q(S/S(t\text{-}1))$ and the prior distribution $\pi(0)$ over the initial state in Markov Chain are required to select. In this research, Gaussian distribution was used for both distributions. The prior distribution is centered at zero $\mu=S(t\text{-}1)$ and $(\sigma=1)$ and the proposal distribution is centered at the previous state of Markov-Chain $(\mu=0 \text{ and } \sigma=1)$.

Convergence of the MCMC to its stationary distribution is a requirement. Unfortunately, there are no universally accepted approaches to prove convergence. In this research, we used the software. In our best knowledge, it utilized the technique proposed by Gelman and Rubin [77]. The technique has two stages. The first, the target distribution is estimated and using this distribution the starting point is produced. Thus, the required number of independent chains are met. The second, the target distribution of the scalar quantity under consideration (e.g., a Student t distribution and the scale parameter) is re-constructed through the last k iterations.

MCMC has a serious impact on solving in a wide range of stochastic problems. Pang et al. [81] used MCMC to estimate wind speed distribution, and Malhotra [82] used it for applications in the network and computer security. Similarly, Ozdemir and Kumral [72] tested fleet efficiency and Mardia et al, [83] implemented MCMC to model rock fractures.

4.3.4 Mean Reversion (MR)

MR is used to create future observations using historical data. MR stochastic process can be formulated as in Eq. 4-21 [84].

$$dx_t = \kappa(\theta - x_t)dt + \sigma\sqrt{x_t}dZ_t \tag{4-21}$$

where x_t is the process level at the initial time, κ is the speed of reversion, θ is the long-term mean level, σ is the volatility, and Z is the increment of standard Brownian Motion.

The parameters κ, θ, and σ can be forecast from a regression equation based on historical data (Eq. 4-22) [84].

$$\frac{\Delta x_t}{x_t} = \beta_0 + \beta_1 \frac{1}{x} + \epsilon \tag{4-22}$$

The variable κ is the negative of the intercept ($-\beta_0$), θ is the negative ratio of the coefficient of $1/x_t$ of the intercept, and σ is the standard error of the residuals.

To simulate the generated MR model, a starting value was calculated from historical data and independent normally distributed error values (uniformly distributed between 0 and 1) were generated using Microsoft Excel©.

MR is used to perform risk analysis and decision making. Therefore, it has rightfully received attention from research in finance and asset management. Detailed information about using this technique can be found in references [85-89].

4.4 Case Study

4.4.1 Reliability Analysis

Historical data were collected from ten rotary drilling machines working at an open pit hard rock mine in the North America over a one-year period (Table 4-1). The time between failures and the time under repair were recorded for each machine. In addition, under the same condition, the drilling length was calculated for each drilling machine to investigate the relationship between reliability and drilling performance.

Table 4-1: Summary of historical data collected from ten rotary drilling machines

Machine	Total No. Failures	Up Time	Down Time	Mean Time Between Failures	Mean Time Under Repair	Total Time
		(hours)				
1	72	4,428	1,794	61.50	25.27	6,222
2	100	4,688	1,751	46.89	17.69	6,439
3	86	4,565	1,406	53.09	16.35	5,971
4	85	5,238	1,269	61.63	14.93	6,507
5	54	3,455	2,039	64.00	37.77	5,494
6	73	4,438	1,536	60.81	21.34	5,974
7	89	4,498	1,762	50.54	20.02	6,260
8	111	4,566	1,923	41.14	17.32	6,489
9	97	4,902	1,425	50.54	14.84	6,327
10	113	4,441	1,737	39.31	15.51	6,178

The parameters of the power law model are listed in Table 4-2 and the reliability plots of the machines are shown in Figure 4-1.

The reliabilities of the drilling machines vary. For example, between 0 and 1,000 hours, the probability of fulfilling the intended functions of Machine 5 is only approximately 30%, whereas the probability for Machine 4 in same time range is approximately 70%.

Once the reliability analysis and the reliability levels were obtained, drilling length was calculated for each drilling machine based on reliability levels by regression analysis (Eq. 4-23).

$$y_n = 5.2764 \times e^{0.0011(x_{[n-(n-20)]})} \tag{4-23}$$

where y_n is the time required to drill for given length (min) and x is the starting point length of the drilling with same drill-bit n is the length increment (m) and 20 is the length of the drill hole. To make a meaningful comparison, the same length for each equipment was used. As can be seen from Figure 1, all equipment reliabilities after 1,400 hours are less than 60%: lower limit of the effective working range. Therefore, the drilling length was calculated for 1,400 hours of operation.

Table 4-2: Parameters of the power law model for each of ten rotary drilling machines

Machine	**Power Law Parameters**	
	β	λ
1	1.1412	0.00036
2	1.1941	0.00019
3	1.0993	0.00024
4	1.1274	0.00015
5	1.1924	0.00031
6	1.1763	0.00019
7	1.0988	0.00037
8	1.1809	0.00031
9	1.0578	0.00028
10	1.0437	0.00049

Eq. 20 shows the relationship between drilling time and drilling length when the variables of the drilling machine (i.e. rotation speed (rev/min), pulldown force (MPa) and bailing air pressure (MPa) are constant as 80, 150, and 1.6, respectively (standard drilling operation application based on the rock characteristics according to manufacturer's recommendation).

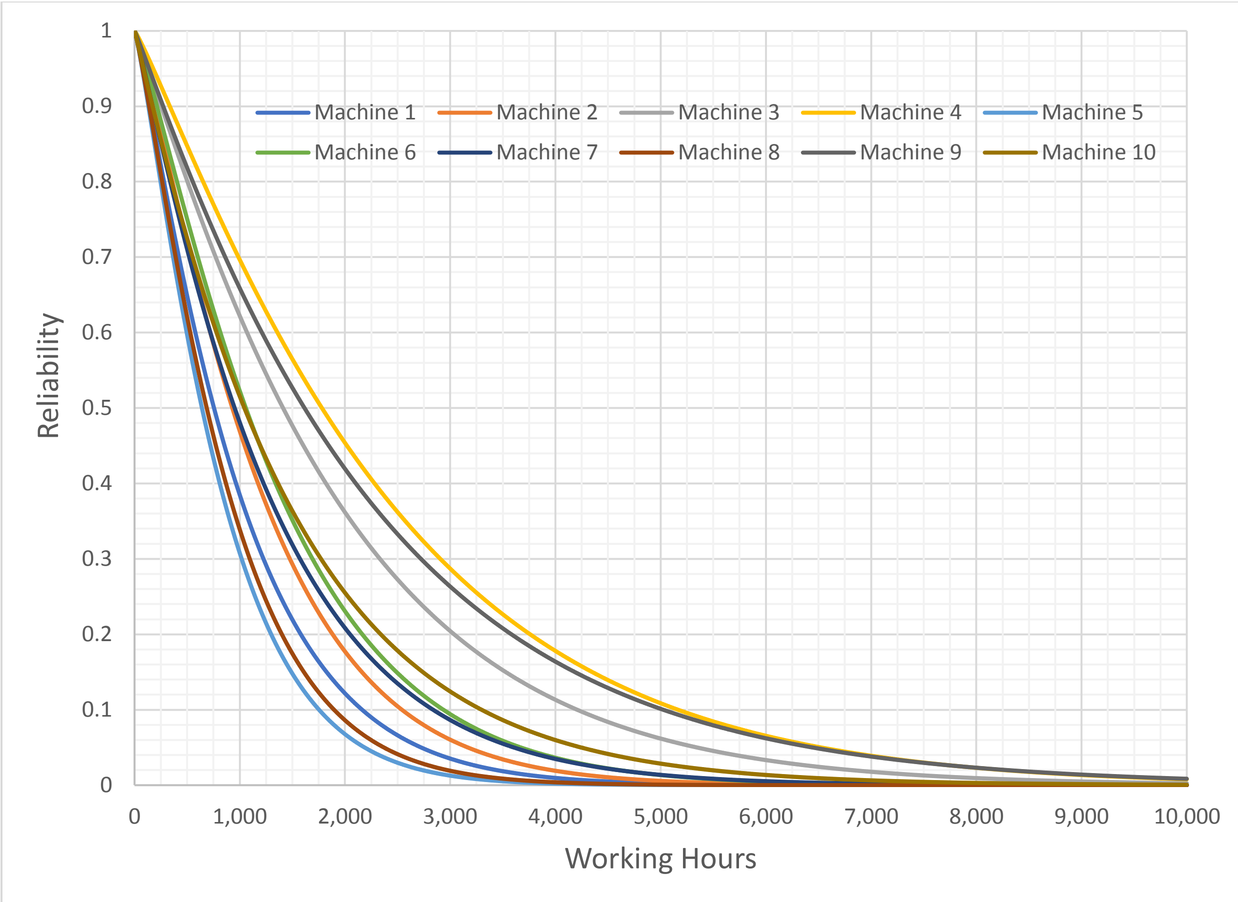

Figure 4-1: Reliability plots of the rotary drilling machines

For simplicity, the drilling length (20 m) was converted to the number of drill holes using JMP© Statistical Software to plots the relationship between reliability and drilling performance by linear regression analysis (Eq. 4-24, Table 4-3).

$$noh = -934.1 + (2{,}663.7 \times r) \tag{4-24}$$

where *noh* is the number of drillable holes and *r* is the reliability level.

Table 4-3: Linear regression output to estimate the number of drill holes from drilling length

Term	Estimated Value	p-Value	R^2
Intercept	-934.1	0.0003	0.76
Reliability	2,663.7	<0.0001	

There is a direct association between a number of drillable holes and reliability, which is a criterion of drilling performance.

4.4.2 Markov Chain (MC)

The number of the available drilling machines and the number of drillable holes can be generated by MC and simulated by MCMC. There are two possible conditions for a machine: in operation (1) or under repair (0). Hence, for ten drilling machines, there are 1,024 (2^{10}) possible states (summarized in Table 4-4).

Table 4-4: Possible states for ten drilling machines

Possible States	**Drilling Machines**									
	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	0	0
4	0	0	1	0	0	0	0	0	0	0
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
1,022	1	1	1	1	1	1	1	1	0	1
1,023	1	1	1	1	1	1	1	1	1	0
1,024	1	1	1	1	1	1	1	1	1	1

The initial probability matrix of each equipment's condition was calculated by Reliasoft© RGA software based on equipment reliability data. The probability of failure and probability of repair were obtained for ten hours of operation, which is one shift (Table 4-5).

Table 4-5: The probability (%) of changing conditions for all drilling machines

Machine	1 → 0 Probability of Failure	1 → 1 Probability of Not Failure	0 → 1 Probability of Repaired	0 → 0 Probability of Not Repaired
1	2.55	97.45	0.90	99.10
2	0.11	99.89	2.33	97.67
3	0.29	99.71	1.58	98.42
4	2.64	97.36	3.93	96.07
5	0.04	99.96	0.03	99.97
6	1.48	98.53	0.45	99.55
7	1.56	98.44	0.90	99.10
8	1.67	98.33	4.04	95.96
9	0.94	99.06	0.72	99.28
10	0.51	99.49	4.74	95.26

If Machine 1 is working, the probability of being under repair is 2.55%, and the probability of being in operation is 97.45% after one shift. On the other hand, if Machine 1 is under repair, the probability of being in operation is 0.90% and the probability of staying under the repair condition is 99.10%.

The initial probability matrix shows the probability of transitioning between stages on shift. Transitioning probability from one stage to another was calculated based on the condition changing probabilities (Table 4-5) and ModelRisk© software was used to obtain transitioning probabilities at different shifts. One step transition matrix (1024 x 1024) based on the initial probability matrix is summarized in Table 4-6. The number of available drilling machines is calculated for each state, and the states are grouped based on the number of available machines.

Table 4-6: Initial transition matrix (%)

State	0	1	2	3	4	5	6	7	8	9	10
0	81.90	16.63	1.40	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.99	82.76	15.08	1.13	0.04	0.00	0.00	0.00	0.00	0.00	0.00
2	0.01	1.99	83.58	13.51	0.88	0.03	0.00	0.00	0.00	0.00	0.00
3	0.00	0.03	3.02	84.36	11.90	0.67	0.02	0.00	0.00	0.00	0.00
4	0.00	0.00	0.07	4.06	85.11	10.27	0.48	0.01	0.00	0.00	0.00
5	0.00	0.00	0.00	0.11	5.12	85.82	8.62	0.32	0.01	0.00	0.00
6	0.00	0.00	0.00	0.00	0.17	6.20	86.49	6.94	0.19	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.24	7.29	87.13	5.24	0.10	0.00
8	0.00	0.00	0.00	0.00	0.00	0.01	0.33	8.40	87.72	3.51	0.03
9	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.43	9.52	88.27	1.77
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.54	10.66	88.78

As an example, if any four drilling machines are in operation, the probability that any five drilling machines will be in operation after one shift (10 hours operation) is 10.27%. On the other hand, the probability that any three drilling machines will be in operation is 4.06%, and the probability that the same number of equipment will stay in operation is 85.11%. It should be noted that the 0.00% probability in the matrices represents small but non-zero probabilities.

After a specified time, the system will reach the steady-state level where the transitioning probabilities do not change in time and the states are constant. The steady-state matrix was calculated by ModelRisk© software and summarized in Table 4-7.

Table 4-7: Steady state matrix (%)

State	0	1	2	3	4	5	6	7	8	9	10
0	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
1	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
2	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
3	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
4	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
5	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
6	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
7	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
8	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
9	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14
10	0.00	0.04	0.55	3.69	12.86	25.11	28.75	19.55	7.70	1.61	0.14

When the steady state matrix is calculated, the number of available drilling machines can be simulated for future shifts. Table 4-8 shows the probabilities of having available drilling machines. The initial matrix helps generate the number of available drilling machines for the next shift. On the other hand, the steady-state matrix helps generate the number of available machines for future shifts when the system reaches the steady-state.

At steady state, the probability of having five drilling machine working is 25.11% and the probability of having six drilling machine working is 28.75%.

Table 4-8: The probability of having available drilling machines

No. Machines in Operation	**Probability (%)**
0	0.00
1	0.04
2	0.55
3	3.69
4	12.86
5	25.11
6	28.75
7	19.55
8	7.70
9	1.61
10	0.14

As mentioned above, reliability data were used to create the initial matrix to implement MC. This process shows that each drilling machine is unique. Even if all equipment is brand-new at the beginning of the operation, the reliabilities and available cannot be same over time due to various factors such as geological heterogeneity, human factors, quality of maintenance and random events. Besides, mining operations use typically varying equipment ages. Therefore, equipment performance is different at a given time point. The probabilities of having available drilling machines will be different as shown in Table 4-9.

Table 4-9: Probability of having available drilling machines when machines are assumed identical

No. Machines in Operation	Probability (%)
0	0.01
1	0.09
2	0.68
3	3.04
4	8.90
5	17.85
6	24.81
7	23.60
8	14.70
9	5.42
10	0.90

Tables 4-8 and 4-9 show that, particularly for long-term plans, it can be misleading to assume that all machines are identical. Therefore, reliability analysis of each machine is necessary to obtain accurate results.

4.4.3 Markov Chain Monte Carlo Simulation (MCMC)

The number of available drilling machines for different shifts was generated by MCMC using ModelRisk© software based on the initial matrix and start vector, which is the initial state where eight of the ten drilling machines are available. The estimation facilitates visualizing the variation in a number of available drilling machines between shifts. Multiple scenarios were generated by replicating MCMC. Figure 4-2 demonstrates possible outcomes of uncertainties for 4 of 100 randomly generated scenarios of available drilling machines. Because of seasonal effects, 90 consecutive days (180 shifts) were simulated (To eliminate seasonal effects such as thermic wear in summer time and drilling of the frozen rock formation in winter time, the datasets were chosen in dry spring time operations). Over time, similar results were obtained by different simulations.

