Electric Rope Shovel Operation Enhancements, Understanding and Modelling the Impact of The Operator

by

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1. ABSTRACT

The loading and haulage system is considered a prominent part of a surface mine operation. Improving the system enhances the productivity and economics of an operation to a great extent. Operators play a critical role in the mine overall performance and production. Autonomous truck fleets have been utilized and proven to be effective in mitigating the influence of operators' and improve mine production. However, there is limited work that focusses on the influence of shovel operators on mine production nor on the potential benefits of autonomous or semi-autonomous shovels.

This thesis uses detailed data available from a shovel health and payload monitoring system to study the important role of an operator in the shovel and mine production and performance. It introduces a metric that captures operators' efficiency, identify opportunities for improvement, and last but not least, proposes a methodology to study the extent to which any proposed improvement including automation could enhance the shovel, truck and mine operation.

Based on the knowledge gained from performing a statistical analysis on a shovel operation database, the "Operator Relative Score" (ORS) is developed. Dig, swing and return times, bucket load and number of passes to load a truck are identified as critical tasks with variations among operators. The ORS is implemented in a case study that led to identify best and worst productive rope shovel operators. To further study the nature and influence of variations among operator practices on overall production, a discrete event simulation submodule is developed that includes operator behavior and this is integrated into a surface mine operation discrete event simulation

model. Results showed that an electric rope shove operator could affect shovel production, number of trucks, and queue times by up to 20, 16, and 41%, respectively.

To mitigate the influence of operators on production two techniques are introduced. “Dynamic Target Loading” (DTL) as a tool to provide an operator with the flexibility needed to reduce loading time and compensate for situations where trucks are waiting at loading queue. Its potential to improve the overall mine production is evaluated using the developed discrete event simulation model. Results confirmed that in addition to lower wait time and number of trucks in queue, the overall shovel production can be increased by 12.1%.

The second measure introduced in this research is “Projected Hourly Production” (PHP). This KPI respects the 10:10:20 rule, combines loaded truck final load ratio with the loading cycle time and compares the result with the best recorded practice. The result provides the operator with tangible feedback on their loading strategies and can help them optimize their tactics. It is envisioned that by having the KPI compare an individual operator’s performance to that of the best operator this will enables mining companies to identify operators that need training. In addition, this KPI can be used by all mining companies to quantify the impact of any piloted advanced technologies.

Lastly, a methodology to investigate the extent to which different levels of shovel automation can improve shovel performance is developed. Using the developed discrete event simulation model four levels of automation are evaluated. Result showed a potential 40.6% increase in production through successful development and deployment of an autonomous shovel. It is envisioned that in some situations there is an opportunity to reduce the shovel fleet size without compromising production level.

2. PREFACE

This thesis is an original work by Ali Yaghini. Following parts of this work have been previously published:

- Human factors and human error in the mining industry: A review and lessons from other industries. A. Yaghini, Y. Pourrahimian, and R. A. Hall, 2017 CIM Journal.
- The Human Factor Analysis and Classification System (HFACS); a review and lessons from other industries. A. Yaghini, Y. Pourrahimian, R. Hall, 2017 CIM MEMO Conference.
- Optimum shovel performance, the underlying role of operators loading practices. A. Yaghini, R. Hall. 2019 CIM MEMO.
- Modeling the influence of electric shovel operator performance on mine productivity. A. Yaghini, R. A. Hall & D. Apel. 2020 CIM Journal.

The mine discrete event simulation model used in this study was partially developed as part of the author's course project in the MIN E 641 and MIN E 661 courses. The original and independent work by the author was carried out under the supervision of Professor Robert Hall in the Department of civil and environmental engineering, school of mining and petroleum.

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7. List of Abbreviations and Acronyms

3D	Three-Dimensional
AHP	Analytic Hierarchy Process
AR	Augmented Reality
BL	Bucket Load
CM	Continuous Miner
DES	Discrete Event Simulation
DTL	Dynamic Target Loading
ERS	Electric Rope Shovel
GPS	Geographical Positioning System
HCD	Human-Centred Design
HE	Human Error
HEP	Human Error Probability
HF	Human Factor
HFACS	Human Factor Analysis and Classification System
HMI	Human Machine Interface
KPI	Key Performance Indicator
MAP	Maintenance Assistance Platform
MEDA	Maintenance Error Decision Aid
NIOSH	National Institute for Occupational Safety and Health
NoP	Number of Passes
OHS	Occupational Health and Safety

ORS	Operator Relative Score
PErforM	Participative Ergonomics for Manual Tasks
PHP	Projected Hourly Production
PSF	Performance Shaping Factors
PTMRS	PulseTerraMetrix Rope Shovel
TFL	Truck Final Load
TLF	Truck Load Factor
VR	Virtual Reality

1. CHAPTER 1: INTRODUCTION

1.1 Background

During the past several decades, the mining industry has focused on improving equipment. This has led to machines with more advanced hardware and software, higher reliability and productivity, and other technological advancements. These actions have improved safety and productivity and have reduced injuries and maintenance workload.

Although today's mining equipment and machinery are technologically advanced and highly reliable, the risk of accidents still exists, and key performance indicators indicate there is room for improvement (Sorensen, 2012). This could be due to insignificant integration of human factors (HF) as part of planning, operation, and maintenance activities. The current mining system is a people system, and inevitably HF and human error (HE) figure prominently in all aspects of this industry. Even the most advanced technologies and innovations require operators and maintainers with significant knowledge and skill, which increases the human's role.

Loading and hauling materials is a critical task in any mining activity; all mine production relies on the haulage system. In surface mining operations, truck and shovel systems are the most prominent type of haulage system and usually account for 35–60% of operating costs (Hustrulid et al., 2013; Chaowasakoo et al., 2017). Small improvements in the haulage system could increase production and reduce operational costs.

The high reliability, low maintenance costs, and long operational life of electric rope shovels (ERS) make their utilization by mines cost-efficient (Awuah-Offei, 2018). The performance of an electric ERS is influenced by machine condition and characteristic (i.e., bucket, lip design, driver and swing speed (AC/DC)), operator practices (i.e., shovel positioning), and muck-pile characteristics (i.e., fragmentation, bench height and geometry) (Osanloo & Hekmat, 2005; Singh & Narendrula, 2006; Vukotic & Kecojevic, 2014). Minor variations in shovel operation can significantly influence the haulage system (Babaei Khorzoughi & Hall, 2016).

The complex nature of mining activities and uncertainties associated with them are difficult to capture using traditional analytical methods (Komljenovic et al., 2015). By comparison, discrete event simulation (DES) has proven to be an effective tool to model, assess, and investigate operational scenarios in the mining industry (Upadhyay, 2016; Zeng, 2018; Moradi Afrapoli et al., 2019a, 2019b). A lack of detailed data related to shovel real-time activities such as dig, load, propel, excitation times, and payload tonnages for each individual load cycle has limited researchers' ability to develop a detailed shovel DES model, resulting in models that either ignore or oversimplify shovel operator behaviour.

To enhance the understanding of shovel operator performance and identify opportunities for improvements, this research focuses on shovel health and payload monitoring system data and discrete event simulation modeling in open pit operations. It is believed that these could be leveraged to not only better understand the role of operators, but also identify and introduce measures to enhance operational excellence, and lastly investigate future technologies potential.

1.2 Research Objectives

Given the important role of an electric rope shovel operator on the mine production and performance, the hypothesis of this research is defined as:

That the use of advanced analytics and discrete simulation on real time electric rope shovel data can lead to the identification of and an understanding of the various influences on shovel productivity and lead to solutions to improve overall performance.

In support of the hypothesis answers to the following questions will be investigated:

Can detailed data available from shovel onboard monitoring systems be leveraged to study and better understand key operator influences on the shovel and other aspects of mining performance and production and propose opportunities for operational improvements?