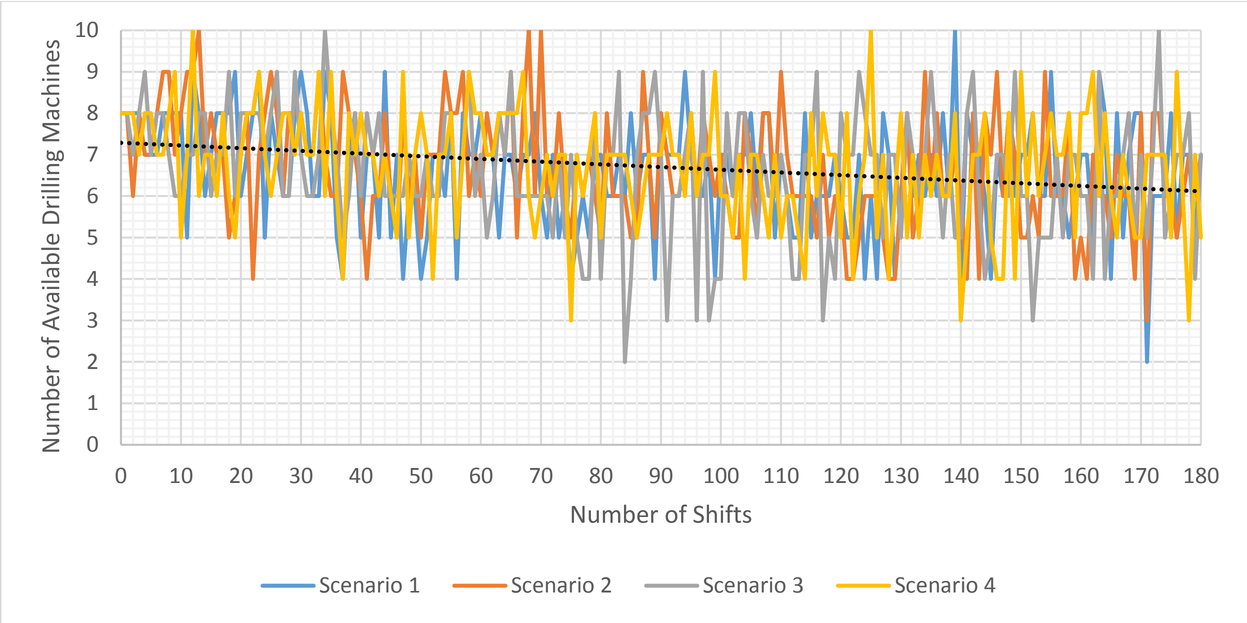

Figure 4-2: Number of available drilling machines simulated by MCMC

The general trend falls between 5 and 8 available drilling machines. The degradation trend is evident, as expected.

Once 100 scenarios were generated, the number of drillable holes was calculated for 180 shifts. The parameters of the drilling machine (rotation speed, pulldown force, and bailing air pressure were set at 80 in rpm, 150 MPa, and 1.6 MPa, respectively. It was assumed that drill bits are changed for every 1,400 m (70 holes), which is the level of effective drilling. Results are illustrated in Figure 4-3.

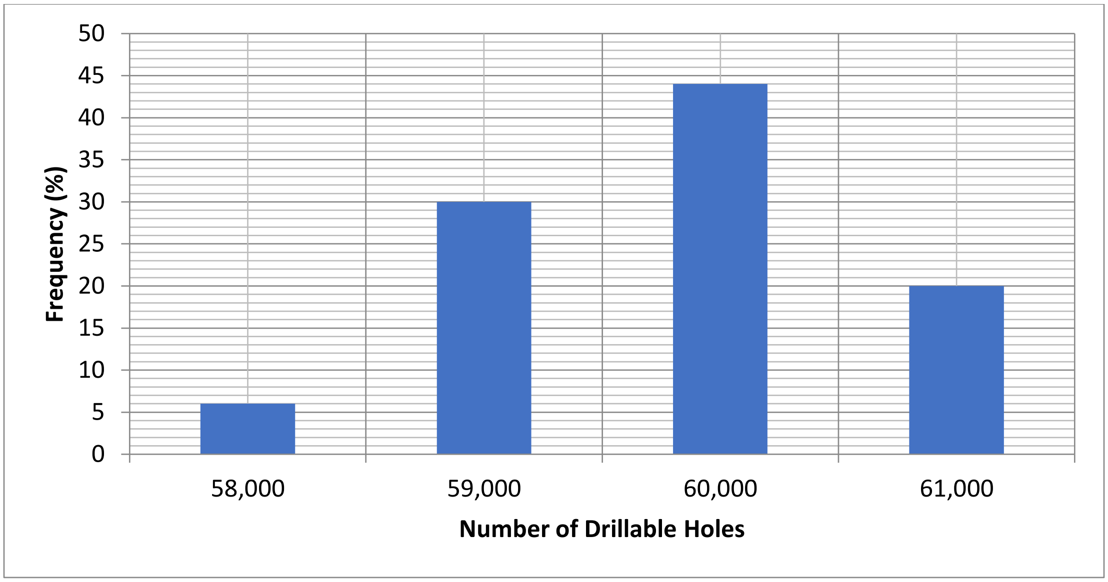

Figure 4-3: Number of drillable holes simulated by MCMC for 180 shifts

4.4.4 Mean-Reverting (MR) Simulation

In the same manner, the number of available drilling machines was simulated by MR using Microsoft Excel©. The parameters of the simulation calculated from historical data are presented in Table 4-10.

Table 4-10: Parameters of MR simulation (see Eq. 4-23)

Parameters	**Value**
Number of Available Machines at Initial Time (X_0)	**8**
Speed (κ)	108
Long-term mean (θ)	6.6
Volatility (σ)	6

Multiple scenarios were generated by the MR process and 100 randomly generated simulations were obtained for 180 shifts. The four simulations that exemplify the uncertainties (Figure 4-4) show that the available number of drilling machines fluctuates between 4 and 8 for most of the shifts, similar to the MCMC results.

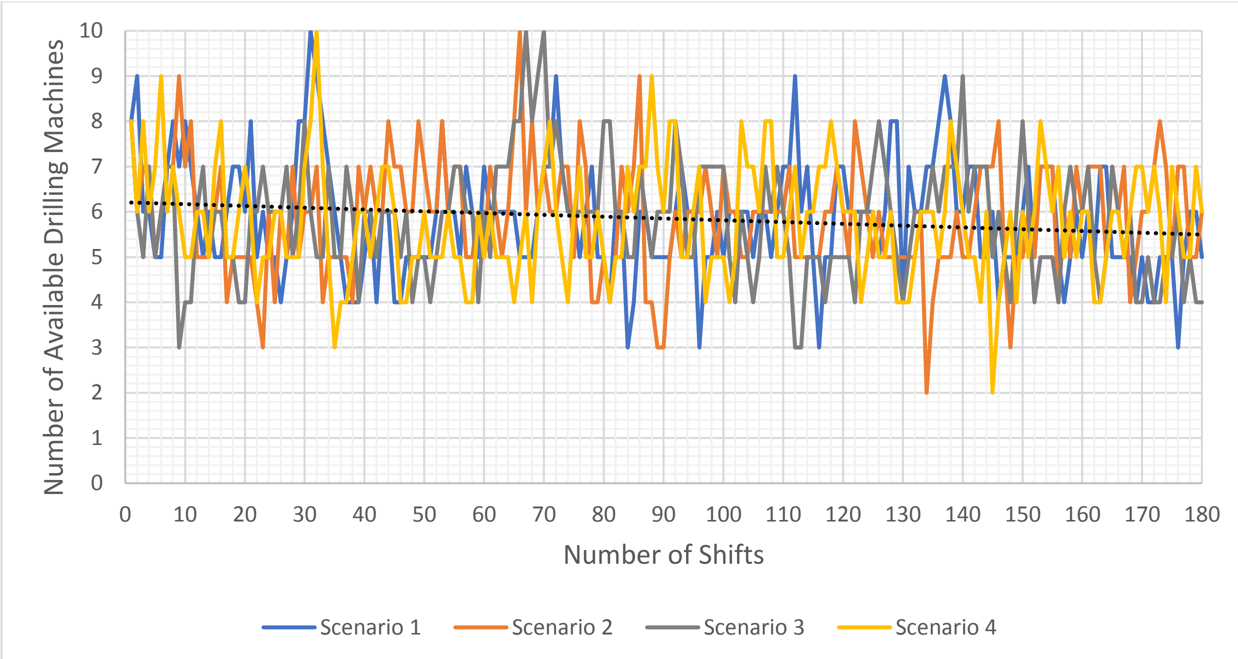

Figure 4-4: Number of available drilling machines simulated by MR for 180 shifts

The number of drillable holes was also calculated for the same drilling circumstances (Figure 4-5).

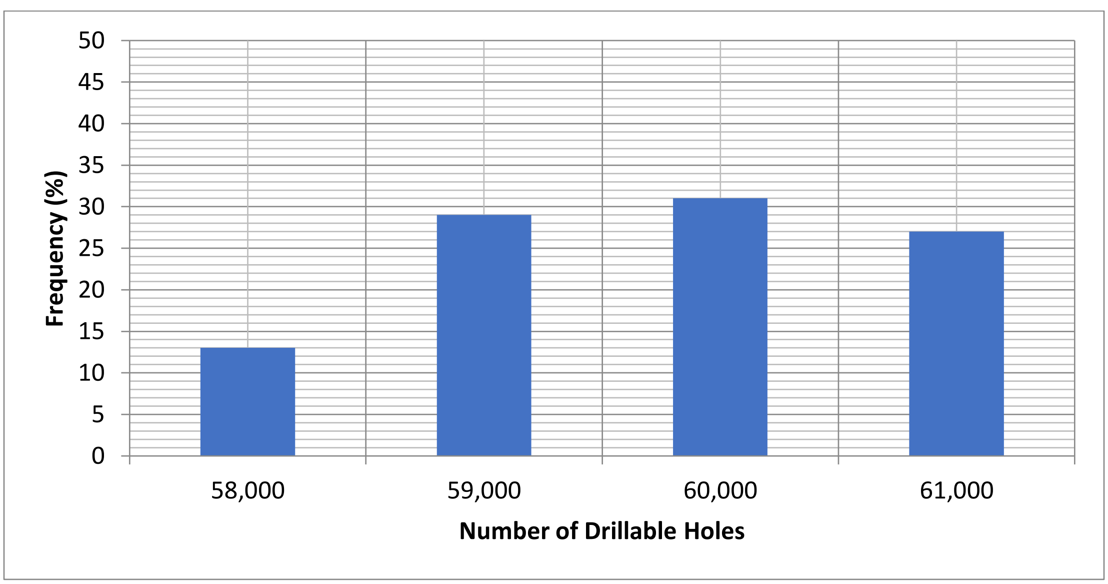

Figure 4-5: The number of drillable holes simulated by MR for 180 shifts

The comparison between MCMC and MR is presented in Table 4-11. The results show that their means are almost same but MCMC has a lower standard deviation than MR.

Table 4-11: The comparison between MCMC and MR

Number of Drillable Holes		
Parameter	MCMC	MR
Mean	59,325	59,235
Standard Deviation	778	966

According to the MCMC simulation, the probability that the number of drillable holes is likely to be between 59,000 and 61,000 is 94% (Figure 4-4). MR results show 87% probability that the number of drillable holes is between the same range (Figure 4-6). There is a 7% difference between the two methods to create a production schedule. There will be around 3% deviation according to the given interval (2,000 out of around 60,000 holes). Given the nature of a mining operation, this is quite acceptable to install production capacity.

To validate the approach, the simulation results and actual realizations are compared. In actual application, the number of drilled holes was 60,391. As can be seen, this result is within the range obtained by simulations. Therefore, as long as there will not be a significant change in rock characteristics, the rest of the operation can be designed with respect to simulation results.

4.5 CONCLUSION

This chapter presents an approach based on a combination of reliability analysis, MC theory, and MR to simulate the number of available drilling machines and the number of drillable holes for a given probability level. Using simulation results, a range of production rates can be generated for a pre-specified probability. First, the power law model was applied to time-between-failure data to determine β and λ parameters. Then, a reliability analysis was conducted to characterize the behavior of drilling machines. Finally, the number of available machines was simulated by the MCMC technique based on reliability analysis and the MR process using historical data. The results of the MCMC simulation indicated a more than 80% probability that five to eight drilling machines will be available for every 10 hour-period (one shift). Using these processes will facilitate more accurate decision-making for production scheduling and risk management. It can be seen from the results of the number of drillable holes that there will be approximately only 3% deviation to plan drilling schedule by using both MCMC and MR process.

Also, the association between drilling machine reliability level and performance was quantified for ten drilling machines. The direct relationship between reliability and performance was demonstrated by regression analysis. The comparison of the reliability of similar drilling machines was illustrated by statistical analysis.

The chapter also discusses the assumption that all machines have identical reliability. The MC results showed that this assumption could be misleading if long-term plans are considered. In this way, the necessity of implementing the reliability analysis for decision-making mechanism and risk management were shown.

4.6 Chapter Conclusion

The effect of equipment condition on the performance was investigated in this chapter. The method which can be used as a tool to forecast the number of available drilling machines for long-term operations was also proposed. It is important to note that the results obtained from the simulations are site-specific. The research outcomes cannot be generalized. For different mines, the methodology should be repeated. To be able to have an accurate production plan, asset management has a crucial impact. In terms of drilling, bits are one of the main components of the system. Exploring the optimum replacement time of the bits is the main concern for cost optimization. In the next chapter, unlike Chapter 3, bit wear will be also formulated as a parameter of drilling operation considering time series datasets. Physical drilling activities will be modeled by discrete event simulation, and the number of required drill bits and drillable holes will be calculated accordingly. The effect of reliability on drilling operation will also be investigated.

CHAPTER 5

5. MANAGEMENT OF DRILLING OPERATIONS IN SURFACE MINES USING RELIABILITY ANALYSIS AND DISCRETE EVENT SIMULATION

5.1 Abstract

Low commodity prices have forced many mining companies to explore strategies to minimize operating costs. One cost-saving strategy is to increase drilling efficiency and performance, specifically in open pit mines; drilling operations are expensive, and they, directly and indirectly, affect most aspects of the mining process. A substantial portion of drilling costs is associated with drill bit consumption due to bit wear. Bit wear decreases the rate of penetration, which reduces drilling efficiency, but changing the bit too early unnecessarily increases drilling costs. In addition to this decision-making dilemma, the inventory management strategy is also crucial to cost minimization. Reliability analysis is an effective method to monitor the efficiency and performance of mining equipment and ensure that performance goals and quality criteria are met. In this chapter, reliability analysis of drilling machines and drill bits was performed and the relationship between reliability and machine performance was established. Moreover, the optimum drill bit change time was determined with discrete event simulation for a range of drill bits based on historical data. The range of drillable holes was also determined. Results of 100 simulations showed that the proposed approach can be an effective tool to facilitate production scheduling and asset management.

5.2 Introduction

Drilling is a primary operation in open-pit mining and unexpected drilling equipment failure has a serious impact on the production schedule: it causes delays in blasting operations and affects the entire production process. Mismanagement of equipment can result in production target shortages and unfulfilled sales agreements [90]. One solution to production losses associated with equipment failure is to create inventory stockpiles, but this approach can lead to a stock surplus, high storage costs and possible opportunity costs [91]. Therefore, asset management plays a key role in mining operation performance.

The immediate engineering problem is to determine the drilling equipment required to manage production plans. Data regarding equipment reliability and availability are needed because the overall system performance directly depends on the performance of the individual system components [92]. Reliability is defined as the probability that a system will perform required functions over a given period without any failures. In other words, it is the probability of a non-breakdown shift. Equipment reliability can be used as a key metric of the success of a system during its operational lifetime [66]. Reliability is closely related to the quality of the product. It also depends on external factors such as operational performance and the maintenance action [65]. Although it is impossible to have a priori knowledge of the exact time of failure of a machine, it is generally possible to obtain information about the possibility of a replacement being required at any particular time [93].

Reliability analysis is the most effective method to determine the condition of the system components. If equipment reliability and availability are modeled appropriately, the production schedule will be more realistic. Reliability analysis is a modeling tool that can help to forecast the future evolution of failure of system components and thus prevent unwanted stoppages. It indicates the probability that a system can fulfill the intended functions [68]. Hence, there is a direct relationship between system reliability and system performance: a system that has a high reliability will perform at a higher level. Therefore, analysis of drilling system reliability and the number of available assets is essential to sustain a mining operation.

Drilling machines are examples of “repairable systems”; they can be restored after equipment failure for satisfactory operation without replacing the entire system [67]. Historical data regarding the time periods between failures and the number of failures at a particular time is needed to analyze system reliability [68]. The power law technique is used to model system intensity function for particularly complex repairable systems such as drilling machines, trucks and loaders [94]. Drill bits are “non-repairable”. When a non-repairable system fails, it cannot be repaired due to economic, logistic or practical reasons. The times between failures are assumed to be independent and identically distributed (i.i.d.). The renewal process can be employed to calculate the number of failures in a specific period [93].

Drilling machine performance is measured by the rate of penetration (ROP)—the distance the bit enters into the rock per unit time. Bit wear decreases the ROP and is affected by both uncontrollable and controllable factors. Uncontrollable factors include the physical and mechanical properties of the rock formation (e.g., hardness, uniaxial compressive strength, mineral composition, quartz content, structure, and binding properties) [95-97]. The relationship between these factors and the ROP is non-linear and complex. Factors that can be controlled by the drilling machine operator (also called operational parameters) are revolutions per minute (RPM), weight on the bit or pull-down force (WOB) and bailing air pressure (BAP) [18].