Can a discrete event simulation framework be developed to model electric rope shovel operator behavior in a truck and shovel surface mining operation and be used to evaluate proposed opportunities for operational improvement?

Can new performance enhancements be introduced in a way that they consider the effect of integrated systems (i.e., load/haul) rather than individual process performance (i.e., loading) and try to optimize the overall system performance versus each individual component.

To address the questions, following steps are taken:

- A thorough literature review of studies related to the role of an electric rope shovel's operator and the role they play in the mining system is done.
- A literature review of the past discrete even simulation modeling efforts and their applications in mining is done.
- Operational data from a shovel on-board health and payload monitoring system data base was obtained and processed.
- A statistical evaluation and analysis of the shovel operator performance is performed.
- A metric to assess operators and rank them is developed. This is built on existing metrics.
- A performance metric is developed to provide to the shovel operator that will allow them to improve their overall performance.
- Loading practices are evaluated and a strategy to improve shovel operator performance under certain scenarios is proposed.
- To explore how the knowledge learned and strategies developed can be used by a mine an operator simulation sub-module is developed and verified.
- The operator sub-module is deployed in a surface mine operation discrete event simulation model.
- The developed discrete event simulation model and operator sub-module are used to assess shovel operator influence on the shovel, truck and mine productivity and performance.
- Potential changes in loading practice on productivity are evaluated using the developed discrete event simulation model and the operator behaviour sub-module.

- Different levels of shovel automation and their influence on both shovel and mine productivity are assessed.

The approach adopted for this research is based on detailed data from a shovel health and monitoring system which will be introduced in the next section.

1.3 Shovel Health and Monitoring System Overview

Data for this research is obtained from the PulseTerraMetrix^{RS} (PTMRS), a commercially available shovel on-board health and payload monitoring system manufactured and supported by BMT Canada. The system comprises several connected standalone GPS, accelerometers, inclinometers, gyro meters, and strain gauge sensors independent of the shovel instrumentation mounted on the bail, crowd, stick and the shovel electrical house itself. The loadcell technology mounted on the bail directly measures bail force and dipper acceleration (Figure 1).

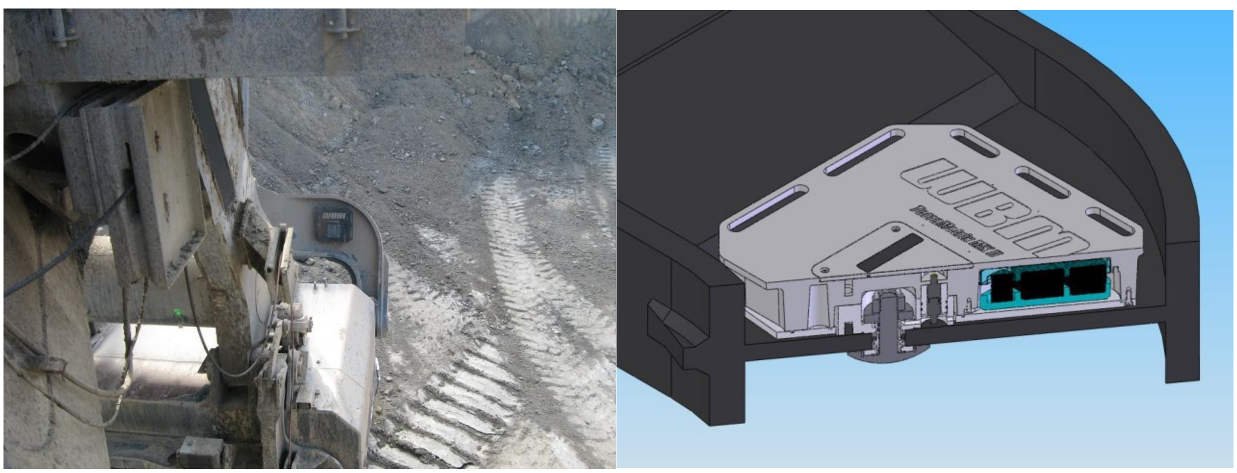

Figure 1. PTMRS bail loadcell (from PTMRS catalogue)

The system goes through a calibration procedure against a known weight upon first initialization and routinely afterward to make sure it works as intended and to verify its accuracy. Compared to the traditional methods that generally use estimates of rope force based on hoist and crowd currents, this direct measurement results in more accurate and precise results and its accuracy and precision has been verified (Babaei Khorzoughi, 2017).

The industrial central processing computer gathers the data from all sensors up to 50Hz in real-time and then processes them using its proprietary algorithm to calculate a set of comprehensive KPIs for each pass such as:

- Shovel state [i.e., ideal, propel, dig, swing, return, and waiting for a truck]
- Propel time
- Digging time
- Swing angle and time
- Dump
- Return angle and time
- Idle time
- Bucket payload
- Bucket carry back
- Shovel position
- Equivalent dig energy
- Maximum dig force
- Diggability index

The system also utilizes wireless technology and a proprietary algorithm to identify trucks being loaded and then obtains their information from a database to calculate the start of a truck loading, truck remaining capacity and truck final load. Those parameters among other operational KPIs are displayed to the operator through the PTMRS human machine interface (HMI) (Figure 2).

Figure 2. PTMRS HMI

For each loaded truck, KPIs and statistics for individual passes are recorded in a local database and are transferred over the network and stored in a central SQL database. Each record in the database includes production information such as date and time, shovel ID, operators ID, truck ID, truck capacity, truck final load, number of passes to load the truck, each pass dig, swing and return times and bucket load.

PTMRS also calculates and records diggability, a measurement that considers the dig path and associated amount of energy needed to dig the material and reflects the overall dig condition. A higher diggability number generally indicates harder dig condition.

1.4 Thesis Outline

Chapter 2 presents the state of the art on the electric rope shovel operator's performance studies, automation and applications of simulation in the mining. The chapter summarizes the findings and discusses opportunities for future work, some of which formed the rationale for this PhD research.

Chapter 3 explains the theoretical framework and components of the analysis part of the thesis. The chapter introduces the conceptual theoretical frameworks, statistical and mathematical methods, and connections between them to achieve the main objectives of the thesis.

Chapter 4 presents the case study and the result of the statistical analysis performed on it. An operator assessment KPI is developed and presented. The KPI is used with the developed simulation sub-module and mine operation simulation model to explore the operator's practices significance.

In Chapter 5 a strategy to improve shovel operator performance under certain scenarios is proposed and its impact on overall production is evaluated using simulation. Additionally, a performance metric to provide to the shovel operator that will allow them to improve their overall performance is introduced. This chapter ends with presenting a methodology to study possible shovel automation scenarios and exploring the extent to which they can improve production and performance.

Finally, chapter 6 presents a brief summary of the research findings and the discussion of the results, followed by the research novel contributions, and future work.

2. CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter is divided into three main sections. Related literature to the subject of this study is reviewed.

Section 2.2 reviews the current literature available about the role that HF and an electric rope shovel operator plays in the mining industry. Studies focused on operators and their influences on the electric rope shovel performance and productivity are investigated followed by a review of the current state of automation in the mining industry in the section 2.3.

Simulation and its application in mining systems are presented in the section 2.4 including a review of available tools. The final section summarizes the findings and discusses opportunities for work that is needed, some of which formed the rationale for this PhD research.

2.2 The Influence of Human Factors in The Mining

During the past several decades, the mining industry has focused on improving equipment, machinery, and methods that have led to more advanced hardware and software, equipment with higher reliability and productivity, and other technological advancements. These actions have improved safety and productivity and have reduced accidents and maintenance workload.

Although today’s mining equipment and machinery are technologically advanced and more reliable, the risk of accidents still exists, and key performance indicators indicate there is room for improvement (Sorensen, 2012). A prominent reason could be due to insignificant integration of human factors (HF) as part of planning, operation, and maintenance activities. The current mining system is a people system, and inevitably HF and human error (HE) figure prominently in all aspects of this industry. Even the most advanced technologies and innovations require operators and maintainers with significant knowledge and skill, which could increase the potential for HE.

Several methods have been developed to understand the HF and HE contributions to industrial activities. Their application in an operation and maintenance context have been largely advanced in aviation and nuclear industries.

This section reviews current efforts in the mining, aviation, and nuclear industries for detecting, reporting, and managing HE and HF. An assessment of the suitability of approaches used in other industries for the mining industry is given, as well as recommendations for next steps to improve how HF and HE are managed in the mining industry.

However, this thesis will later mainly focus on identifying and quantifying the impact of shovel operators on shovel productivity and overall mine productivity. Should the results from this work identify significant opportunities for improvement in shovel operators the logical next step would be to examine HF and HE that contribute to variability on shovel operator performance.

2.2.1 HUMAN ERROR

Generally, HE is defined as the failure to complete a required task (or execute a forbidden action) that could lead to the interruption of normal scheduled actions, damage to assets, or compromised safety (Reason, 1990; Amalberti, 2001; Wiegmann & Shappell, 2003; Dhillon & Liu, 2006). Reason (1990) defined error as “a generic term to encompass all those occasions in which a planned sequence of mental or physical activities fails to achieve its intended out-come.” Woods at al. (2010) defined error as “causal attribution of the psychology and sociology of an event.” Papic and Kovacevic (2016) defined error as

> *failure (omission, unsuccessful attempt) to execute a required function, wrong decision in a response to certain problem, performing of function that shouldn't be executed, unsuccessful in recognition (observation, revealing) of a dangerous condition that requires corrective measures, bad timing and bad response to unpredicted circumstances.*

Human error has only been studied in the last 60 years (Dhillon & Liu, 2006). In general, the literature presents discussions of HE with minimal technical analysis and seems to be an under-researched area that is not fully understood (Saward & Stanton, 2015). For the reader interested in a general discussion, see Reason (1990), Perrow (1999), Wiegmann and Shappell (2003), Flin et al. (2008), and Woods et al. (2010).

Human error has been considered inevitable (Reason 1990; Maurino et al., 1998; Perrow, 1999; Wiegmann & Shappell, 2003; Woods et al., 2010); for instance, in the aviation industry, it is associated with 70–90% of accidents (Hollnagel, 1993; Adams, 2006; Begur & Ashok Babu, 2016). The Civil Aviation Authority Safety Regulation Group (2002) stated that *"it is an unequivocal fact that whenever men and women are involved in an activity, HE will occur at some point."*

The poor condition of the working area (inadequate lighting, high noise levels), insufficient operator training or skill, improper tools, poorly designed equipment and poorly written equipment maintenance procedures, and complicated operating processes have been recognized as some of the main reasons for the occurrence of HE (Dhillon & Liu, 2006). Dhillon (1986) classified HE into six categories:

- operating errors.
- assembly errors.
- design errors.
- inspection errors.
- installation errors; and
- maintenance errors.

Additionally, HE consequences are not always immediately apparent. Sometimes they might have hidden, undetected consequences that can lead to a latent error condition and delayed undesired outcomes.

2.2.2 HE AND HF IN THE MINING AND MINERAL INDUSTRY

The mineral industry generally refers to a group of activities related to mining, namely, the extraction, processing, and transportation of minerals (Horberry et al, 2013). The mining and mineral industry is one of the largest worldwide employers and key revenue earners; for example, mining contributed C$56 billion to Canada's gross domestic product in 2015 (Energy and Mines Ministers' Conference, 2016).

Traditionally, mining is considered an inherently high-risk industry. Nevertheless, the introduction of new technology and an increased concern for safety has significantly decreased incident and injury rates during the past several years. To speed up this process, the HF associated with operation and maintenance need to be addressed (Patterson, 2009). Human error is present in mining and mineral industry operation and maintenance. It is an important factor influencing the safety, success, and effectiveness of operation and maintenance tasks, and it can have undesired consequences if errors pass undetected and uncorrected.

The economy has always had a direct influence on the amount of attention that organizations and governments give to mining HF and ergonomics. For example, the 1980s virtual collapse of the coal industry in the U.K. caused a drop in the amount of British work in the field of mining HF and HE (Simpson et al., 2009).

In the literature, with some overlap, HF and HE generally fall into the following five categories:

- safety- and ergonomic-related risks.

- injuries and accidents.
- mining equipment.
- automation and new technologies; and
- mineral processing plants.

2.2.2.1 Safety and ergonomics

Morgan (1988) provided a step-by-step guide to developing and upgrading a program for safety and technical training for cement plant workers. Mason (1996) described an attitude survey of electricians in a coalfield to improve electricians' safety. Burgess-Limerick and Steiner (2006) presented several possible controlling measures such as hydraulic cable reelers, handrails on continuous miner (CM) platforms, a redesign of CM platforms and bolting rigs to reduce reach distances during drilling and bolting, and improved guarding of bolting controls.

Badri at al. (2011) proposed a new concept called "hazard concentration," based on the number of hazards and their influence. This method calculates a weight for each category of hazard related to an undesirable event by an analytic hierarchy process (AHP) method to integrate occupational health and safety (OHS) into risk management in an open-pit mining project in Quebec, Canada. The result of their project helped the company choose a suitable accident-prevention strategy for its operational activities. Later, Badri et al. (2013) developed a new approach based on their hazard concentration concept and AHP to risk management in mining projects. They constructed a database of approximately 250 potential hazards in an underground gold mine in Quebec, Canada and showed the importance of considering OHS in all operational activities of the mine.

Burgess-Limerick et al. (2012) developed the operability and maintainability analysis technique (OMAT) technique to analyze risks associated with operation and maintenance tasks, to engage with mining equipment manufacturers to accelerate improvements in the safe design of mining equipment. Horberry et al. (2013) investigated challenges associated with information collection and management during underground coal-mining emergencies from a human-centred perspective. They looked at decision-making deficiencies in incident-management teams, and organizational issues related to mining control rooms during emergencies to highlight the role of HF in mining emergency management. Nadeau et al. (2013) outlined the challenges faced by deep mining operations to determine how to ensure safe and sustainable working environments. They argued that a solution could be designing new intelligent personal protective equipment that considers HF.

Ergonomics is generally defined as fitting a job to a worker. Torma-Krajewski et al. (2007) presented results from the implementation of an ergonomics process designed to identify and reduce exposures to ergonomic risk factors found in a United States surface coal mine. They reported that mechanics and heavy-equipment operators had the most concern about ergonomics. Torma-Krajewski and Lehman (2008) presented several examples of task-specific interventions that helped to reduce exposure to risk factors through implementing an ergonomics process that addresses exposure to risk factors that could result in musculoskeletal disorders or other types of injuries/illnesses. Their work was a joint research project conducted by the United States National Institute for Occupational Safety and Health (NIOSH) and a private mining company. Torma-Krajewski and Burgess-Limerick (2009) presented three case studies describing the steps that three mining companies in the United States had taken to apply ergonomics to lower worker exposure to risk factors and musculoskeletal disorders and to improve productivity.

2.2.2.2 Injuries and accidents

Burgess-Limerick et al. (2007) implemented the participative ergonomics for manual tasks (PErforM) program at four Australian underground coal mines to facilitate ongoing miner participation in reducing injury risks associated with manual tasks. They presented several examples of the risk assessments undertaken with potential control suggestions and discussed the lessons learned. Paul and Maiti (2007) investigated the role of behavioural factors in underground mine accidents and incidents. By carrying out the study in two coal mines in India, they concluded that the group of workers who had experienced an onsite accident were less satisfied with the job and more negatively affected compared to workers without accidents.