During most field operations, the decision to change the drill bit is based on operator experience; the drill bit is changed when the operator observes high vibration. In addition, in some applications, the operator let the bit drop into a hole and this may cause some issues such as safety problems in blasting and failures in crushers. An alternative is to monitor and optimize drilling parameters and then use statistical methods to determine drill bit replacement time. Recent advances in simulation technology have made it possible to model the production schedule and management of open pit mines [40]. Discrete event simulation (DES) can be used to deal with the high uncertainty and variability of the mining environment to generate probable images of the future [98]. This stochastic mathematical modeling technique can simulate physical activities for discrete and probabilistic circumstances [34]. DES assigns the behavior of compound and complex systems as a discrete sequence of time-ordered events. It is commonly used to monitor and predict the behavior and the performance of the system with a trial and error approach as a dynamic simulation technique [36]. Furthermore, DES can combine system variability with probability distributions to model the system variables with uncertainty and risk [37]. Therefore, the complexities and interdependencies of components can be accommodated for a system. Botín, Campbell [36] used DES to minimize the highest risk parameters in a block caving project. Yuriy and Vayenas [37] analyzed maintenance actions of mining operations using DES. Ozdemir and Kumral [99] developed a DES model to evaluate the feasibility of a mining plan under an uncertain operating environment.

The present study uses DES to simulate drilling activity in order to estimate the probable number of required drill bits and drillable holes. The uncontrollable factors listed above that affect the ROP make it challenging to develop a model to predict ROP [42]. Thus, rock characteristics were assumed to be homogeneous for a given bench. In addition, given that laboratory experiments in a controlled environment may neglect important factors operating in a field environment [42], multiple regression, time-series regression, and reliability analyses were performed on field data collected over a year period by measurement while drilling (MWD) systems. MWD is widely used in the mining industry as a drill monitoring technique. It provides wellbore position, drill bit information and operating parameters, as well as real-time drilling information for rock mass characterization, short- and long-term mine planning, blast design and optimization of fragmentation [42]. The data collected include time, depth, feed force, RPM, ROP, rotation torque, air pressure, and vibration.

Study objectives were to 1) determine the optimum drill bit replacement time based upon reliability analysis and representation of inventory management using historical data (with DES); and 2) calculate the range of drillable holes. Distribution parameters were calculated for each drilling machine and drill bit. Historical data were used to investigate the relationship between reliability level and machine performance. Furthermore, in order to obtain accurate results, drilling machines were assigned “machinery index” values according to their drilling performance using the equally weighted moving average method.

The originality of this chapter rests upon (a) determining the number of drill bits required in a given period and (b) computing the number of holes to be drilled using these bits. Moreover, uncertainties (e.g., drill bit changing time, maintenance time and drilling time) associated with this process are assessed.

5.3 Research Methods

The research in this chapter has three stages: (i) reliability analysis of individual drilling machines and drill bits, (ii) using the reliability models derived in the previous stage to quantify wear rate and (iii) DES to compute probable realizations of total drill hole length in a given period. A power law model was fitted to drilling machines and the model parameters were calculated using ReliaSoft® software. Historical data collected by MWD systems were used to investigate the relationship between machine reliability and performance. The behavior of drill bits was modeled through a Weibull distribution using ReliaSoft® software. Bit wear was quantified by time series regression analysis of drill bit monitoring data and the optimum replacement strategy was determined based on reliability analysis. Finally, the number of required drill bits and the range of drillable holes were simulated by DES (100 simulations in Arena® for each drilling machine) for trimester periods.

5.3.1 Reliability Analysis

Reliability analysis helps to deal with the uncertainty and to make an informed decision. The general expression for the function of reliability is given by Eq. 5-1 [65].

$$R(t) = \Pr\{T \geq t\} \tag{5-2}$$

Where *R(t)* is the reliability at time *t*, *T* is the time to failure of the system or piece of equipment and *R (t)* ≥ 0, *R (0)* = 1. More information can be found in [68, 94, 100].

The failure rate can be defined as the probability of the incremental change in the number of failures per associated incremental change at any time *t* in the life of a system. Hazard rate refers to the rate of failure for an item at a given time *t*. The relationship between reliability *(R*), failure rate (*f*) and hazard rate (*h*) at time *t* is illustrated by Eq. 5-5-3 [66].

$$R(t) = \frac{f(t)}{h(t)} \tag{5-3}$$

The Weibull distribution is commonly used to analyze and model reliability. It represents the i.i.d. life data of the system and is used to estimate parameters and fit the function closely with the data [93]. The Weibull distribution allows a decision maker to make reasonably accurate statistical predictions about a system's life and estimate significant characteristics of the system (e.g., reliability, failure rate and mean lifetime) with a small sample size. It also can provide quantitative information for qualitative decision making because it is very versatile, being capable of modeling both symmetric and skewed data. Therefore, the Weibull distribution is one of the easiest distributions to implement and interpret [93]. The three defining parameters of the Weibull distribution are the shape parameter (β), also known as the Weibull slope, scale parameter (η) and location parameter (γ), also known as shift parameter. The shape of the distribution is controlled primarily by β when η and γ are constant; η stretches or shrinks the distribution and γ shifts the distribution in time. Sometimes γ is set to zero (2-parameter Weibull distribution) [101]. The reliability function, failure rate function and hazard rate function for the 2-parameter Weibull distribution are given by Eq. 5-3, 5-4 and 5-5, respectively [93].

$$R(t) = e^{-(\frac{t}{\eta})^{\beta}} \tag{5-4}$$

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{\left[-\left(\frac{t}{\eta}\right)^{\beta}\right]} \tag{5-5}$$

$$h(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{5-6}$$

Historical data were collected from ten rotary drilling machines working at an open pit mine over a year period. The time between failures, the time under repair and the drilling length were recorded for each machine. Reliability analysis followed the power law technique and the parameters were determined by ReliaSoft® software.

Four drilling machines (from low to high reliability: Machines A, B, C, and D) were selected based on reliability analysis to investigate the effect of reliability on drilling performance. Multiple regression and time series regression methods were selected to describe the relationship between reliability and drilling performance, due to complex interactions between several independent variables and drilling operations. To simplify the analysis, the degradation of a drill bit was assumed to be linear. The drilling time at each hole was selected as a measure of drilling performance (dependent variable) and the operating parameters RPM, WOB and BAP were independent variables. To quantify drill bit wear, the number of drillable holes was added to the time series regression equation as an independent variable because data were collected over time. Regression analysis was conducted with SPSS® software.

The equally weighted moving average method was used to compare the performance of the drilling machines based on the time series data. This method is suitable only when the data have random variation [102]. It is generally used to determine seasonal effects in sales estimation for short-term forecasting; in this case, the drilling machines can be considered seasons and the number of drilled holes can be considered a number of sales. Therefore, the machine performance based on reliability level at a particular time can be indexed to forecast more accurate results. Eq. 5-6 shows the calculation of centered average values [102]:

$$\frac{x_1 + x_2 + \ldots + x_s}{s} = \bar{x}_{\frac{s+1}{2}}$$

$$\frac{x_2 + x_3 + \ldots + x_{s+1}}{s} = \bar{x}_{\frac{s+1}{2}+1}$$

$$\vdots \tag{5-7}$$

$$\frac{x_{N-s+1} + x_{N-s+2} + \ldots + x_N}{s} = \bar{x}_{N-\frac{s+1}{2}+1}$$

where *s* is the number of the grouped values, and *N* is the total number of values. Then, the real value is divided by the centered average to calculate the percentage of average value. The average of the percentage of average values is calculated to assign an index of the drilling machine. The index of each machine can be called as Machinery Index. A relatively low machinery index indicates relatively less drilling time.

5.3.2 Drill bit Replacement Strategy

In previous studies, the optimum drill bit replacement time was estimated by deterministic methods, and replacement time was set at fixed time intervals. However, this approach is unrealistic given the uncertainties in material properties and geology noted above. Failure models such as reliability, failure rate, and hazard rate significantly affect optimal replacement policy [103]. Unlike previous studies, the optimum replacement time of the inventories was determined based on the failure time distribution of the component.

5.3.3 Discrete Event Simulation (DES)

Mining activities consist of a discrete sequence of events can be considered a non-Markovian process in which each event depends on the previous state. Therefore, dynamic simulation techniques based upon the Monte Carlo method can be used to model mining events [72]. The Monte Carlo method determines the impact of potential risks and investigates the behavior of complex systems. Random sampling is performed for different tasks to generate a range of possible outcomes by running simulations [104].

The detailed discrete-event system is illustrated in Figure 5-1. When a drilling machine arrives at a bench, the initial bit changing time is generated from a probability distribution formed by historical events. Then, machine reliability is checked based on historical failure time data to decide the necessity of maintenance activity. If the reliability is less than 40% at a given time interval, maintenance is required. The drilling machine is sent to a maintenance facility and a maintenance delay is applied based on the distribution modeled by the historical data. If maintenance is not required, drill bit reliability is controlled based on historical failure time data to decide whether drill bit replacement is required. When the bit needs to be changed, it is recorded, and a new changing time is generated based on the distribution. Subsequently, moving and leveling time are assigned based on historical data. The drilling time is calculated based on regression analysis and the machinery index. Once a hole is drilled, it is recorded, and the system goes back to the state where the mechanical reliability is checked for drilling another hole. This cycle continues until the end of the simulation for all machines. The stopping criteria are assigned as the drilling time interval: trimester periods.

The DES simulation of a number of required drill bits and number of drillable holes for trimesters were based on the reliability, regression analyses and the results of the equally weighted moving average method. Maintenance requirement and drill bit changing time were determined by reliability analysis and failure distributions. The parameters of the distributions of the power-law model and the machinery index were used to identify the performance differences between drilling machines to optimize simulation results. Moreover, the drilling time was calculated using the results of the multiple regression analysis and the drill bit changing time was determined by fitting a distribution. Finally, multiple scenarios were generated for each drilling machines. To eliminate the seasonal effect on drilling operation, 90 consecutive days (180 shifts) were simulated.

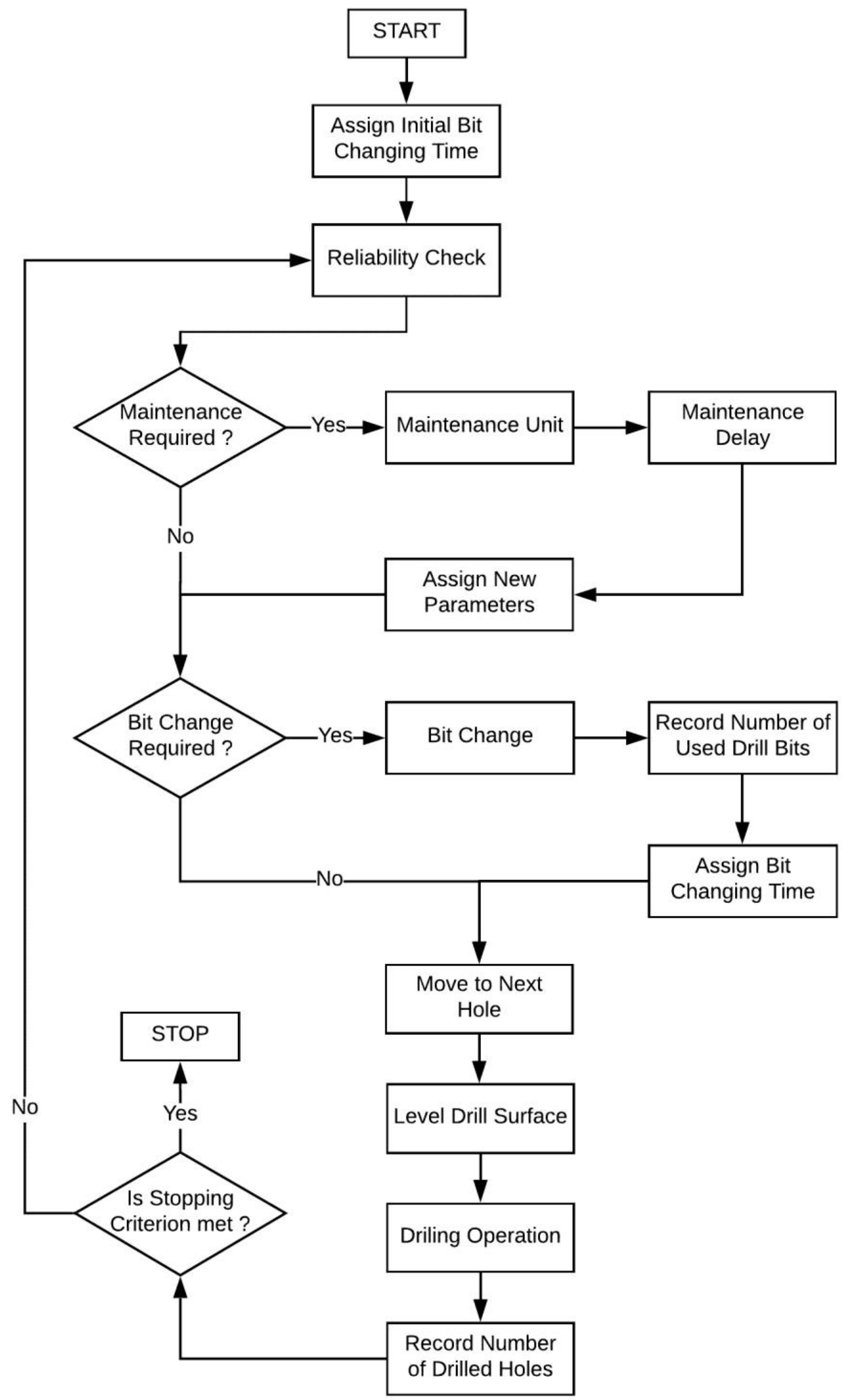

Figure 5-1: DES model of the drilling operation

5.4 Field Data Analysis

The data were collected from the sensors installed in the drilling machines used in a Canadian mining operation. Drilling time was recorded for each drill hole for every time interval and operational parameters were collected by MWD sensors which were placed on the drill rigs. The production performance (evolution of drilling time) of four drilling machines on four benches shows that as the drill bit wear increased, drilling time increased (Figure 5-2). The minimum time spent to drill a hole was 10 min and the maximum was 59 min. The broad range can be explained by bit deterioration. Sharp drops in drilling time indicate that the drill bit was replaced (green arrows in Figure 5-2) and suggested that the ROP is a reliable indicator of the optimum drill bit changing time.

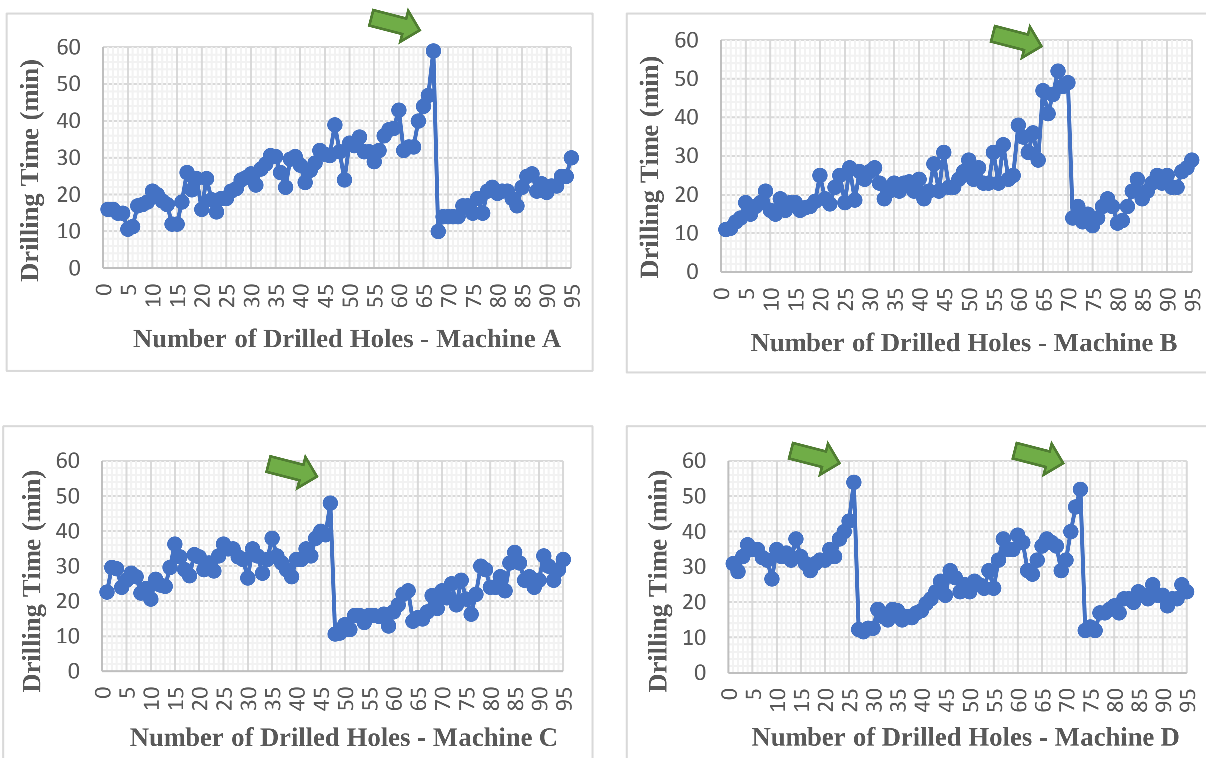

Figure 5-2: Drilling time on four benches for four drilling machines (arrows indicate bit replacement)

The moving time followed triangle distribution (1.5, 2.0 and 2.5 min), and the leveling time was 2.48 ± 0.84 min (± standard deviation) and followed a lognormal distribution.