Ruckart and Burgess (2007) analyzed data from the hazardous substances emergency events surveillance (HSEES) system for the period of 1996–2003 and concluded that HE-related events in mining and manufacturing resulted in almost four times as many events with human injury and almost three times as many events with evacuations, compared to events where HE was not a contributing factor. Also, the night shift had no apparent influence on the events attributable to HE. Reardon et al. (2014) reviewed United States mining maintenance and repair fatal reports (2002–2011) and developed a classification system to identify patterns and contributing human and nonhuman factors in fatalities during maintenance and repair operations in mining. They suggested several potential interventions to reduce fatality occurrences for coal, metal, and nonmetal mines. Sanmiquel et al. (2015) analyzed 70,000 occupational accidents and fatality reports between 2003 and 2012 in the Spanish mining sector using statistical methods such as Bayesian classifiers, decision trees, or contingency tables to identify behavioural patterns. From the identified behavioural patterns, they developed potential prevention policies to decrease injuries and fatalities.

Clough (2015) presented a relationship between a rise in the fatality rate in the Australian mining industry during the last few years and a fall in commodity prices.

2.2.2.3 Human factor analysis and classification system (HFACS)

The HFACS is a well-known framework for analyzing and classifying the underlying HF associated with accidents and incidents. It has been applied in the aviation industry for many years (Wiegmann & Shappell, 2001; Wiegmann et al., 2005; Tvaryanas & Thompson, 2008; Daramola, 2014).

The original HFACS contained 19 categories placed in one of four levels: unsafe acts, preconditions for unsafe acts, unsafe supervision, and organizational influences. Each tier is dependent on the previous one and factors are assumed to progress from active to latent conditions as they progress up the hierarchy from unsafe acts to organizational influences.

The HFACS has been modified and applied in several areas, for example, to investigate railway accidents (i.e., HFACS-RR; Baysari et al., 2008; Reinach & Viale, 2006; Kim et al., 2010), to assess the factors disturbing performance in a hospital operating room (ElBardissi et al., 2007), and to improve patient safety in a hospital environment (Milligan, 2007).

Patterson and Shappell (2010) used the HFACS method to analyze 508 incident and accident cases from the state of Queensland, Australia, to identify HF trends and system deficiencies within mining. They concluded that, although the original HFACS method is valid for applying in aviation accidents, the nomenclature and examples in some of the causal categories are incompatible with the mining industry; therefore, they modified the original HFACS framework and developed a new HFACS-mining industry (HFACS-MI) framework (Table 1).

Table 1. Human factor analysis and classification system (HFACS) and HFACS-mining industry (MI) framework (asterisks indicate HFACS-MI framework)		
Outside factors*	Regulatory factors	Effects of government regulations and policies on the mine's operation, health, and safety
	Other	Effects of social, economic, and environmental concerns on the health and safety of a mine site
Organizational influences	Organizational climate	Prevailing atmosphere/vision within the organization (e.g., policies and culture)
	Operational process	Formal process by which the vision of an organization is carried out (e.g., operations and procedures)
	Resource management	Management of the human, monetary, and equipment resources necessary to carry out the vision
Unsafe supervision	Inadequate supervision (leadership*)	Oversight and management of personnel and resources
	Planned inappropriate operations	Management and work assignment (e.g., aspects of risk management, crew pairing, and operational pacing)
	Failure to correct known problems	Deficiency-related safety areas are "known" to the supervisor yet remain uncorrected
	Supervisory violations (leadership violation*)	Willful disregard for existing rules, regulations, instructions, or standard operating procedures by management during their duties
Preconditions for unsafe acts	Environmental factors	Technological: Factors including the design of equipment and controls, display/interface characteristics, checklist layouts, task factors, and automation
		Physical: Factors including the operational setting (e.g., weather, altitude, and terrain) and the ambient environment (e.g., heat, vibration, lighting, and toxins)
	Condition of operators	Adverse mental states: Acute psychological and/or mental conditions that negatively affect performance, such as mental fatigue, pernicious attitudes, and misplaced motivation
		Adverse physiological states: Acute medical and/or physiological conditions that preclude safe operations, such as illness, intoxication, and pharmacological and medical abnormalities known to affect performance
		Physical/mental limitations: Permanent physical/mental disabilities that might adversely impact performance, such as poor vision, lack of physical strength, mental aptitude, general knowledge, and other chronic mental illnesses
	Personnel factors	Crew resource management: Communication, coordination, and teamwork issues that affect performance
		Personal readiness: Off-duty activities required to perform optimally on the job, such as adhering to crew rest requirements, alcohol restrictions, and other off-duty mandates
Unsafe acts	Errors	Decision errors: "Thinking" errors representing conscious, goal-intended behaviour that proceeds as designed yet proves inadequate or inappropriate for the situation
		Skill-based errors: Errors in highly practiced behaviour that occur with little or no conscious thought
		Perceptual errors: Errors arising when sensory input is degraded, such as flying at night, in poor weather, or in otherwise visually impoverished environments
	Violations	Routine: Repeated "bending of the rules"
		Exceptional: Isolated departures from authority, neither typical of the individual nor condoned by management

[1]From Yaghini et al. (2018)

Lenné et al. (2012) analyzed 263 significant mining incidents in Australia from 2007 and 2008 using HFACS. They recommended focusing on HFACS categories at the higher levels such as organizational climate, planned inadequate operations, and inadequate supervision to reduce the number of unsafe acts at an operational level. Furthermore, research has been conducted in China, primarily in the coal mining sector, to investigate mine accidents and safety-system deficiencies (Jian-wei & Wen-yu, 2011; Chen et al., 2014; Zhao at al., 2014; Xie at al., 2015).

2.2.2.4 Mining equipment

Burgess-Limerick and Steiner (2006) investigated 959 injuries between 2002 and 2005 associated with CMs, shuttle cars (SCs), load-haul-dump machines, and personnel-transport (PT) vehicles in underground coal mines in New South Wales, Australia, to determine opportunities for controlling injury risks. They found the most common work activities that led to injuries were

> *strain while handling CM cable (96 injuries); caught between or struck by moving parts while bolting on a CM (86 injuries); strains while bolting on CM (54 injuries); and slipping off a CM during access, egress or other activity (60 injuries).*

Burgess-Limerick (2011) investigated 4,633 injuries occurring in underground coal mines between 2005 and 2008 in New South Wales to identify opportunities for controlling equipment-related injuries. He concluded that in 46% of injuries, equipment (continuous miner [12%], bolting machines [6%], LHD [8%], longwall [7%], personnel transport [4%], shuttle car [3%], and other equipment [6%]) was involved. Several high potential consequence events were reported during that period, including interactions between personnel and mobile equipment, interactions between personnel and longwall shield movements, and transport equipment collisions. He suggested a series of possible short-term control measures for these risks.

Horberry et al. (2013) presented three case studies of HF focused on reducing risks, developing emergency-response management systems, and recognizing the value of participatory ergonomics in improving the design of mining equipment. They showed that properly dealing with HF is a key part in any sustainability initiative. In another study, Horberry (2012) reviewed the present technologies and their possible associated HF issues and presented a four-stage research and development process to increase the safety and health benefits for operators of new technologies.

Papic and Kovacevic (2016) used a combination of a cause-effect diagram and the "5 Why?" technique to detect and categorize HF and HE that affect the results of the mining machines maintenance operation. They suggested using a proactive approach for solving potential HF problems in mining machine maintenance, using the system of error proofing or Poka Yoke (Shingo, 1986), and providing training in the area of HF to reduce the number of errors in mining machine maintenance.

2.2.2.5 Automation and new technologies

Tichon and Burgess-Limerick (2009) reported several experiments on the implementation of virtual reality (VR) as a medium for safety-related training in the mining industry and discussed a range of associated issues. They concluded that novice drivers' hazard perception abilities and maintenance inspection tasks can be improved through training in a VR environment. Also, Tichon and Burgess-Limerick (2011) reviewed the evidence for the value of VR as a medium for safety-related training in mining. They argued the need for a large-scale, systematic assessment of the results of safety-related training through virtual mining environments for future training. Later, Pedram et al. (2014) evaluated the impact of VR-based training sessions on operator performance, safety standards, and mine productivity, and used a cost-benefit analysis to investigate the added value of the VR. In another study, Alem et al. (2011), as part of a human-system integration project within the CSIRO Minerals Down Under Flagship, presented a remote guiding system called HandsOnVideo to support and help a mobile local worker maintain complex equipment in mine sites remotely. They tested the usability of the system in a real industry situation.

Lynas and Horberry (2010) presented a literature review and a database of existing and emerging technologies of available automated mining equipment. They used this to explore how new technologies can be developed with an optimal interface design to eliminate performance gaps if they take into account HF in determining the required skills and cognitive capabilities to operate or maintain the new technology. They concluded that de-skilling of the operators and maintainer, over-reliance on the technology by operators, poor operator acceptance of new technologies, and poor HF design of equipment interfaces are real problems. In another study, Lynas & Horberry (2011a) discussed lessons related to the impact of HF in automation learned from other industries. They argued several potential problems and their solutions. Also, Lynas and Horberry (2011b) reviewed HF and ergonomics (HF and HE) work in mining and investigated the emerging trends and HF and HE issues associated with automated mining in Australia through a semi-structured interview process. They concluded several issues such as automation, safe design, and workforce skill requirements and organizational issues are related to HF and HE in the mining industry.

Horberry and Lynas (2012) investigated operator interaction with automated mining equipment by preparing a database that considers existing and emerging technologies. They used this to analyze the main HF issues for such technology. Recently, Horberry et al. (2016) introduced the application of human-centred design (HCD) in the mining industry and explained the benefits of an HCD approach, providing several successful examples in this industry.

2.2.2.6 Mineral processing plant

Li et al. (2011) investigated the current status of control-room operators at two types of Australian mineral processing plants from an HF perspective to explore the underlying difficulties in their workplace. They concluded that developing effective human-machine interfaces (HMI) and alarms, improving operator training, and optimizing organizational factors are key elements to improve the integration of operators and technologies. Later, Li et al. (2012) investigated the status of control-room operations in two types of mineral industries in Australia and explored the HF and underlying barriers in the operators' work environment. They concluded that poorly designed HMI and alarms, insufficient operator training, and inappropriate task allocations are among the deficiencies in the current information and organizational environments constraining operator-control ability.

Table 2 summarizes the year of study for published papers on HF in the mining and mineral industry and the country of origin where the study was done. Table 3 presents a classification of published papers based on the considered factor. Figure 3 illustrates the number of papers based on considered factor and Figure 4 shows the percentage of papers based on area of study.

Table 2. Number of published papers on human factors (HF) in the mining and mineral industry per country of origin

Year	Australia	China	U.S.A.	Canada	U.K.	India	South Africa	Turkey	Spain	Serbia
1974	–	–	1	–	–	–	–	–	–	–
1998	1	–	–	–	–	–	–	–	–	–
2006	1	–	–	–	–	–	–	–	–	–
2007	1	–	3	–	1	1	–	–	–	–
2008	–	–	1	–	–	–	–	–	–	–
2010	3	1	–	–	–	–	1	–	–	–
2011	6	2	–	1	–	–	–	–	–	–
2012	6	1	1	–	–	–	–	–	–	–
2013	1	–	–	2	–	–	–	1	–	–
2014	1	2	1	–	–	–	–	–	–	–
2015	–	2	–	–	–	–	–	–	1	–
2016	1	–	–	–	–	–	–	–	–	1
Total	21	8	7	3	1	1	1	1	1	1

*From Yaghini et al. (2018)

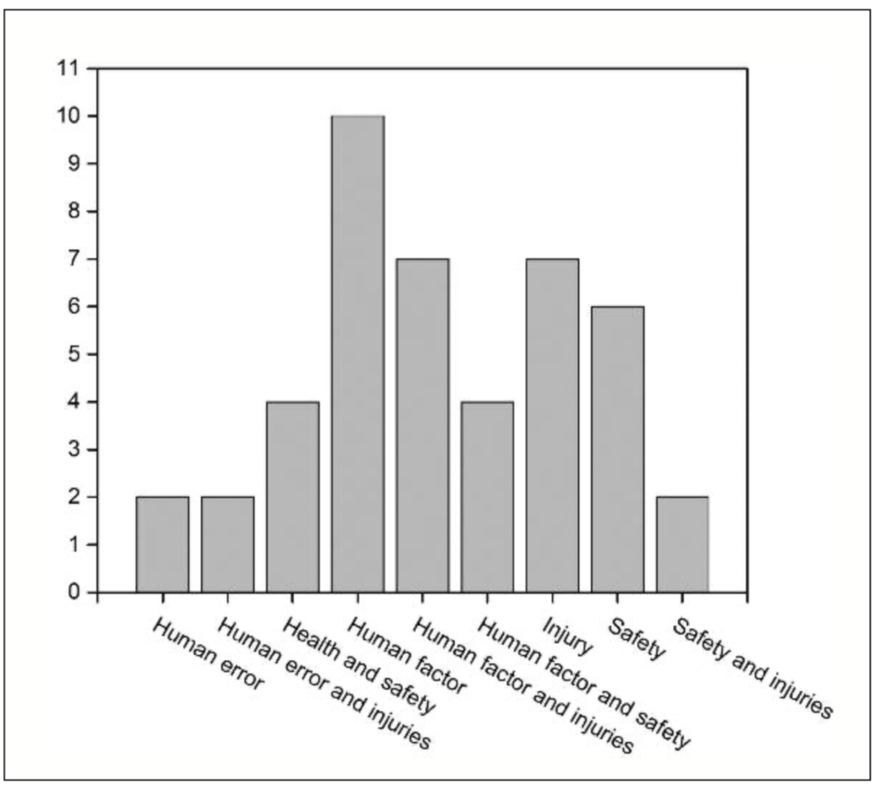

Figure 3. Published papers corresponding to the considered factor in mining industry (from Yaghini et al. (2018))

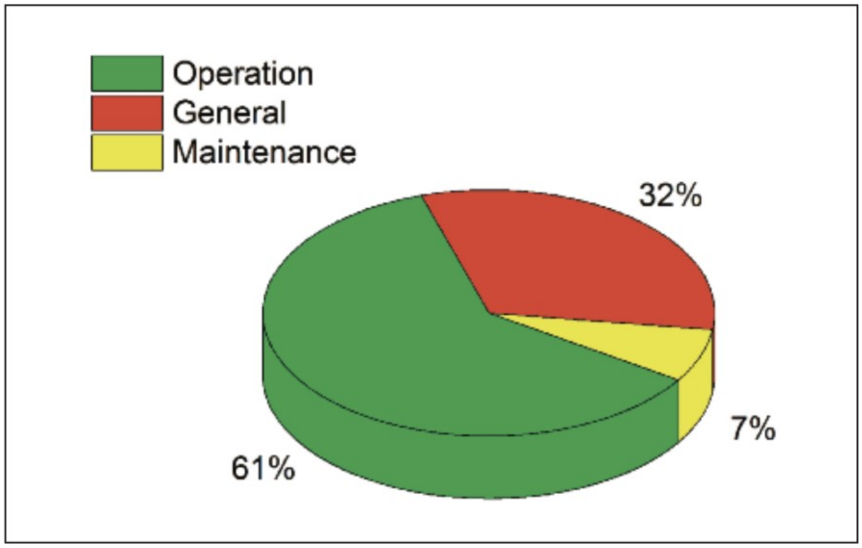

Figure 4. Published papers corresponding to the area of study in mining industry (from Yaghini et al. (2018))