Figure 5-3 shows the replacement time for 495 drill bits from the four drilling machines. The bit life ranged from 20 to over 60 h (because of the uncontrollable factors listed above) and follows a Weibull distribution. The mean bit life (± standard deviation) was 38±13 h for Machines A and B (85% confidence interval = 35–55 h) and 40±11 h for Machines C and D (85% CI = 40–60).

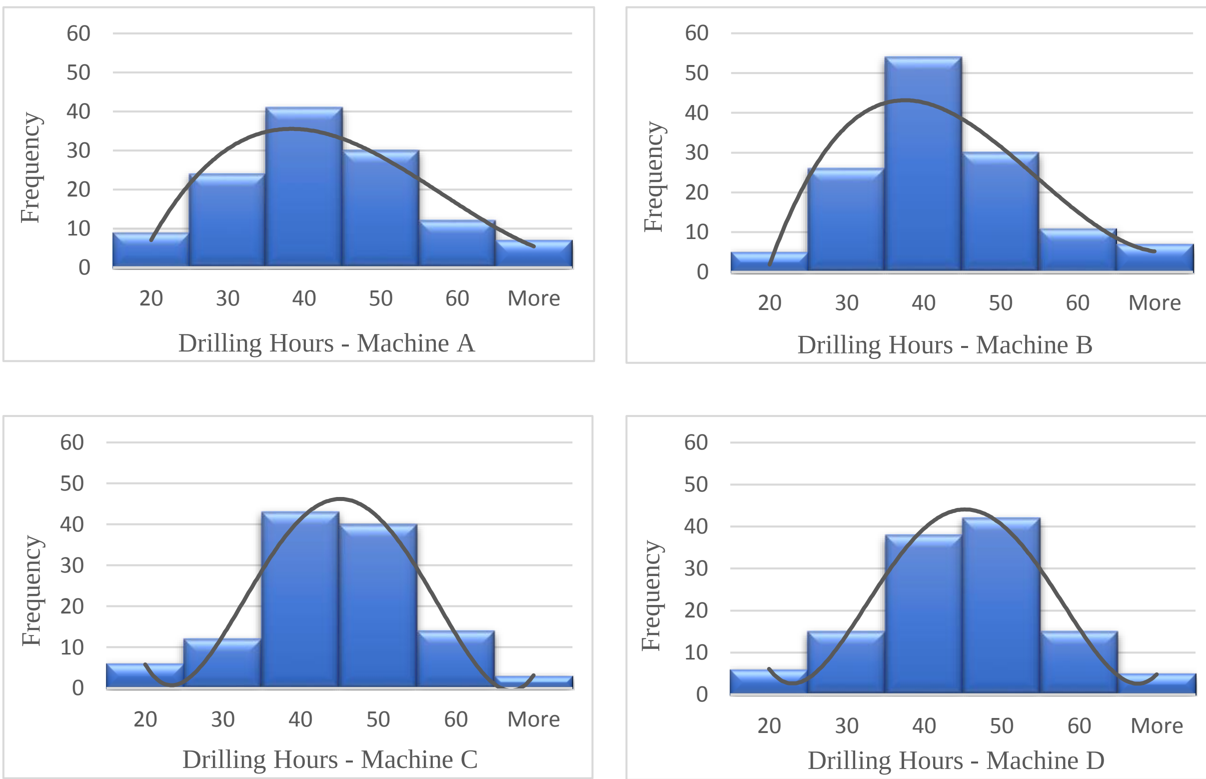

Figure 5-3: Histogram of time to failure for 495 drill bits of four drilling machines

Due to the complex interaction between several independent variables and drilling operation, multiple regression and time series regression methods were selected to build prediction models. To make the analysis simpler, the degradation of a drill bit is assumed as linear while determining the coefficients of independent variables.

5.5 Case Study

In this study, historical data were collected from ten rotary drilling machines working at an open pit mine over a year period. The time between failures, the time under repair and the drilling length were recorded for each machine.

5.5.1 Reliability Analysis

5.5.1.1 Reliability analysis of drilling machines and performance measurement

The parameters of the power law model are listed in Table 5-1 and reliability plots of the machines are demonstrated in Figure 5-4.

Table 5-1: Parameters of the power law model for each of ten rotary drilling machines

Machine	β_p	λ_p
1	1.189	0.00045
2	1.225	0.00031
3	1.268	0.00019
4	1.058	0.00143
5	1.124	0.00063
6	1.237	0.00031
7	1.232	0.00023
8	1.076	0.00109
9	1.319	0.00011
10	1.082	0.00087

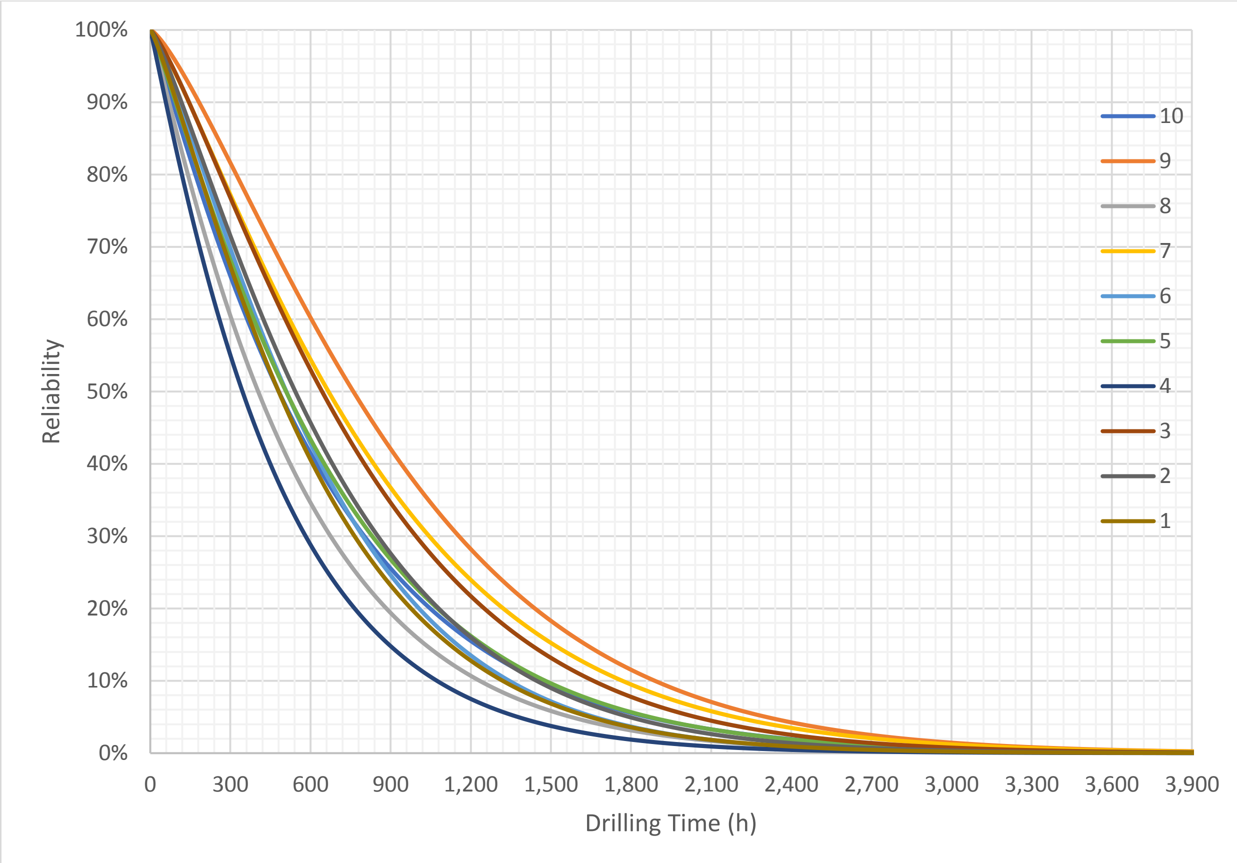

Figure 5-4: Reliability plots of the rotary drilling machines

Figure 5-4 shows that the reliabilities of the machines vary. For instance, between 0 and 900 hours, the probability to fulfill the intended operation of Machine 4 is only 14%, whereas the probability for Machine 9 is around 42% in the same range.

Multiple regression models were constructed to predict drilling time (min) from RPM, WOB, and BAP for the four machines (Table 5-2). The p-value of the analysis was less than 0.0001 in all cases which shows that it is statistically significant. The length of each hole was 17 m. The unstandardized coefficient (B_r) provides the average change of a dependent variable when an independent variable changes one unit. As expected, an inverse relationship was observed between drilling time and operational parameters. The standardized coefficient (β_r), which compares the relative importance of each independent variable in a regression model [105], shows that WOB had the greatest effect on drilling time in the long term. Approximately 40% of the variation of the drilling time ($1 – R^2$) cannot be explained by the operational parameters. Therefore, further analyses were required to explain the variation of drilling time. Drill bit wear must also be taken into account.

Table 5-2: Regression analysis for operational parameters of four drilling machine

Machine	**Parameter**	B_r	β_r	**Sig.**	R^2	***p-value***
A	Intercept	248.378		0.000	0.669	0.000
	RPM	–1.247	–0.320	0.000		
	WOB	–0.405	–0.464	0.000		
	BAP	–0.086	–0.206	0.000		
B	Intercept	228.889		0.000	0.607	0.000
	RPM	–0.954	–0.255	0.000		
	WOB	–0.262	–0.494	0.000		
	BAP	–0.039	–0.108	0.042		
C	Intercept	213.422		0.000	0.615	0.000
	RPM	–0.840	–0.251	0.001		
	WOB	–0.287	–0.449	0.000		
	BAP	–0.028	–0.092	0.047		
D	Intercept	209.353		0.000	0.637	0.000
	RPM	–1.358	–0.314	0.000		
	WOB	–0.171	–0.419	0.000		
	BAP	–0.002	–0.007	0.009		

To understand the effect of bit wear and other parameters on the drilling operation, a detailed analysis was conducted with coded values ranging from –1 to +1 for 10 selected benches where drilling was begun with new bits. Multiple regression analyses were conducted on drill holes 1, 10, 20, 30 and 40 (Table 5-3). The β_r values show that RPM was the most influential operational parameter, particularly when the bit was new. However, as the bits deteriorated, WOB became more important. In other words, when the bit is worn, the effects of RPM are not sufficient to maintain the desired ROP. Therefore, it is necessary to increase WOB to compensate. In addition, the R^2 values decreased (residual errors increase) from hole 1 to 40 as a consequence of drill bit degradation. When a bit is worn, the impact of the controllable factors on the drilling operation decrease, and more parameters are needed to explain the variation in drilling time.

To quantify the influence of bit wear, time series regression analysis was conducted on time series data sets with operational parameters. In time series regression analysis, data are exposed to log-transformation to better capture seasonal effect . A direct relationship existed between the number of drilled holes and drill bit wear (Table 5-4). Therefore, the number of drilled holes was added to the regression analyses to quantify bit wear (Table 5-5). The model in Table 4 is statistically insignificant ($p > 0.05$); therefore, a model without bit wear cannot represent the drilling operation. The regression model in Table 5 shows that bit wear was the most influential parameter for the drilling operation; 86% of the variation of drilling time could be explained by operational parameters and drill bit wear.

Table 5-3: Regression analysis on five drill holes in each of 10 benches

Hole	**Parameter**	B_r	β_r	**Sig.**	R^2	***p*-value**
1	Intercept	26.428		0.000	0.913	0.013
	RPM	–1.758	–0.714	0.038		
	WOB	–1.723	–0.569	0.045		
	BAP	–1.005	–0.520	0.039		
10	Intercept	29.085		0.000	0.860	0.030
	RPM	–1.843	–0.430	0.018		
	WOB	–1.228	–0.415	0.046		
	BAP	–0.889	–0.320	0.041		
20	Intercept	33.660		0.000	0.825	0.036
	RPM	–1.951	–0.453	0.035		
	WOB	–2.076	–0.395	0.023		
	BAP	–1.440	–0.334	0.042		
30	Intercept	45.033		0.000	0.807	0.039
	RPM	–2.331	–0.496	0.019		
	WOB	–2.427	–0.601	0.016		
	BAP	–2.063	–0.458	0.034		
40	Intercept	54.082		0.000	0.751	0.044
	RPM	–3.602	–0.570	0.008		
	WOB	–4.823	–0.763	0.002		
	BAP	–2.012	–0.332	0.040		

Table 5-4: Time series regression without bit wear as a variable

R			0.459					
R²			0.211			**Regression**	***B_r***	***p*-value**
Adjusted R²			0.123			**Intercept**	3.531	0.000
ANOVA	**df**	**SS**	**MS**	**F**	**Sig F**	**RPM**	–0.085	0.102
Regression	4	0.524	0.131	2.332	0.075	**WOB**	–0.057	0.308
Residual	35	1.968	0.056			**BAP**	–0.069	0.202
Total	39	2.492						

Table 5-5: Time series regression with bit wear as a variable

R			0.927			**Regression**	***B_r***	***p*-value**
R²			0.862			**Intercept**	3.008	0.000
Adjusted R²			0.839			**Bit Wear**	0.181	0.000
ANOVA	**df**	**SS**	**MS**	**F**	**Sig F**	**RPM**	–0.093	0.000
Regression	5	2.143	0.429	41.702	0.000	**WOB**	–0.064	0.010
Residual	34	0.351	0.010			**BAP**	–0.041	0.041
Total	39	2.492						

The equally weighted moving average method was used to quantify the effect of reliability based on time series data. The drilling times for drill holes 10, 20, 30, and 40 were used to evaluate the performance of drilling machines. All machines started to drill with new bits and this application was replicated four times. Based on the machine performance, a machinery index was assigned to each drilling machine (Table 5-6). At a given time, the machine with a higher reliability level (D) spent less time drilling a hole than the one with a lower reliability level, as indicated by mean machine index. Therefore, there was a direct relationship between reliability and machine performance; the machinery index can be used to forecast more accurate results when the drilling time is calculated from a regression equation. Note: The drilling time calculated from multiple regression can be multiplied by the machinery index to account for performance differences between machines.

Table 5-6: Machinery Index

Holes	**Machines**			
	A	B	C	D
10.			0.962	0.992
20.	1.012	1.025	1.019	0.942
30.	1.027	1.008	0.989	0.968
40.	1.017	1.017		
Mean	1.019	1.017	0.990	0.967
Adjustment Factor	1.001			
Machinery Index	1.021	1.019	0.992	0.969

5.5.1.2 Reliability analysis of drill bits

The results above show no trend in the failure data of each machine's drill bits. Therefore, the renewal process was applied to these i.i.d. data using ReliaSoft® software. Goodness-of-fit tests showed that the best fit distribution is the 2-parameter Weibull distribution (Table 5-7). Reliability plots of the drill bits of the four machines were similar (Figure 5-5). However, the condition of the machine had a slight impact on drill bit performance, according to reliability analysis.