Table 3. Summary of published papers about the effect of human factors (HFs) and human error (HE) in the mining and mineral industry (AHP, analytic hierarchy process; HFACS, human factor analysis and classification system; OHS, occupational health and safety; OMAT, operability and maintainability analysis technique; SPA, set pair analysis)

Reference	Scope	HFs	HE	Safety/ health	Accidents/ injuries	Country	Mining method	Operation/ maintenance
Lawrence (1974)	Injury data analysis	–	Accident causes	–	HE	United States	Underground mining	General
Mitchell, Driscoll, & Harrison (1998)	Injury data analysis	–	–	–	Work-related fatalities	Australia	General	General
Burgess-Limerick & Steiner (2006)	Accident data analysis	–	–	–	Equipment-associated injuries	Australia	Underground mining	Operation
Burgess-Limerick et al. (2007)	Reduce operation injury	–	–	–	Participative ergonomics for manual mining tasks (PErforM)	Australia	Underground mining	Operation
Coleman & Kerkering (2007)	Injury data analysis	Safety, injuries, and lost workdays	–	Defining lost workdays as indicators of risk	–	United States	General	Operation
Paul & Maiti (2007)	Safety management	–	–	Role of behavioural factors	–	India	Underground mining	Operation
Ruckart & Burgess (2007)	Accident data analysis	–	Time of occurrence	–	–	United States	General	General
Torma-Krajewski, Steiner, Lewis, Gust, & Johnson (2007)	Reduce exposure to risk	–	–	Implementation of an ergonomics process	–	United States	Surface mining	Operation
Torma-Krajewski & Lehman (2008)	Reduce exposure to risk	–	–	Ergonomic interventions	–	United States	Surface mining	Operation
Burgess-Limerick, Krupenia, Zupanac, Wallis, & Steiner (2010)	Equipment design	–	Reducing control selection errors	–	–	Australia	Underground mining	Operation
Green et al. (2010)	Automation	–	–	Improving safety using robots	–	South Africa	General	Operation
Lan & Qiao (2010)	Accident data analysis	–	HE reliability using gray relational theory	–	–	China	Underground mining	General
Lynas & Horberry (2010)	Automation	HF challenges of automated mining equipment	–	–	–	Australia	General	Operation
Patterson & Shappell (2010)	Accident data analysis	–	–	–	HFACS	Australia	General	General
Alem, Huang, & Tecchia (2011)	Automation	Remote collaboration	–	–	–	Australia	General	Maintenance
Badri, Nadeau, & Gbodossou (2011)	Reduce exposure to risk	–	–	Integration of OHS into risk management	–	Canada	Surface mining	Operation
Jian-wei & Wen-yu (2011)	Safety analysis	–	–	HFACS, coal-mine safety-system deficiencies, and unsafe acts	–	China	Underground mining	Operation
Li, McKee, Horberry, & Powell (2011)	Mineral process control-room operation	Human machine interface	–	–	–	Australia	Mineral processing	Operation
Lynas & Horberry (2011a)	Automation	HF issues with automated mining equipment	–	–	–	Australia	General	General
Lynas & Horberry (2011b)	Automation	Review of Australian HF research and stakeholder opinions	–	–	–	Australia	General	Operation

Table 3. Summary of published papers about the effect of human factors (HFs) and human error (HE) in the mining and mineral industry (AHP, analytic hierarchy process; HFACS, human factor analysis and classification system; OHS, occupational health and safety; OMAT, operability and maintainability analysis technique; SPA, set pair analysis)

Reference	Scope	HFs	HE	Safety/ health	Accidents/ injuries	Country	Mining method	Operation/ maintenance
Tichon & Burgess-Limerick (2011)	Reduce exposure to training-related risk in mining	–	–	A review of virtual reality as a medium	–	Australia	General	Operation
Wu et al. (2011)	Accident data analysis	–	–	–	Accident data analysis	China	Underground mining	General
Burgess-Limerick, Joy, Cooke, & Horberry (2012)	Safety management	–	–	Safety improvement and injury prevention, OMAT	–	Australia	General	Operation
Chen, Qi, Long, & Zhang (2012)	Accident data analysis	–	–	–	Characteristics of HFs	China	General	Operation
Drury, Porter, & Dempsey (2012)	Accident data analysis	–	–	–	Patterns in mining haul-truck accidents	United States	General	Operation
Horberry (2012)	Automation	–	–	Review of benefits of new technologies in mining	–	Australia	General	Operation
Lenné, Salmon, Liu, & Trotter (2012)	Accident data analysis	–	–	–	HFACS	Australia	General	Operation
Li, Powell, & Horberry (2012)	Mineral process control-room operation	Human-system integration	–	–	–	Australia	Mineral processing	Operation
Badri, Nadeau, & Gbodossou (2013)	Risk management	–	–	AHP, OHS	–	Canada	Underground mining	Operation
Horberry, T., Burgess-Limerick, R., & Fuller, R. (2013)	Sustainability	Role of HFs in a sustainable mineral industry	–	–	–	Australia	General	Operation
Horberry, T., Xiao, T., Fuller, R., & Cliff, D. (2013)	Mining emergency management	Role of HFs and ergonomics	–	–	–	Australia	Underground mining	Operation
Onder (2013)	Accident data analysis	–	–	–	Logistic regression models	Turkey	Surface mining	Operation
Chen, Yin, Zeng, Li, & Li (2014)	Accident data analysis	–	–	–	HFACS, Bayesian network	China	Underground mining	Operation
Horberry (2014)	Equipment design	Safety in design	–	–	–	Australia	General	General
Reardon, Heberger, & Dempsey (2014)	Accident data analysis	–	–	–	Hazard classification	United States	General	Maintenance
Zhao et al. (2014)	Accident data analysis	–	–	–	HFACS	China	Underground mining	Operation
Gui and Chun (2015)	Accident data analysis	–	–	–	Research on responsible person	China	Underground mining	Operation
Sanmiquel, Rossell, J. M., & Vintró (2015)	Accident data analysis	–	–	–	Bayesian network, data mining	Spain	General	Operation
Xie, Yang, & Xu (2015)	Safety analysis	–	–	HFACS, SPA	–	China	General	Operation
Papic & Kovacevic (2016)	Equipment maintenance	Cause-effect diagram and event tree analysis	–	–	–	Serbia	General	Maintenance
Horberry, Burgess-Limerick, & Steiner (2016)	Equipment design	Human-centred design	–	–	–	Australia	General	General

*From Yaghini et al. (2018)

2.2.3 Aviation, nuclear, and other industries

The aviation and nuclear industries have conducted a significant amount of research to investigate the impacts of HF and HE in their maintenance activities (Dhillon & Liu, 2006) and continue to overcome many remaining and newly introduced HF- and HE-related challenges (Begur & Ashok Babu, 2016).

It is believed that there are many aspects of the mining industry that to some degree have similarities in nature with aviation and nuclear industries as all three of them rely heavily on humans for their operation and maintenance. Hence, studying those industries' effort can be useful for the mining industry and lessons learned from their work and their methodology could assist the mining industry as it considers HF and HE. To demonstrate the progression of methods and theories, the contributing HF and HE in maintenance and operation activities are reviewed separately.

2.2.3.1 Maintenance

Because of the complex nature of the procedures, including the removal and replacement of different components and the detecting of faults that, in many cases, are uncommon and difficult to spot and require high levels of attention and expertise, tough working conditions, difficult ergonomic body positions, and frequent time pressures, maintenance tasks are vulnerable to HE (Pennie et al., 2007).

Human error in maintenance has been a contributing factor in several high-profile accidents across different industries (Pennie et al., 2007). HE in aircraft maintenance is cited for 15–20% of aviation mishaps (Manwaring et al., 1998; Patankar & Taylor, 2004; Rashid at al, 2013; Begur & Ashok Babu, 2016) and at least 70% of naval aviation safety occurrences in the U.K. (Saward & Stanton, 2015).