Table 5-7: Parameters of the Weibull model for each drilling machine's drill bits

Machine	**Shape Parameter (B_w)**	**Scale Parameter (η_w)**
A	3.266	41.962
B	3.738	41.532
C	4.166	43.692
D	4.161	44.078

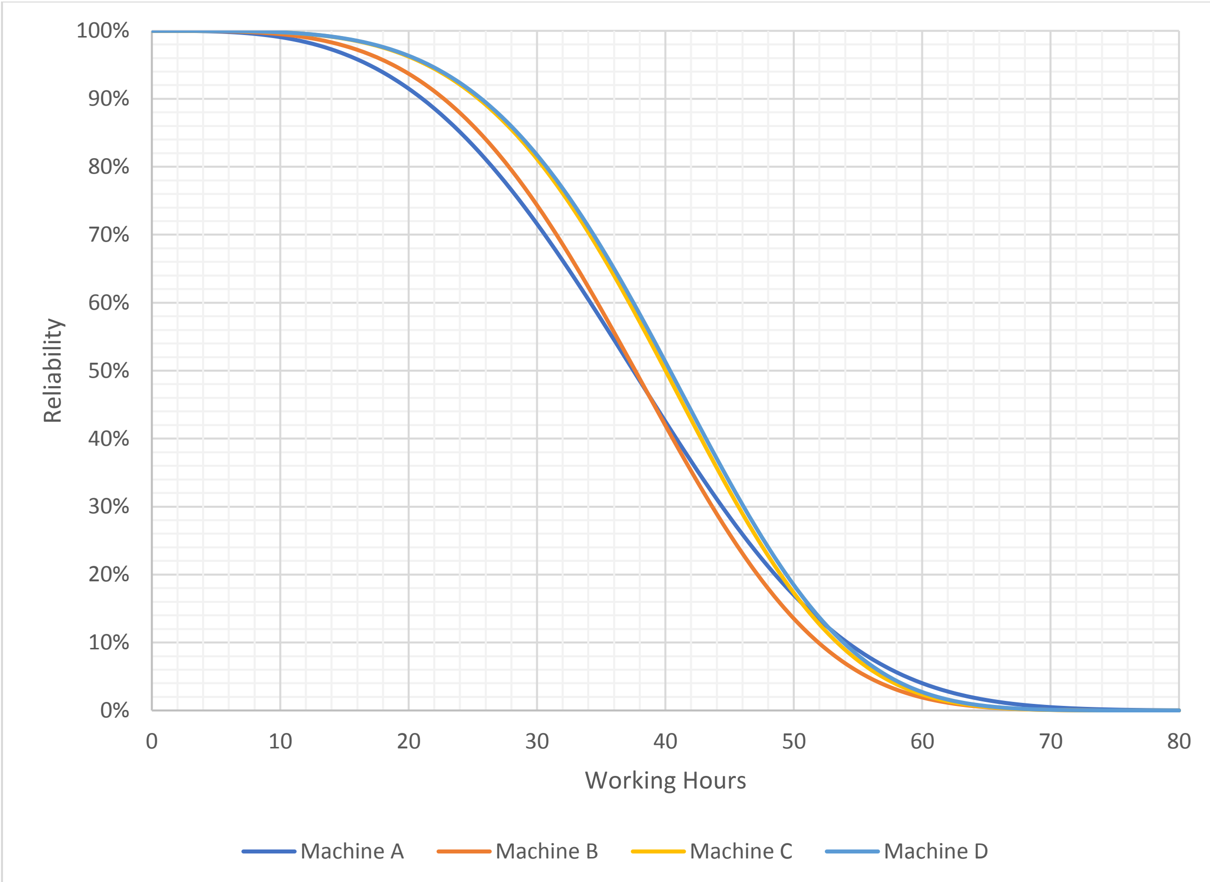

Figure 5-5: Reliability plots of the drill bits

Table 5-8 shows the results of failure density, hazard rate and reliability analysis for drill bits used by the four drilling machines for 10 h intervals.

Table 5-8: The results of failure models for drill bits for 10 hours intervals

Machine		**Hours**					
	Model	10	20	30	40	50	60
A	Failure Density	0.073	0.195	0.333	0.244	0.098	0.057
	Hazard Rate	0.073	0.211	0.456	0.612	0.632	1.000
	Reliability	1.000	0.927	0.732	0.398	0.154	0.057
B	Failure Density	0.038	0.195	0.406	0.226	0.083	0.053
	Hazard Rate	0.038	0.203	0.529	0.625	0.611	1.000
	Reliability	1.000	0.962	0.767	0.361	0.135	0.053
C	Failure Density	0.051	0.102	0.364	0.339	0.119	0.025
	Hazard Rate	0.051	0.107	0.430	0.702	0.824	1.000
	Reliability	1.000	0.949	0.847	0.483	0.144	0.025
D	Failure Density	0.050	0.124	0.314	0.347	0.124	0.041
	Hazard Rate	0.050	0.130	0.380	0.677	0.750	1.000
	Reliability	1.000	0.950	0.826	0.512	0.165	0.041

5.5.2 Appropriate Replacement Time

The optimum replacement times were fitted to a lognormal distribution (39.86 ± 9.90 h) by ModelRisk® software. The probabilities of optimum replacement times of drill bits are shown in Table 5-9.

Table 5-9: Probabilities of optimum replacement times

Replacement time (h)	Probability
< 25.86	0.05
25.86 – 49.85	0.90
49.85 <	0.05

5.5.3 DES Results

Figure 5-6 demonstrates possible outcomes of drill bit usage for 100 randomly generated scenarios of four drilling machines. The probability that the number of used drill bits is between 44 and 48 is approximately 90% for Machines C and D, 60% for Machine A and 50% for Machine B.

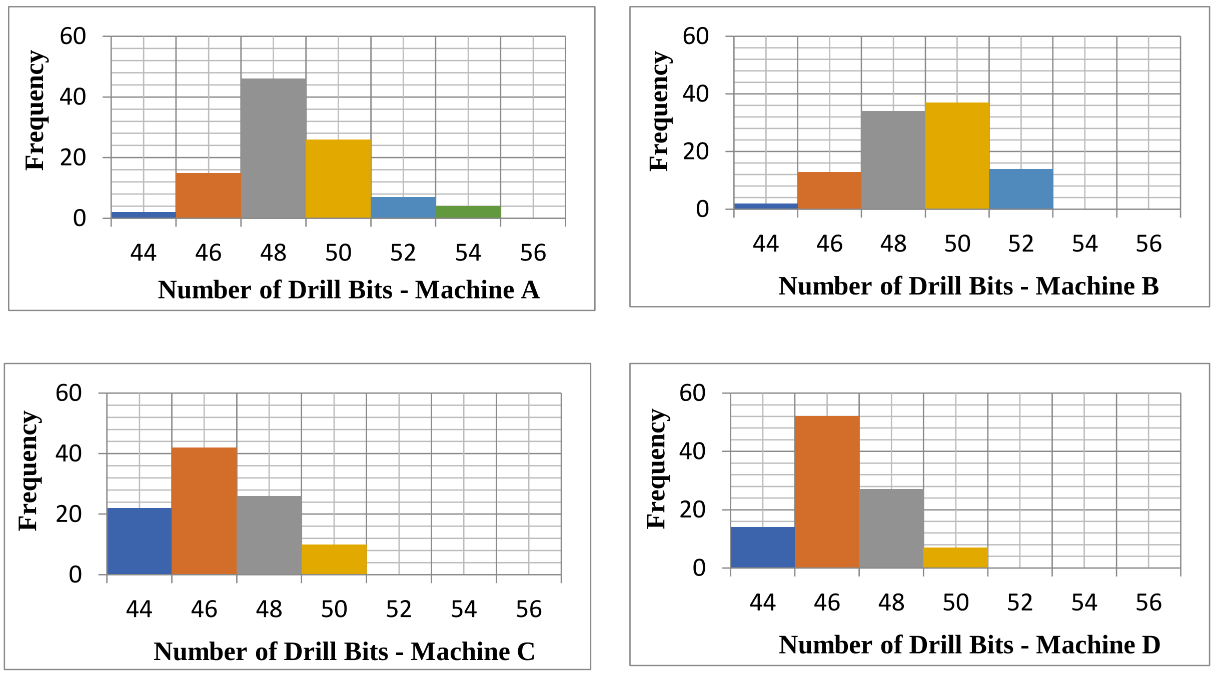

Figure 5-6: Simulation results – The number of drill bits for each machine

Once 100 scenarios were generated, the number of drill holes that can be drilled was also calculated for 180 shifts. The probability that the number of drillable holes is between 2,400 and 2,450 is 75% for Machines C and D (Figure 5-7). However, this probability is lower for Machines A and B (50%). The main reason for this significant difference is machine condition. Operator experience should also be taken into consideration.

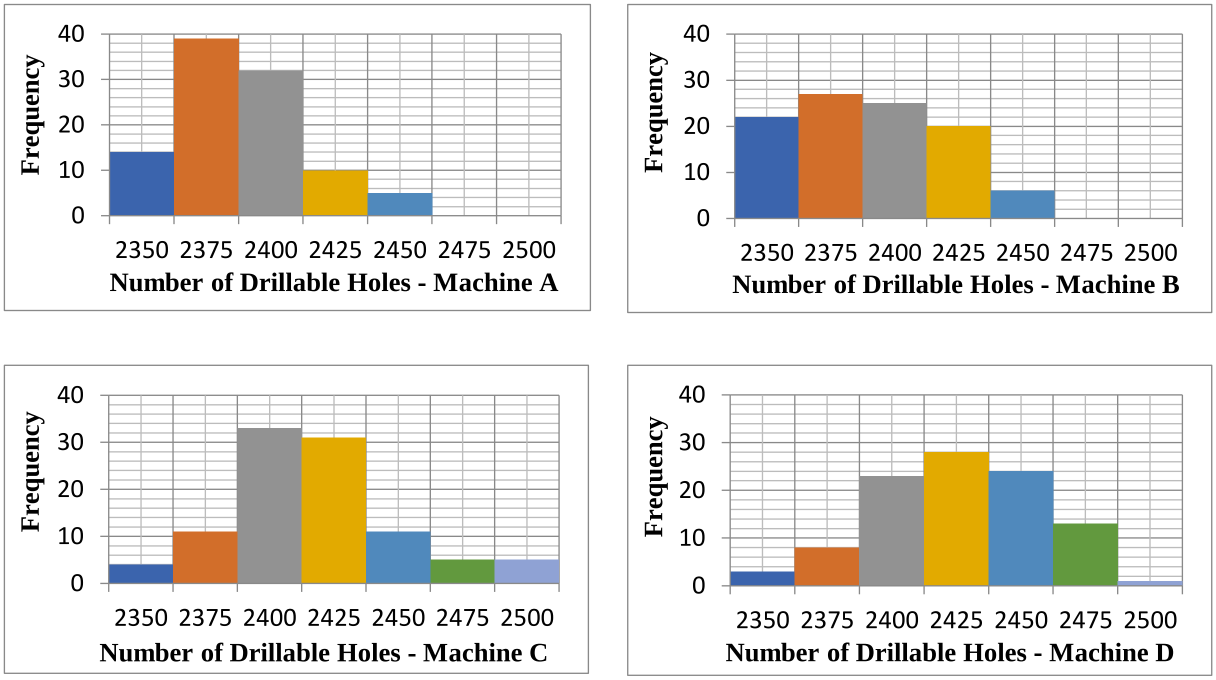

Figure 5-7: Simulation results – The number of drill holes for each machine

5.6 Conclusion

This part of the thesis presents an approach for managing bench drilling operations based on a combination of data analysis, reliability analysis, the equally weighted moving average technique, and DES to simulate the number of drill bits and the number of drillable holes for a given period. Parameters affecting drill bit performance and the behavior of drilling operation from the first drill hole to the end of the drill bit life were determined. First, the effects of operational parameters were analyzed by multiple regression analysis and found to be insufficient to account for the variation in drilling time. Second, multiple regression analysis was conducted on specific drill holes with a new bit to understand the influence of bit wear. Finally, bit wear was quantified by a new regression model. The results are consistent with our previous studies [94, 106-108], but differ in that time series datasets were also analyzed for the long term. These results showed that the effects of the operational parameters changed with time because of bit deterioration; the changes can be used to indicate drill bit changing time.

The number of drill bits and a number of drillable holes were simulated by DES based on reliability analysis, regression analysis, and historical data. The simulations indicated the probability that the number of drill bits was 46–50 is 80% for each drilling machine for three months operation. However, the number of drillable holes varied depending on the machine performance. The proposed approach highly depends on the type of equipment and the operation.

This chapter also quantified the relationship between reliability and machine performance. A direct relationship was demonstrated with the equally weighted moving average method. This made it possible to compare the performance of drilling machines.

5.7 Chapter Conclusion

Bit wear was quantified as a parameter of drilling operation considering time series datasets. Then, it was added to the regression analysis as an independent variable in order to calculate the number of required drill bits and drillable holes through modeling drilling operation phases. The effect of reliability, as a parameter, on drilling operation was also investigated in this chapter. All the results obtained are case specific and the proposed models can be seen as a continuous improvement tool. In the next chapter, replacement costs will be incorporated into the research to quantify the effect of maintenance costs on optimum drill bit replacement time. The drill bit replacement time will be optimized considering replacement cost. The relationship between the total expected replacement cost and replacement time will also be investigated.

CHAPTER 6

6. OPTIMIZATION OF DRILL BIT REPLACEMENT TIME IN OPEN-CAST COAL MINES

6.1 Abstract

To gain a competitive edge within the international and competitive setting of coal markets, coal producers must find new ways of reducing costs. Increasing bench drilling efficiency and performance in open-cast coal mines has the potential to generate savings. Specifically, monitoring, analyzing, and optimizing the drilling operation can reduce drilling costs. For example, determining the optimal drill bit replacement time will help to achieve the desired penetration rate. This chapter presents a life data analysis of drill bits to fit a statistical distribution using failure records. These results are then used to formulate a cost minimization problem to estimate the drill bit replacement time using the evolutionary algorithm. The effect of cost on the uncertainty associated with replacement time is assessed through Monte-Carlo simulation. The relationship between the total expected replacement cost and replacement time is also presented. A case study shows that the proposed approach can be used to assist with designing a drill bit replacement schedule and minimize costs in open-cast coal mines.

6.2 Introduction

During open-cast coal mining, several benches must be created in both the overburden strata and the coal seam. A drilling operation is required where the overburden is hard. As a primary operation, drilling affects both the production and overall operating costs [109]. The efficiency of the drilling operation depends primarily on energy consumption and on the drill bit life [2] because a worn bit significantly decreases the rate of penetration (ROP). The driver of drill bit consumption is wear due to the interaction between the bit and the rock. Given that the bit cost is considered the most expensive part of a drilling operation, accounting for approximately 21% of total operating costs [48], it is vital to determine the ideal time to replace drill bits.

In current practice, a bit is replaced either when it drops into a drill hole during the operation, or the operator determines it is worn based on professional judgment (e.g., high vibration can indicate a worn drill bit). In the latter case, the bit might be changed before its beneficial life has expired, which increases drilling costs unnecessarily. On the other hand, waiting to replace a bit until it is worn negatively affects the production rate. Although operator experience clearly plays an important role in drilling operations, a more objective approach to support bit replacement decisions is to monitor and analyze life datasets and use cost minimization methods [110].

The optimum replacement interval is the time period when the total operating cost is at its lowest [93]. Various researchers have developed strategies such as corrective and predictive maintenance [111] to determine optimal maintenance and replacement intervals [112]. According to Tsang [111], the high cost of maintenance activities is due to 1) unscheduled events that stop ongoing operations and increase total downtime, thus delaying production targets and increasing labor costs; and 2) unexpected failures that may damage other parts of the system and result in health and safety problems. Critical to the development of a replacement policy is determining the optimum replacement interval to maximize the production rate, avoid unexpected failures, and minimize operation costs [93].

Weibull analysis is a commonly used failure analysis technique because it has the ability to forecast with small samples numbers and the flexibility to represent most of the failure cases (i.e., it is capable of modeling both symmetrical and skewed datasets). It can also provide accurate statistical predictions about characteristics of the system (reliability, failure rate, hazard rate, and mean lifetime) and help decision-makers formulate reasonable predictions about the system [93]. Thus, Weibull analysis is extremely useful for planning maintenance schedules.

Most research on bit replacement strategies has focused on two factors: bit age (reliability) and ROP (production efficiency). For example, Godoy, Pascual [113] modeled replacement strategy based on condition-based reliability. Hatherly, Leung [21] suggested using measurement while drilling (MWD) systems to monitor bit wear. Li and Tso [114] proposed a method to determine tool replacement time based on measurable signals such as cutting speed and feed rate. Tail, Yacout [48] proposed a fixed reliability threshold to determine replacement time. Ghosh, Schunnesson [42] and Karpuz [2] used ROP as an indicator of drill bit replacement time, whereas Bilgin, Copur [6] used rock condition as the indicator.

Unlike previous studies, optimal drill bit replacement time is calculated in this chapter based on the minimization model of total expected replacement cost per unit time by the evolutionary algorithm (EA). The outcomes of the study are tested by Monte Carlo simulation (MC) with 100 randomly generated scenarios using Arena® simulation software. In addition, a regression analysis is conducted to determine the relationship between the replacement time and the total cost of replacement. The originality of this paper resides in presenting a practical approach to determine the optimum drill bit replacement time based on the minimization of total expected replacement cost. Also, the relationship between replacement time and the related costs is quantified.

6.3 Research Methods

The research was conducted in three stages: (i) life data (Weibull) analysis of drill bits, (ii) cost minimization based on optimal replacement time, and (iii) risk analysis based on the differences between costs of predicted replacement and failure replacement. Failure data were provided by

MWD systems to analyze the behavior of drill bits. A Weibull model was fitted to drill bits, and the model parameters were calculated using ReliaSoft® software. Finally, the optimization procedure was applied to determine the optimal replacement time with minimum total expected replacement cost per unit time based on the operating and maintenance cost.

6.3.1 Life Data Analysis (Weibull Analysis)

Replacement decision depends on changes in the performance, reliability, or risk when the equipment or the tool ages. Operating and maintenance records chronicle changes in operating performance, failure rate, and maintenance cost [110] to support replacement decisions. Life data analysis helps to forecast bit life by fitting a statistical representative distribution using failure records. The probability density function *f(t)*, also called the failure density function in reliability work, is used to describe the distribution [115]. It can be defined by Eq. 6-1 [100].

$$f(t) = \frac{dF(t)}{dt} \tag{6-1}$$

where *F(t)* is the cumulative distribution function.

Drill bits are non-repairable items and the times between failures are independent and identically distributed. Therefore, the renewal process can be applied to determine the time to failure. The Weibull distribution is one of the most widely used distributions for life data analysis of independent and identically distributed variables because it can characterize a variety of data forms [115]. The probability density function of the 2-parameter Weibull distribution is given by Eq. 6-2 [101].

$$f(t) = \frac{\beta}{t}\,\frac{t^{\beta}}{\alpha}\;e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{6-2}$$

where β is a shape parameter and α is a scale parameter. The system behavior can be estimated based on β. When β=1, the system is constant. If β<1, the system is improving (i.e., the system reliability increases after the maintenance operation). If β>1, then the system reliability is decreasing [38]. More information can be found in [116].

Mean Time to Failure (MTTF) is one of the most commonly used statistics of life data analysis for non-repairable systems. The general expression of MTTF is presented in Eq. 6-3 and Eq. 6-4 [66].

$$M(t) = \int_0^{\infty} R(t)\, dt \tag{6-3}$$

or

$$M(t) = \int_0^{\infty} t\, f(t) dt \tag{6-4}$$

where $M(t)$ is MTTF and $R(t)$ is the reliability for the specified period of time.\

In the case study, the ModelRisk® software was used to determine the Weibull distribution according to the Schwarz information, Akaike information, and Hannan-Quinn information criteria goodness-of-fit tests.

6.3.2 Cost Minimization Model

The objective is to estimate replacement time to schedule planned replacements, which are less costly than failure replacements. Since it is not possible to find the exact time of a failure, the goal is to reduce the failure replacements to minimize the total expected replacement cost per unit time (C_{tu}), which can be calculated by Eq. 6-5 [117].

$$C_{tu} = \frac{C_t}{t_e} \tag{6-5}$$

where C_t is the total expected replacement cost and t_e is the expected length of a bit usage. C_t and t_e are calculated in Eq. 6-6 and Eq. 6-7, respectively [117].

$$C_t = C_p \times R_{tu} + C_f \times [1 - R_{tu}] \tag{6-6}$$

where C_p is the cost of a predicted replacement, R_{tu} is the probability of a predicted replacement, C_f is the cost of a failure replacement, and $1 - R_{tu}$ is the probability of a failure replacement.

$$t_e = t_p \times R_{tu} + S_p \times [1 - R_{tu}] \tag{6-7}$$

where t_p is the predicted bit usage time, which is the optimum replacement time, and S_p is the expected length of a failure cycle. From Eq. 6-6 and 6-7, C_{tu} can be expressed by Eq. 6-8 [117].

$$C_{tu} = \frac{C_p \times R_{tu} + C_f \times [1 - R_{tu}]}{t_p \times R_{tu} + S_p \times [1 - R_{tu}]} \tag{6-8}$$

The failure density function can also be displayed on a plot (Figure 6-1). The area under the curve is used to determine the probability of the failure in the specified period of time [115].

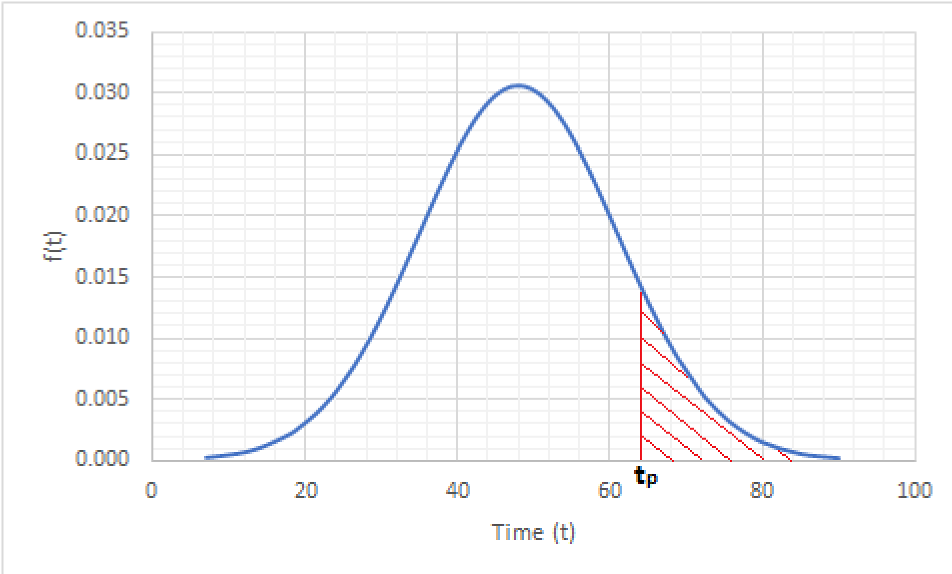

Figure 6-1: Probability density function

The unshaded area of Figure 6-1 represents the probability of a failure occurring before t_p, which is denoted $1\text{-}R_{tu}$. The shaded area is the probability of a failure occurring after t_p, which is denoted R_{tu}. S_p is the mean of the unshaded area (Eq. 6-9) [117].

$$S_p = \int_0^{t_p} \frac{t\, f(t)dt}{1 - R_{tu}} \tag{6-9}$$

The problem is formulated to determine optimal t_p with minimum C_{tu}. The formulation of the minimization of C_{tu} by changing t_p, C_p and C_f is given below. All variables needed to develop an optimization model are calculated from Eq. 5 to Eq. 9. C_p and C_f are constant, and C_{tu} and S_p are functions of t_p. The objective function is given by Eq. 10.

$$Minimize\ C_{tu} = \frac{C_p \times R_{tu} + C_f \times [1 - R_{tu}]}{t_p \times R_{tu} + S_p \times [1 - R_{tu}]} \tag{6-10}$$

The following assumptions must be met.

- The cost of a failure replacement cannot be less than the cost of a predicted replacement.

$$C_f > C_p \tag{6-11}$$

- The predicted length of a bit usage, the cost of a predicted replacement and the cost of a failure replacement are positive integer numbers (N).

$$t_p, C_p \text{ and } C_f \in \mathrm{N} \tag{6-12}$$

- The predicted length of a bit usage is larger than the mean time of the failure times.

$$t_p > S_p \tag{6-13}$$

- The cost of a failure replacement is larger than the cost of a predicted replacement (Otherwise, drill bits can be used until the failure time.).

$$C_f > C_p \tag{6-14}$$

The EA approach provided in the Excel Solver MS Office tool was used to solve this problem. EA is a problem-solving technique based on the principles of biological evolution and commonly used for probabilistic optimizations. It provides feasible solutions called individuals. Recombination (crossover) and mutation are applied to individuals to create new individuals [118]. Possible solutions are represented by the population, which is a dynamic object, unlike the individuals. In most EA applications, the population size is constant, and the worst individual in the population is selected to be replaced by the new better individual (the mutation rate must be small in order to increase the searching ability of the algorithm) [119]. Convergence is a list of criteria that ensure finding the optimal solution in infinite time. More information can be found in [119, 120]. The steps to create the EA model used in this study are given below.

1. Initial EA parameters (e.g., population size and mutation probabilities) are entered.
2. Initial solutions corresponding to population size are created.
3. Solutions are assessed relative to the fitness function.
4. Using crossover and mutation operators and rank evaluation, previous solutions are perturbed, and the new solutions are generated and ordered.
5. These solutions are assessed relative to the fitness function.
6. The best solution is recorded.
7. Steps 4–6 are repeated until EA converges.

6.3.3 Single-Variable Sensitivity Analysis

Sensitivity analysis is used to quantify the effect of variation in input variable C_f in the model, which has a significant effect on the output and consequently, the cost. Single-variable sensitivity analysis is a technique to quantify the effect of variation of a single factor on the outcome while keeping the other factors constant [25].

It is common to use sensitivity analysis in mining research. Al-Chalabi, Lundberg [25] used sensitivity analysis to quantify the effect of the purchase price, operating cost, and maintenance cost of the drilling machine. de Werk, Ozdemir [121] proposed a model to compare the parameters of two different material haulage systems by sensitivity analysis. Ozdemir and Kumral [122] applied sensitivity analysis to determine the impact of variations of explosive price, the unit cost of equipment, and electricity price on the total mining operating cost. Yüksel, Benndorf [123] performed sensitivity analysis to prevent long-range spurious correlations for block size localization in open-cast coal mines.

6.3.4 Monte Carlo Simulation (MC)

MC generates random realizations to find an appropriate solution to a stochastic problem [124]. Sembakutti, Kumral [125] proposed an approach to model fleet availability in open-pit mines by MC. de Werk, Ozdemir [121] applied MC to assess the uncertainty design parameters of material handling systems in open-pit mines. Ozdemir and Kumral [126] generated random variables from a probability distribution with MC for uncertain variables of a material handling system (e.g., loading time, hauling time, and payload).

The failure behavior of the drill bits is simulated to assess the bit replacement decision. First, the failure time is assigned from the 2- parameter Weibull distribution (Figure 6-2). If the predicted time (t_p) is longer than the failure time (t_f), the replacement decision is recorded as a predicted replacement; otherwise, it is recorded as a failure replacement. Once all the replacement decisions are classified, the total cost of the replacement is calculated. This cycle continues until the end of the simulation for a month period.

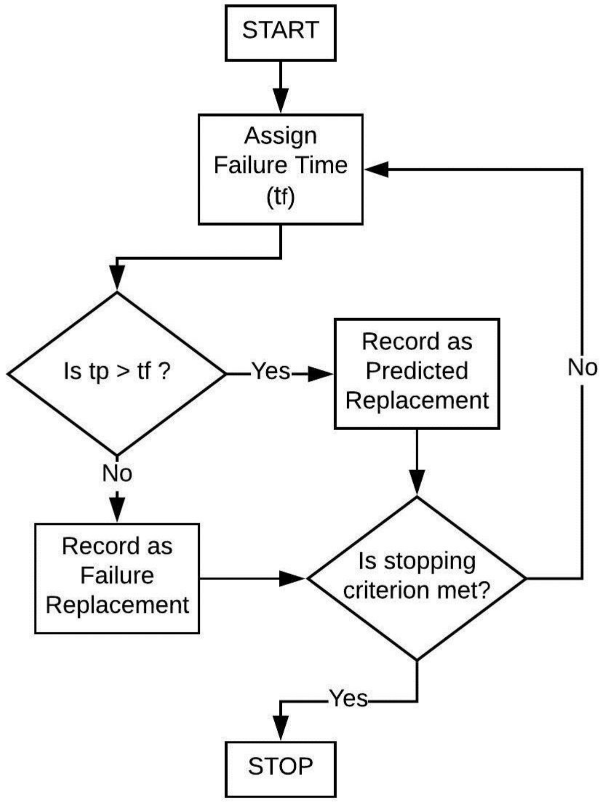

Figure 6-2: Flowchart of the MC simulation model

6.4 Case Study

To evaluate the performance of the proposed approach, a case study was carried out in an open-cast coal mine using the time to failure data collected for 123 rotary drill tri-cone rock roller bits by MWD tools. The probability of drill bit changes being required was 90% between 29 and 67 hours, and the MTTF was approximately 47 hours (Figure 6-3). Bit replacement times varied because of the operating conditions, the heterogeneity on the rock, and geologic characteristics. These results show no trend in the failure data; therefore, the renewal process was conducted, and the 2-parameter Weibull distribution was determined, using $\alpha = 3.8$ and $\beta = 53.3$.

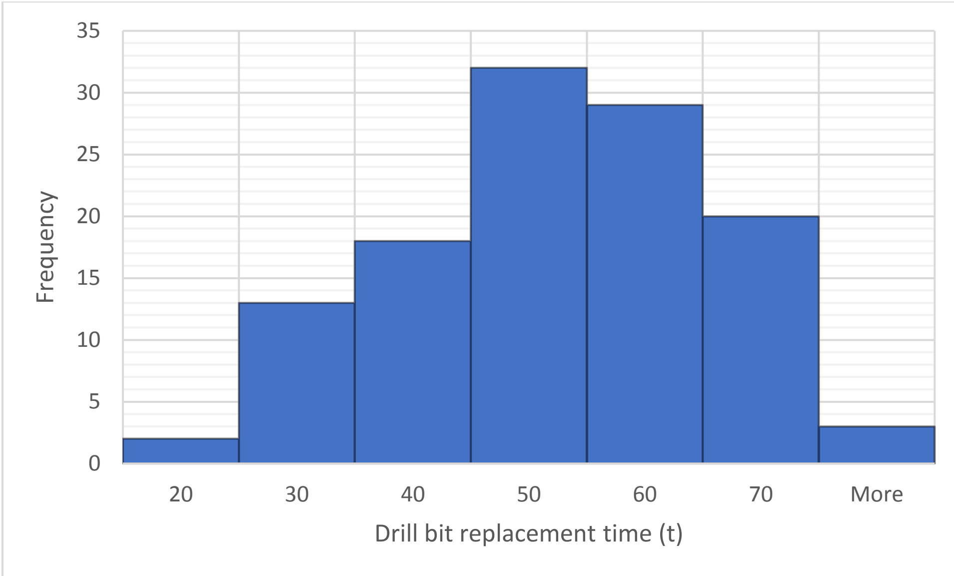

Figure 6-3: Histogram of the failure times of 123 rotary drill tri-cone rock roller bits

After parameter estimation, the failure density function of the drill bits was determined by Eq. 2, and the results were plotted in Figure 6-4. The initial variables, such as R_{tu}, $1\text{-}R_{tu}$, S_p and t_p were selected based on the MTTF.

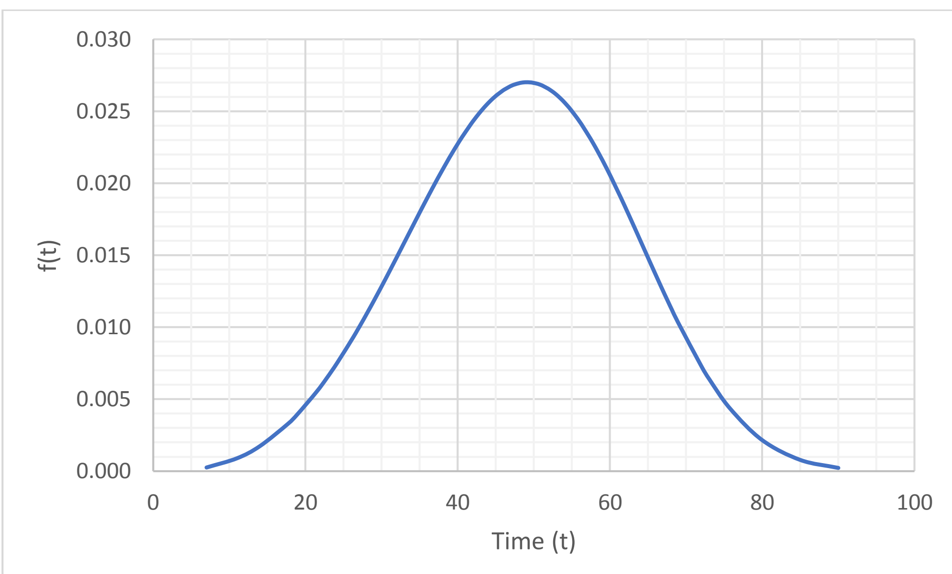

Figure 6-4: Weibull distribution showing failure density function ($f(t)$) of drill bits

The following initial EA parameters were selected: convergence, 0.0001; mutation rate, 0.075; and population size, 100. The solver engine explored 98,319 subproblems in approximately 52 seconds. The optimal variables are given in Table 6-1 and the optimal drill bit replacement time that minimizes C_{tu} (t_p = 51 hours) is illustrated in Figure 6-5. Note that all costs are in Canadian dollars.