2.2.3.2 Aviation

Drury (1991) offered a taxonomy and means of eliminating maintenance errors in the aviation industry and Graeber and Marx (1993) showed the economic aspect of maintenance error.

Shepherd and Johnson (1995) described several research products that are currently improving safety and efficiency in maintenance applications worldwide. Hobbs and Williamson (1995) investigated the types of errors made by maintainers in corporations with an air carrier in the Asia-Pacific region. Havard (1996) presented British Airways' initiatives regarding HF. Kania (1996) investigated causal factors contributing to HE. O'Connor and Bacchi (1997) presented an error taxonomy to classifying HE in maintenance and dispatch operations. Witts (1997) discussed the impact of HF on aircraft maintenance in Air UK Engineering. Reason (1997) claimed that maintenance-related error is one of the largest single HF problems in modern aircraft systems. Ford (1997) discussed the impact of HE in airline maintenance on safety and discussed what is required to lessen the safety inadequacies. Shepherd and Kraus (1997) investigated the effect of several factors such as technician teaming and advanced technology, and the evaluation of simplified English on the performance of maintainers. Amalberti and Wioland (1997) argued the relationship between aviation accidents and errors and the systemic safety approach for large socio-technical systems. Nelson, Haney et al. (1997) presented a structured method to identify, assess, and prevent HE in space operation, which can be applied. Koli et al. (1998) developed two HF audit methods in aircraft inspection and maintenance process tasks to detect the human-system mismatches that can lead to errors: an inspection audit and a maintenance audit, which can be used either in a hard-copy version or on a portable computer. McGrath (1999), regarding airworthiness and safety, discussed aviation management imperatives to improve the professionalism of the field personnel's culture. Latorella and Prabhu (2000) reviewed current trends in dealing with HE in aviation maintenance and inspection. Wenner and Drury (2000) presented a method for analyzing the HE reports. Reason (2000) presented a job-oriented approach to determine the human performance problem in aviation.

Strauch and Sandler (1984) discussed the important role of the aviation maintenance technician (AMT) in the safe operation of an aviation system. Hibit and Marx (1994) anticipated that using a maintenance error decision aid (MEDA) can improve safety and maintenance system reliability. Allen and Rankin (1995) evaluated MEDA through a field test. Rankin et al. (2000) also evaluated the development and implication of MEDA to determine and eliminate the factors that contribute to maintenance error. Bao and Ding (2014) used MEDA and correspondence analysis methods to analyze maintenance error in 3,783 aviation safety reporting system incident reports submitted during the period of January 1, 2008 to December 31, 2008. They argued that a large proportion of maintenance errors had been initiated by maintenance and non-maintenance personnel, and individual- and management-related factors are the most common reasons for maintenance error.

Liang et al. (2010) developed an online maintenance assistance platform (online MAP) for technicians to remove HE in performing aviation maintenance and inspection tasks. Chang and Wang (2010) determined nine significant human risk factors out of 77 preliminary and 46 primary risk factors in aircraft maintenance technicians by conducting an empirical study of Taiwan's airlines to improve maintenance operations. Atak and Kingma (2011) presented a case study about the safety culture of an aircraft maintenance organization and analyzed the various roles and tensions between the quality assurance and maintenance management departments to stress the paradoxical relationship between safety and economic interests. Rashid et al. (2013) investigated the impact of human reliability on aviation maintenance safety and introduced a new model indicating the commencement and spread of critical maintenance HE within aviation maintenance organizations. Cromie et al. (2013) described an initiative being used by a European aviation maintenance company to overcome the challenge of integrating human and organizational factors (HOF) training within a risk-management context in a European aviation maintenance company. Chen and Huang (2014) introduced the Bayesian network (BN) approach to perform human reliability analysis (HRA) in aviation maintenance visual inspection activities. Chen (2014) analyzed the characteristic, cause, and mode of the aviation maintenance error to address the appropriate management and control method for specific aviation maintenance HE. Rashid et al. (2014) proposed the aviation maintenance monitoring process: an integrated process to identify HE causal factors using fuzzy analytic network process theory. Shanmugam and Robert (2015) reviewed and analyzed HF in aircraft maintenance. They concluded that the application of HF principals has created a great impact on the design of aircraft maintenance facilities, task cards, and equipment, and these HF principals are applied to enhance the safety behaviour in aviation maintenance workstations. Saward and Stanton (2015) described the nature and extent of individual latent situational error in naval aircraft maintenance by combining prospective memory, attentional monitoring, and schemas theories. Begur and Ashok Babu (2016) presented a method to collect and assess data to analyze and reduce HF in aircraft maintenance and to improve maintenance practices to decrease the potential number of aviation mishaps.

2.2.3.3 Nuclear power

Seminara and Parsons (1985) presented an overview of HF research conducted under the sponsorship of the Electric Power Research Institute (EPRI). They identified HF problem areas and future research opportunities rather than provide direct solutions for deficiencies. Jacobsson and Svensson (1991) investigated psychosocial work demands of a maintenance group in a nuclear plant during the annual maintenance outage, based on a stress paradigm. They found that increased work strain, shiftwork including night work, and reduced social support had a negative impact on performance. Gertman (1992) presented a review of a mainframe version of a computer code for simulating maintainer performance. Pyy et al. (1997) investigated approximately 4,400 HE in nuclear power plant (NPP) maintenance between 1992 and 1994 to identify common cause failure mechanisms. They suggested that enhanced coordination and review, post installation checking, and startup testing programs might decrease the number of errors. Kim (1997) described the Korean version of the human performance enhancement system (HPES) program and the current status of a CASHPES (computer-aided system for HPES) development to reduce HE and to enhance human performance in nuclear power plants.

Nakatani, Nakagawa et al. (1997) proposed a new method, called DIAS (Dynamic Interaction Analysis Support System), to evaluate the human interface design of nuclear power plant equipment from the viewpoint of HE in maintenance activities. Lee et al. (1997) presented HF research including the development of an HF experimental facility, the development of an operator task simulation analyzer, and analysis of HE cases performed by the Korean Atomic Energy Research Institute. Sola et al. (1997) described an overview of the main activities carried out by CIEMAT (Spain Research Centre for Energy, Environment and Technology) in the nuclear power plant industry regarding HF. Huang and Zhang (1998) analyzed root causes and discussed protective measures with respect to safety for HE events in operating and maintenance activities at the Daya Bay nuclear power plant, China. Röwekamp and Berg (2000) analyzed the operational behaviour of different fire-protection features based on the examination of reported results of regular inspection and maintenance programs for German nuclear power plants. Antonovsky et al. (2014) investigated 38 maintenance-related failures in the petroleum industry using an HF investigation tool (HFIT) based on Rasmussen's model of human malfunction to identify the role of HF. They determined three frequent HF contribute to the maintenance failures: assumption (79% of cases), design and maintenance (71%), and communication (66%).

2.2.3.4 Operation

Mogford (1997) introduced the taxonomy of unsafe operations for accident investigation and human causal factor classification, including the condition of operators and supervisory error. Li et al. (2001) investigated 329 major airline crashes, 1,627 commuter/air-taxi crashes, and 27,935 general aviation crashes from 1983 to 1996 to determine the role of pilot error. They also investigated the probable relationship between pilot certificate rating, age, gender, and flight experience as measured in total flight time. Wiegmann and Shappell (2001) used HFACS for the first time to analyze the human causes of commercial aviation accidents between January 1990 and December 1996. They confirmed the viability of HFACS framework for use within the civil aviation arena. Hirotsu et al. (2001) investigated all incidents in nuclear power plants (NPPs) during the last 31 years using multivariate analysis to find HE occurrence patterns in this industry. They concluded wrong unit/train/component, slip due to inattentiveness, improper setting value, inappropriate action, misconnection or miswiring of terminals, insufficient tightening or inadequately fitted objects, and insufficient torque management were major HE types during maintenance. Additionally, wrong unit/train/component, operational slip due to inattentiveness, and operational deviation or disorder were major HE types during operation.