Table 6-1: Optimum variables

Variable	Value
C_p (C$)	10,000
C_f (C$)	15,000
R_{tu}	0.43
$1–R_{tu}$	0.57
S_p (h)	38.00
t_p (h)	51.00
C_{tu} (C$/h)	293.77

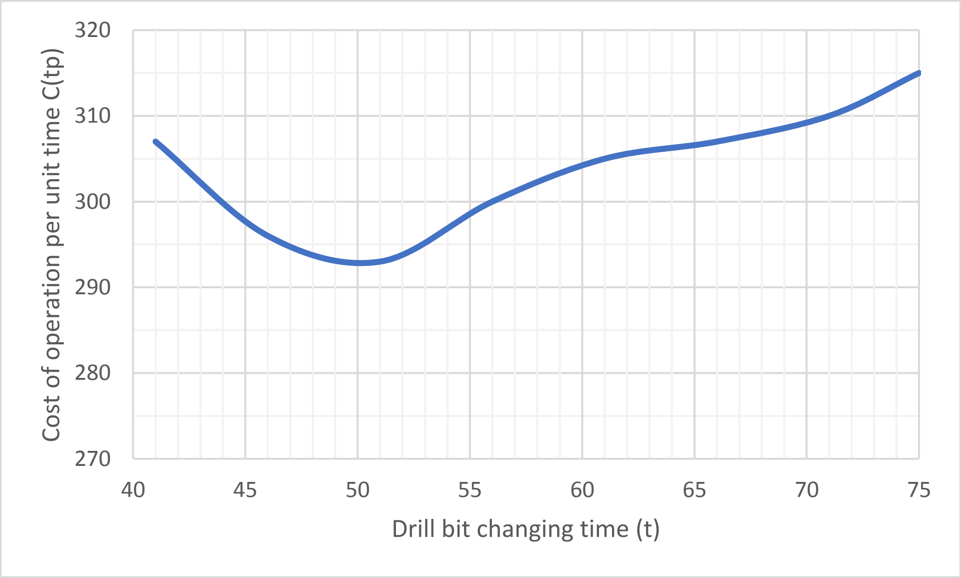

Figure 6-5: Optimal drill bit replacement time

From Figure 6-5, it is evident that there is a slight difference between changing the bit in 47 hours and 51 hours in terms of the cost of operation per unit time ($0.5). However, changing the bit before the end of beneficial life incurs a substantial cost to the company, approximately 8% less operation time per bit. In other words, drill bit consumption increases by approximately 14 bits per machine per year, a cost of around $70,000. On the other hand, if the bit is changed 4 hours after t_p, the cost increases $7.0 per unit time and the probability of failure increases by 70%.

These results strongly depend on the cost of failure replacement, which affects the risk of the replacement decision. Therefore, a single-variable sensitivity analysis was performed to identify the effect of the variation (Table 6-2). An increase in the C_f has a considerable positive impact on C_{tu} and negative impact on t_p. The latter impact is due to the increased risk of replacement decision-making. A 10% increase in the C_f, leads to an increase in C_{tu} of approximately $17 and a decrease in t_p of 5 hours.

Table 6-2: Results of sensitivity analysis

Variation of C_f (%)	**C_{tu} ($)**	**t_p (h)**
0	293.77	51
10	310.35	46
20	326.00	45
30	341.14	44
40	353.60	40

To test the feasibility of the proposed approach, 100 randomly scenarios were created by MC using six predicted times to replace drill bits for six circumstances used to compare the minimization results. The possible outcomes of the total replacement cost in a month (assuming C$5,000 per bit) are given in Table 6-3. The total bit usage and replacement costs were lowest for the 51-hour replacement time. Compared to the 47-hour replacement time, the total replacement cost is 11% lower, which agrees with the optimization results shown in Figure 6-5.

To investigate the relationship between the predicted replacement time and the total drill bit replacement cost, a regression equation was fitted using SPSS® software (Eq. 6-15).

$$C_t = 485.49 \times t_p^2 - 49462 \times t_p + 151 \times 10^4 \quad (6\text{-}15)$$

The R-square of the proposed quadratic model is 0.89, showing that the fitted curve is close to the model.

Table 6-3: Predicted drill bit replacement times and costs based on MC

Predicted Replacement Time (h) (t_p)	Number of Predicted Replacements	Number of Failure Replacements	Total number of bit used	Total Replacement Cost (C$) (Replacement Cost + Bit Cost) (C_t)
43	12	5	17	280,000
47	11	5	16	265,000
51	9	5	14	235,000
55	6	9	15	270,000
59	4	11	15	280,000
63	4	13	17	320,000

6.5 Conclusion

This chapter proposes a practical approach through a cost minimization model to determine optimum replacement time for drill bits based on replacement costs. The approach presented herein is based on failure data of the drill bits and the maintenance cost of the replacements. First, the

Weibull life data analysis was applied to time-to-failure data to obtain the parameters of the model. Replacement time was formulated as a minimization problem. In a case study, the EA was used to determine the optimum time to change the drill bits for an open-cast mining operation. Model results show that increasing the operating time of drill bits by 8% can make a considerable impact on the total replacement cost of a drilling operation. The proposed approach can be used to facilitate decision-making for replacement scheduling.

In addition, a sensitivity analysis was conducted to quantify the relative importance of the cost of a failure replacement. Results indicate that increasing the cost of a failure replacement negatively affects the total cost of expected replacements per unit time and the length of the predicted cycle (the optimum replacement time). In other words, when the cost of a failure replacement increases, the optimum interval time to use the drill bits decreases. Thus, the proposed approach can also be used to assess the risk of the replacement decision.

MC simulation was implemented to determine the variation of total replacement cost. The total replacement cost can be reduced by approximately 11% by using a 51-hour replacement time relative to a 47-hour replacement time. Hence, the simulation results support the consistency of the proposed approach.

Lastly, the relationship between drill bit replacement time and the total drill bit replacement cost was formulated by a quadratic regression equation using the results of the MC simulation. Using this equation, the total replacement cost can be calculated when the drill bit replacement time is chosen.

CHAPTER 7

7. CONCLUSION AND FUTURE WORK

7.1 Conclusion

This thesis introduced a variety of statistical tools and simulation techniques aimed to help mining companies to optimize drilling operations in order to reduce operating costs. The contribution of this research is to provide scientific solutions for decision-making problems instead of experience-based solutions. In this thesis, modeling, simulation, and optimization procedures were applied to rotary drilling with tri-cone tungsten carbide bits in surface mining operations in order to develop a continuous improvement tool for bench drilling operations. Given that the production plans are dependent on mining activities, the proposed approach increases the feasibility of production plans. All the results obtained are case-specific. For each mine, the proposed approach should be repeated.

Early phases of the research were dedicated to using experimental design tools to determine the best configuration of controllable drilling parameters that increase the ROP and optimize operating cost. Through a detailed analysis of the monitored data, the optimum drilling time for a hole was calculated for different bit conditions.

Drilling operation performance was quantified based on energy consumption. A cost minimization problem was formulated to establish a relationship between controllable parameters and energy cost and bit replacement time was modeled using evolutionary algorithms. The effects of controllable parameters based on the bit condition were described. Results of a case study showed that the proposed approach could be used as a tool for optimizing controllable parameters associated with cost minimization.

The risks emerging from production rate and mine management were quantified. Through reliability analysis, the production amount was associated with the number of holes to be drilled based on the number of available drilling machines. Since equipment availability is stochastic, a range of holes can be drilled corresponding to a specified probability level, determined based on historical data. A case study assessed the performance of the proposed approach using two stochastic modeling methods: Markov Chain Monte Carlo and Mean Reverting. Multiple simulations were generated by both methods to quantify the risk of uncertain events such as drill bit changing time, maintenance time, drilling time, the number of pieces of equipment available, the required number of drill bits, and the number of intended drill holes. The consistent simulation results demonstrated that the proposed method could be a useful tool to assist in production scheduling and assess the associated risk.

The subsequent part of the research involved forecasting the required number of drill bits associated with the optimum replacement time of the bits. To quantify the evolution of the wear over the time, a comprehensive regression analysis was carried out based on time series data. The relationship between reliability and machine performance was also quantified by the equally weighted moving average method, which allows practitioners to use reliability as an independent variable in a drilling operation. The drilling operation was then modeled and simulated by DES to measure the feasibility of the production plans and assist production scheduling and asset management.

Finally, the effect of replacement cost on the optimum replacement time was incorporated to assess the risk of the replacement decision. Replacement time was formulated, and then the optimum replacement interval was determined based on cost minimization. A variation of total replacement cost based on predicted and failure costs was demonstrated by the implementation of the Monte

Carlo simulation. Lastly, the relationship between replacement time and the total replacement cost was established by a quadratic regression equation using the results of the simulation. By using this equation, the total replacement cost can be practically calculated based on the replacement time.

The methods explored in the thesis can be used to contribute to developing sustainable operations with continuous improvement. These methods are not applicable for the feasibility studies of a mining operation because historical datasets such as failure times of the equipment, operating parameters, drilling time and ROP, as well as rock characterization, are needed to apply proposed models.

7.2 Future Work

Although this thesis has elucidated detailed information about rotary drilling operations, additional field studies are needed to quantify the effects on the drilling operation of physical and mechanical properties of the rock formation such as UCS, hardness, abrasiveness, and elasticity. In addition, monitoring of drilling operations offers great potential to optimize mining applications and consequently minimize operating costs. However, the link between the drilling operation and other phases of the production cycle should also be considered to investigate the impact of the drilling operation on blasting and materials handling. Furthermore, many sensors are used in drilling operation such that more information about rock can be collected. The proposed statistical tools can be integrated with information of sensor data. Thus, the efforts of autonomous drilling can benefit from this research.

The importance of maintenance activities is inevitable. Thus, in future studies, the variables that affect the maintenance cost should also be investigated in detail. The constants of the objective function, the cost of a failure replacement, and the cost of a predicted replacement should be modeled as the functions of maintenance cost elements, and the total cost of the replacement should be re-formulated with these cost elements.

In addition, this thesis has not addressed the quantification of seasonal effect. The efficiency of drilling operation is directly affected by the condition of the rock formation. In winter time, the resistance of a material to break under compression increases and the ground is more stabilized due to the frozen environment. Therefore, it is hard to handle drilling operation with the frozen ground condition. More energy is needed to achieve desirable operation. In spring and fall time, blast-holes might be wet. It decreases the efficiency of the cutting tools, and it also makes harder to eject rock cutting from blast-holes because the particles can stick on the drill bit and the drill rod. Thus, ROP might be decreased. Moreover, additional operations such as dewatering might be needed to fill explosives to the holes. In summer time, the risk of the thermic wear is getting higher due to high temperature. It reduces the life length of the drill bits. Therefore, the seasonal differences have a huge impact on the condition of the rock formation and it is important to quantify this impact in order to have the desired drilling operation.

REFERENCES

[1] Lopez Jimeno C, Lopez Jimeno E, Ayala Carcedo FJ. Rock Drilling Methods. Drilling and blasting of rocks. Rotterdam: A.A. Balkema; 1995. p. 1-7.

[2] Karpuz C. Energy efficiency of drilling operations. Energy Efficiency in the Minerals Industry: Springer; 2018. p. 71-86.

[3] Gokhale BV. Surface rock excavation scenario. Rotary drilling and blasting in large surface mines. Leiden, The Netherlands: CRC Press/Balkema; 2011. p. 1-14.

[4] Strelec S, Gazdek M, Mesec J. Blasting design for obtaining desired fragmentation. Tehnički vjesnik. 2011;18:79-96.

[5] Lopez Jimeno C, Lopez Jimeno E, Ayala Carcedo FJ. Properties of explosives. Drilling and blasting of rocks. Rotterdam: A.A. Balkema; 1995. p. 98-105.

[6] Bilgin N, Copur H, Balci C. Physical and Mechanical Properties of Rocks, Soils and Coals. Mechanical excavation in mining and civil industries: CrC Press; 2013. p. 23-48.

[7] Committee ADIT. Drilling Equipment and Methods. In: Hilliard V, editor. Drilling–The manual of methods, applications, and management. 4th ed. Boca Raton,Florida: Lewis Publishers; 1997. p. 51-110.

[8] Lopez Jimeno C, Lopez Jimeno E, Ayala Carcedo FJ. Rotary percussive drilling. Drilling and blasting of rocks. Rotterdam: A.A. Balkema; 1995. p. 8-35.

[9] AtlasCopco. Blasthole Drilling in Open Pit Mining. In: Solutions ACD, editor. 3 ed. Garland, USA2012.

[10] Kricak L, Miljanovic I, Mitrovic S, Negovanovic M, Nuric A, Nuric S. Development of a fuzzy model for predicting the penetration rate of tricone rotary blasthole drilling in open pit mines. Journal of the Southern African Institute of Mining and Metallurgy. 2015;115:1065-71.

[11] Lopez Jimeno C, Lopez Jimeno E, Ayala Carcedo FJ. Rotary drilling with tricone bits. Drilling and blasting of rocks. Rotterdam: A.A. Balkema; 1995. p. 48-63.

[12] Gokhale BV. An overview of blasthole drilling. Rotary drilling and blasting in large surface mines. Leiden, The Netherlands: CRC Press/Balkema; 2011. p. 15-29.

[13] Plinninger RJ, Spaun G, Thuro K. Predicting tool wear in drill and blast. Tunnels & Tunneling International Magazine. 2002:1-5.

[14] Gokhale BV. Flushing the blasthole. Rotary drilling and blasting in large surface mines. Leiden, The Netherlands: CRC Press/Balkema; 2011. p. 295-326.

[15] Aboujaoude CE. Feedback control of vibrations in surface rotary blasthole drilling [PhD Thesis]: McGill University, Canada; 1997.

[16] Teale R. The concept of specific energy in rock drilling. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts: Elsevier; 1965. p. 57-73.

[17] Scoble M, Peck J, Hendricks C. Correlation beween rotary drill performance parameters and borehole geophysical logging. Mining Science and Technology. 1989;8:301-12.

[18] Liu H, Karen Yin K. Analysis and interpretation of monitored rotary blasthole drill data. International Journal of Surface Mining, Reclamation and Environment. 2001;15:177-203.

[19] Peck JP. Application of drill monitoring to rock mass characterization [Master's]. Montreal, Canada: McGill University; 1986.

[20] Peck JP. Performance monitoring of rotary blasthole drills [PhD]. Montreal, Canada: McGill University; 1989.

[21] Hatherly P, Leung R, Scheding S, Robinson D. Drill monitoring results reveal geological conditions in blasthole drilling. International Journal of Rock Mechanics and Mining Sciences. 2015;78:144-54.

[22] Ghosh R, Schunnesson H, Kumar U. The use of specific energy in rotary drilling: the effect of operational parameters. International Symposium on the Application of Computers and Operations Research in the Mineral Industry: 23/05/2015-27/05/20152015.

[23] Ataei M, KaKaie R, Ghavidel M, Saeidi O. Drilling rate prediction of an open pit mine using the rock mass drillability index. International Journal of Rock Mechanics and Mining Sciences. 2015;73:130-8.

[24] Ergin H, Kuzu C, Balci C, Tunçdemir H, Bilgin N. Optimum bit selection and operation for the rotary blasthole drilling using a Horizontal Drilling Rig (HDR)-A case study at KBI Murgul Copper Mine. International Journal of Surface Mining, Reclamation and Environment. 2000;14:295-304.

[25] Al-Chalabi H, Lundberg J, Ahmadi A, Jonsson A. Case Study: Model for economic lifetime of drilling machines in the Swedish mining industry. The Engineering Economist. 2015;60:138-54.

[26] Lucifora D. Autonomous surface rotary blasthole drilling. Comprehensive Examination Report McGill University; 2019.

[27] Rafezi H. Drill bit wear monitoring and failure prediction. Comprehensive Examination Report McGill University; 2019.

[28] Rahimdel MJ, Ataei M, Khalokakaei R. Reliability Analysis and Maintenance Scheduling of the Electrical System of Rotary Drilling Machines. Current Trends in Reliability, Availability, Maintainability and Safety: Springer; 2016. p. 623-32.

[29] Barabadi A, Barabady J, Markeset T. Application of reliability models with covariates in spare part prediction and optimization–a case study. Reliability Engineering & System Safety. 2014;123:1-7.

[30] Ghodrati B, Kumar U. Operating environment-based spare parts forecasting and logistics: a case study. International Journal of Logistics Research and Applications. 2005;8:95-105.

[31] Balaraju J, Govinda Raj M, Murthy C. Estimation of reliability-based maintenance time intervals of Load-Haul-Dumper in an underground coal mine. Journal of Mining and Environment. 2018;9:761-70.

[32] Javanmard H, Koraeizadeh Aa-W. Optimizing the preventive maintenance scheduling by genetic algorithm based on cost and reliability in National Iranian Drilling Company. Journal of Industrial Engineering International. 2016;12:509-16.

[33] Basu AJ, Baafi EY. Discrete event simulation of mining systems: current practice in Australia. International Journal of Surface Mining, Reclamation and Environment. 1999;13:79-84.

[34] Dindarloo S, Siami-Irdemoosa E. Merits of discrete event simulation in modelling mining operations. SME Annual Meeting. Phoenix, AZ.2016.

[35] Dindarloo S, Osanloo M. Results of discrete event simulation in a large open pit mine. SME Annual Meeting. Denver, CO.2015.

[36] Botín JA, Campbell AN, Guzmán R. A discrete-event simulation tool for real-time management of pre-production development fleets in a block-caving project. International Journal of Mining, Reclamation and Environment. 2015;29:347-56.

[37] Yuriy G, Vayenas N. Discrete-event simulation of mine equipment systems combined with a reliability assessment model based on genetic algorithms. International Journal of Mining, Reclamation and Environment. 2008;22:70-83.

[38] Najim K, Ikonen E, Daoud A-K. Stochastic processes: estimation, optimisation and analysis: Elsevier; 2004.

[39] Kaba FA, Temeng VA, Eshun PA. Application of Discrete Event Simulation in Mine Production Forecast. Ghana Mining Journal. 2016;16:40-8.

[40] Yarmuch J, Epstein R, Cancino R, Peña JC. Evaluating crusher system location in an open pit mine using Markov chains. International Journal of Mining, Reclamation and Environment. 2017;31:24-37.

[41] Ortiz J, Magri E, Líbano R. Improving financial returns from mining through geostatistical simulation and the optimized advance drilling grid at El Tesoro Copper Mine. Journal of the Southern African Institute of Mining and Metallurgy. 2012;112:15-22.

[42] Ghosh R, Schunnesson H, Kumar U. Evaluation of operating life length of rotary tricone bits using Measurement While Drilling data. International Journal of Rock Mechanics and Mining Sciences. 2016;83:41-8.

[43] Fox B. Putting rotary drilling into perspectvie. Blasthole Drilling in Open Pit Mines: Atlas Copco; 2012. p. 6.

[44] Fiscor S. New System Manages Main Compressor on Rotary Drills. Engineering and Mining Journal2011. p. 4.

[45] Kahraman S, Balcı C, Bilgin N. Prediction of the penetration rate of rotary blast hole drills using a new drillability index. International Journal of Rock Mechanics and Mining Sciences. 2000;37:729-43.

[46] Taheri A, Qao Q, Chanda E. Drilling penetration rate estimation using rock drillability characterization index. Journal of The Institution of Engineers (India): Series D. 2016;97:159-70.

[47] Irawan S, Rahman AMA, Tunio SQ. Optimization of weight on bit during drilling operation based on rate of penetration model. Research Journal of Applied Sciences, Engineering and Technology. 2012;4:1690-5.

[48] Tail M, Yacout S, Balazinski M. Replacement time of a cutting tool subject to variable speed. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture. 2010;224:373-83.

[49] Hoseinie S, Ataei M, Osanloo M. A new classification system for evaluating rock penetrability. International Journal of Rock Mechanics and Mining Sciences. 2009;46:1329-40.

[50] Sheu S-H, Chien Y-H, Chang C-C, Chiu C-H. Optimal Trivariate Replacement Policies for a Deteriorating System. Quality Technology & Quantitative Management. 2014;11:307-20.

[51] Myers RH, Montgomery DC, Anderson-Cook C. Response surface methodology2009.

[52] Montgomery DC. Introduction to statistical quality control: John Wiley & Sons (New York); 2009.

[53] Jeong I-J, Lee D-H. Generating evenly distributed nondominated solutions in dual response surface optimization. Quality Technology & Quantitative Management. 2017:1-17.

[54] Box GE, Draper NR. Empirical model-building and response surfaces: John Wiley & Sons; 1987.

[55] Mourabet M, El Rhilassi A, El Boujaady H, Bennani-Ziatni M, El Hamri R, Taitai A. Removal of fluoride from aqueous solution by adsorption on Apatitic tricalcium phosphate using Box–Behnken design and desirability function. Applied Surface Science. 2012;258:4402-10.

[56] Candioti LV, De Zan MM, Cámara MS, Goicoechea HC. Experimental design and multiple response optimization. Using the desirability function in analytical methods development. Talanta. 2014;124:123-38.

[57] Liu J, Tang L. A modified genetic algorithm for single machine scheduling. Computers & Industrial Engineering. 1999;37:43-6.

[58] Lamghari A, Dimitrakopoulos R. A diversified Tabu search approach for the open-pit mine production scheduling problem with metal uncertainty. European Journal of Operational Research. 2012;222:642-52.

[59] Kumral M. Optimizing ore–waste discrimination and block sequencing through simulated annealing. Applied Soft Computing. 2013;8:3737-44.

[60] Kumral M, Ozer U. Planning additional drilling campaign using two-space genetic algorithm: A game theoretical approach. Computers & geosciences. 2013;52:117-25.

[61] Shishvan MS, Sattarvand J. Long term production planning of open pit mines by ant colony optimization. European Journal of Operational Research. 2015;240:825-36.

[62] Eren T, Ozbayoglu ME. Real time optimization of drilling parameters during drilling operations. SPE Oil and Gas India Conference and Exhibition: Society of Petroleum Engineers; 2010.

[63] Hall RA, Daneshmend LK. Reliability modelling of surface mining equipment: data gathering and analysis methodologies. International Journal of Surface Mining, Reclamation and Environment. 2003;17:139-55.

[64] Rahimdel MJ, Ataei M, Kakaei R, Hoseinie SH. Reliability Analysis of Drilling Operation in Open Pit Mines/Analiza niezawodności urządzeń wiertniczych wykorzystywanych w kopalniach odkrywkowych. Archives of Mining Sciences. 2013;58:569-78.

[65] Ebeling CE. An introduction to reliability and maintainability engineering: Tata McGraw-Hill Education; 2004.

[66] Elsayed EA. Reliability engineering: John Wiley & Sons; 2012.

[67] Wang P, Coit DW. Repairable systems reliability trend tests and evaluation. Reliability and Maintainability Symposium, 2005 Proceedings Annual: IEEE; 2005. p. 416-21.

[68] Rahimdel MJ, Ataei M, Khalokakaei R, Hoseinie SH. Reliability-based maintenance scheduling of hydraulic system of rotary drilling machines. International journal of mining science and technology. 2013;23:771-5.

[69] Nageshwaraniyer SS, Son Y-J, Dessureault S. Simulation-based optimal planning for material handling networks in mining. Simulation. 2013;89:330-45.

[70] Geyer C. Introduction to markov chain monte carlo. Handbook of markov chain monte carlo. 2011:3-48.

[71] Pilipovic D. Energy risk: Valuing and managing energy derivatives: McGraw-Hill New York; 1998.

[72] Ozdemir B, Kumral M. Stochastic Assessment of the Material Haulage Efficiency in the Earthmoving Industry. Journal of Construction Engineering and Management. 2017;143.

[73] Basarir H, Karpuz C. Preliminary estimation of rock mass strength using diamond bit drilling operational parameters. International Journal of Mining, Reclamation and Environment. 2016;30:145-64.

[74] Al-Chalabi H, Hoseinie H, Lundberg J. Monte Carlo reliability simulation of underground mining drilling rig. Current Trends in Reliability, Availability, Maintainability and Safety: Springer; 2016. p. 633-43.

[75] Crow LH. Reliability analysis for complex, repairable systems. Army Material Systems Analysis Activity Aberdeen Proving Ground MD; 1975.

[76] Alessandro B. Reliability engineering theory and practice. Springer Heidelberg Dordrecht London New York; 2010. p. 458-88.

[77] Gelman A, Rubin DB. Inference from iterative simulation using multiple sequences. Statistical science. 1992;7:457-72.

[78] Hillier F, Lieberman G. Markov Chains. Advance Praise for Introduction to Operation Research 7th ed. New York, USA: McGraw-Hill Higher Education; 2001. p. 802-33.

[79] Andrieu C, De Freitas N, Doucet A, Jordan MI. An introduction to MCMC for machine learning. Machine learning. 2003;50:5-43.

[80] Kumral M, Sari YA. Simulation-based mine extraction sequencing with chance constrained risk tolerance. Simulation. 2017;93:527-39.

[81] Pang W-K, Forster JJ, Troutt MD. Estimation of wind speed distribution using Markov chain Monte Carlo techniques. Journal of Applied Meteorology. 2001;40:1476-84.

[82] Malhotra Y. Markov Chain Monte Carlo Models, Gibbs Sampling, & Metropolis Algorithm for High-Dimensionality Complex Stochastic Problems. 2014.

[83] Mardia K, Nyirongo V, Walder A, Xu C, Dowd P, Fowell R, et al. Markov Chain Monte Carlo implementation of rock fracture modelling. Mathematical Geology. 2007;39:355-81.

[84] Hong G, Sarkar S. Commodity betas with mean reverting output prices. Journal of Banking & Finance. 2008;32:1286-96.

[85] Carcano G, Falbo P, Stefani S. Speculative trading in mean reverting markets. European Journal of Operational Research. 2005;163:132-44.

[86] Exley J, Mehta S, Smith A. Mean reversion. Finance and Investment Conference: Citeseer; 2004. p. 1-31.

[87] Swishchuk AV. Explicit option pricing formula for a mean-reverting asset in energy market. Journal of Numerical and Applied Mathematics. 2008;1:216-33.

[88] Triantafyllopoulos K, Montana G. Dynamic modeling of mean-reverting spreads for statistical arbitrage. Computational Management Science. 2011;8:23-49.

[89] Zhang Q, Zhuang C, Yin G. Stochastic Algorithms and Numerics for Mean-Reverting Asset Trading. Stochastic Analysis, Stochastic Systems, And Applications To Finance: World Scientific; 2011. p. 245-61.

[90] Leite A, Dimitrakopoulos R. Stochastic optimization of mine production scheduling with uncertain ore/metal/waste supply. International journal of mining science and technology. 2014;24:755-62.

[91] Louit D, Pascual R, Banjevic D, Jardine AK. Optimization models for critical spare parts inventories—a reliability approach. Journal of the Operational Research Society. 2011;62:992-1004.

[92] Jamshidi M, Osanloo M. Reliability analysis of production schedule in multi-element deposits under grade-tonnage uncertainty with multi-destinations for the run of mine material. International journal of mining science and technology. 2018.

[93] Jardine AK, Tsang AH. Maintenance, replacement, and reliability: theory and applications: CRC press; 2013.

[94] Ugurlu OF, Kumral M. Reliability-based performance analysis of mining drilling operations through Markov-Chain Monte-Carlo and Mean Reverting process simulations. Under Review. 2018.

[95] Bilgin N. Investigations into the mechanical cutting characteristics of some medium and high strength rocks: University of Newcastle; 1977.

[96] Koronka F, Takacs F, Andras I. The influence of rock properties on the wear of mining tools for rotating drilling. Revista Minelor/Mining Revue. 2009;15.

[97] Basarir H, Tutluoglu L, Karpuz C. Penetration rate prediction for diamond bit drilling by adaptive neuro-fuzzy inference system and multiple regressions. Engineering Geology. 2014;173:1-9.

[98] Shqair M, Altarazi S, Al-Shihabi S. A statistical study employing agent-based modeling to estimate the effects of different warehouse parameters on the distance traveled in warehouses. Simulation Modelling Practice and Theory. 2014;49:122-35.

[99] Ozdemir B, Kumral M. Appraising production targets through agent-based Petri net simulation of material handling systems in open pit mines. Submitted. 2018.

[100] Dhillon BS. Mining equipment reliability, maintainability, and safety: Springer Science & Business Media; 2008.

[101] Tobias PA, Trindade D. Weibull Distribution. Applied reliability. Boca Raton, FL: CRC Press; 2012. p. 87-113.

[102] Janacek GJ. Practical time series. New York: Oxford Unversity Press; 2001.

[103] Mathew S, Kennedy D. A strategy for optimal equipment replacement. Production Planning & Control. 2003;14:571-7.

[104] Atanassov E, Dimov IT. What Monte Carlo models can do and cannot do efficiently? Applied Mathematical Modelling. 2008;32:1477-500.

[105] Freedman DA. Statistical models: theory and practice: cambridge university press; 2009.

[106] Ugurlu OF, Kumral M. Analyzing drilling machine in aid to improve open pit mining operations. Rock Mechanics and Rock Engineering: From the Past to the Future2016. p. 171.

[107] Ugurlu OF, Kumral M. Drilling Operation Monitoring with Statistical Tools. 6th International Conference on Computer Applications in the Minerals Industries. Istanbul, Turkey: AGRO ARGE; 2016.

[108] Ugurlu OF, Kumral M. Optimization of Drill Bit Replacement Time in Bench Drilling. 24th World Mining Congress Rio de Janeiro, Brazil2016. p. 357-66.

[109] Afeni TB. Optimization of drilling and blasting operations in an open pit mine—the SOMAIR experience. Mining Science and Technology (China). 2009;19:736-9.

[110] Hastings NA. Physical asset management: Springer; 2010.

[111] Tsang AH. Condition-based maintenance: tools and decision making. Journal of Quality in Maintenance Engineering. 1995;1:3-17.

[112] Verma A, Srividya A, Gaonkar R. Maintenance and replacement interval optimization using possibilistic approach. International Journal of Modelling and Simulation. 2007;27:193-9.

[113] Godoy DR, Pascual R, Knights P. Value-based optimisation of replacement intervals for critical spare components. Int J Min Reclam Environ International Journal of Mining, Reclamation and Environment. 2017:1-9.

[114] Li X, Tso S. Drill wear monitoring based on current signals. Wear. 1999;231:172-8.

[115] ReliaSoft. Life Data Analysis Reference. Tucson, Arizona: ReliaSoft Corporation; 2015. p. 438.

[116] Ugurlu OF, Kumral M. Evaluation of bench drilling operations based on reliability analysis and discrete event simulation in surface mines. Under Review. 2018.

[117] Campbell JD, Jardine AK. Maintenance excellence: optimizing equipment life-cycle decisions: CRC Press; 2001.

[118] Muszyński J, Varrette S, Bouvry P, Seredyński F, Khan SU. Convergence analysis of evolutionary algorithms in the presence of crash-faults and cheaters. Computers & Mathematics with Applications. 2012;64:3805-19.

[119] Eiben AE, Smith JE. Introduction to evolutionary computing: Springer; 2003.

[120] Ugurlu OF, Kumral M. Cost optimization of drilling operations in open-pit mines through parameter tuning. Under Review. 2018.

[121] de Werk M, Ozdemir B, Ragoub B, Dunbrack T, Kumral M. Cost analysis of material handling systems in open pit mining: Case study on an iron ore prefeasibility study. The Engineering Economist. 2017;62:369-86.

[122] Ozdemir B, Kumral M. A system-wide approach to minimize the operational cost of bench production in open-cast mining operations. International Journal of Coal Science & Technology. 2018.

[123] Yüksel C, Benndorf J, Lindig M, Lohsträter O. Updating the coal quality parameters in multiple production benches based on combined material measurement: A full case study. International Journal of Coal Science & Technology. 2017;4:159-71.

[124] Shonkwiler RW, Mendivil F. How can random numbers solve problems. Explorations in Monte Carlo methods. Dordrecht Springer Verlag; 2009. p. 1-9.

[125] Sembakutti D, Kumral M, Sasmito AP. Analysing equipment allocation through queuing theory and Monte-Carlo simulations in surface mining operations. International Journal of Mining and Mineral Engineering. 2017;8:56-69.

[126] Ozdemir B, Kumral M. Appraising production targets through agent-based Petri net simulation of material handling systems in open pit mines. Simulation Modelling Practice and Theory. 2018;87:138-54.