Shorrock and Kirwan (2002) introduced TRACEr, a HE identification (HEI) technique, for the analysis of cognitive errors in air traffic control in the U.K. Grech et al. (2002) analyzed maritime accidents to identify the role of HE and situation awareness (SA). Their results revealed that loss of SA had a partial role in the majority of investigated maritime accidents. Khan et al. (2006) developed a new HE probability index (HEPI) for offshore operation based on the success likelihood index methodology (SLIM) to constrain the chances of HE occurrence and reduce the consequences of such errors through changes in training, design, safety systems, and procedures, which would lead to a more error-tolerant design and operation.

Bellamy et al. (2008) analyzed a small sample of major chemical accidents to find logical patterns of associations that can be used in the applied contexts of inspection and auditing. The result of their work helps inspectors and chemical companies understand how HF and safety management systems fit together.

2.2.3.5 Lessons for mining industry

This section revealed the following shortcomings as well as opportunities for future work related to the mining industry:

- Like the aviation industry, HF and HE related performance deficiencies in the mining operation and maintenance activities need to be identified.
- Then, their economic aspects could be quantified. The result would give professionals, researchers, and even managers an exact indicator of the influence of each HF and HE in their job activities. In addition to the possibility of revealing yet unseen HF and HE during this process, finding the magnitude of the economic impact of each HF and HE can facilitate improvements by revealing and addressing the most critical factors.
- Performance-shaping factors (PSF) are a number of direct or indirect factors and aspects of the task, person, or environment that are likely to increase the chance of HE; therefore, to identify and reduce the HE, it is necessary to further analyze the PSF involved in mining and mineral operation and maintenance activities. The results of this type of study would help the mining industry reduce HE and improve PSF involved in their activities by considering necessary changes to equipment, tools, or process, as well as changes in management approaches.
- Cognitive biases—generally defined as systematic patterns of deviation from the norm or rationality in judgment (Haselton et al, 2015)—and their role in incidents and disasters, as

well as how they alter decision making and lead to undesirable outcomes, needs to be investigated.

- The HE probability (HEP) assessment methods to quantify human reliability is an under-researched area in the mining and mineral industry. Further studies to identify a suitable HEP method among the different available methods, such as subjective judgment HEP methods (e.g., absolute probability judgment (APJ), paired comparisons (PC), SLIM [Embrey et al., 1984]) and AHP-SLIM or HE database methods (e.g., HE assessment and reduction technique [HEART; Williams, 1986], JEHDI, and THERP [Swain & Guttmann, 1983]) for each individual mining sector and activity can enable researchers and professionals in this industry to properly address the related issues.
- To reduce the rate of accidents, the HF associated with them need to be addressed. Despite a few mining and mineral industry accident-analysis studies, there are currently no reports about the main HF- and HE-caused accidents and incidents in Europe and North America. More studies are needed to better understand the systemic factors contributing to mining accidents, and to evaluate those organizational and supervisory failures that lead to HF and HE. The results would provide the information necessary to reduce mine accidents.
- Even though HFACS has been approved as a practical method for investigating the role of HF in accidents and incidents, it suffers from some inherent deficiencies. HFACS analysis is based on accident reports. Reporting an accident often involves subjectivity and filtering and the causal inference might be manipulated by the data collection method. Also, considering the different background, position, and education level of the people writing them, accident reports will differ in content and format. More study is needed to create a comprehensive reporting form based on the HFACS method to enable people across the

industry to write universal, extensive, and detailed reports of the accidents and incidents. The predefined form approach would prevent the loss of information for some aspects of incidents or accidents and would ensure consistent analysis of data.

- The final reporting system also facilitates analyzing accidents to look for logical patterns of associations. The idea is that, once identified, the patterns can be applied to operations and maintenance. If the patterns can be found in practice, they can be used to identify weaknesses that could cause major accidents. Similarly, the patterns can be used to understand accident causation during accident investigations.

2.2.4 The Role of an ERS Operator in Shovel Performance and Productivity

Research has shown that shovel operators can greatly affect equipment performance, productivity, and energy consumption. For example, Hendricks (1990) studied the productivity of four electric rope shovels and found that electric rope shovel operators adjust digging practices to cope with variations in muck-pile conditions.

Jessett (2001) studied four P&H5700 rope shovel operators' loading "styles" during 1501 working cycles. Jessett defined style as:

> *"the way the operator commands the swing, crowd, and hoist machinery; including the level of interaction realized between these systems."*

Although, their monitoring system could not measure the payload, variation among operators' times to load trucks were observed. Additionally, during their trial they observed differences among operators' swing and dig time average and standard deviation from cycle-to-cycle.

They studied swing-phase hoist current as an indirect measure of the bucket payload and suggested that there are differences among operators' bucket loads. Also, by monitoring the operator' s manipulation of the crowd and hoist systems they established variation in digging style from operator-to-operator.

While their novel research shed light on many previously unknowns, it can be argued that the absence of the required technology to measure shovel payloads at that time limited their research to only an estimate of bucket payloads. As argued by the author, this measurement has limitations and only could be used to compare operators in terms of the payload-per-pass. Also, a statistical analysis that demonstrate and proves the variations among operators' cycle times is required.

Onederra et al. (2004) investigated the influences of operator skills and dig condition on shovel productivity. They used indirect data from the Modular Mining Inc.'s Dispatch software. A high degree of variability was observed in all loading cycle components that they argued it was linked to the variation in both muck-pile and operators dig tactics.

Patnayak and Tannant (2005) observed significant variations among operators at an oil sands operation in terms of hoist power use while working with the same equipment, digging conditions, and material. Patnayak et al. (2008) quantified shovel performance in an oil sands mine and determined that operators could account for up to 25 and 50% of the variability in hoist power and productivity, respectively. Operators with higher productivity (mean tonne per shift) had higher hoist motor energy consumption.

Also, Vukotic (2013) and Vukotic and Kecojevic (2014) investigated three productivity related KPIs of an electric rope shovel (i.e. time to load a truck, time that the shovel spends in its digging phase during cycle time, and bucket payload) and energy to load. They developed a multi-attribute decision-making model that uses the aforementioned production KPIs to model shovel energy consumption. They also used PROMETHEE II analysis, a decision-making tool designed to provide decision makers with ranking options for their problem components, to rank operators based on their cycle time, bucket volume and dig time. They recommended a more comprehensive ranking system that includes more parameters for future work.

They concluded that volume of material in the bucket followed by dig time are the most important parameters for evaluating the performance of operators in terms of production rate and energy consumption. They also argued that PROMETHEE’s subjectivity when selecting criteria weights and selecting a preference function are two disadvantages of this ranking method.

Babaei Khorzoughi and Hall (2016) and Babaei Khorzoughi (2017) monitored the energy consumption of electric rope shovels during dig cycles and introduced a diggability index. They investigated the effect of operator on machine productivity using clustering analysis. Both studies confirmed the variation in operator performance seen in earlier studies. The review by Awuah-Offei (2018) of studies related to energy efficiency of rope shovels recommended investigating the role of human factors in the design of operator assistance systems to improve the shovel performance.

2.3 Automation in Mining

Automation is generally defined as the intelligent operation of equipment using technology without direct human contribution (Sheridan, 2002). The mining industry has been considered a slow industry in adopting and implementing new technologies (Bellamy & Pravica, 2011). The combination of the long time for new technology development -between seven to ten years-, the often short term financial focus, and the risk of failed technology are contributors to the mining industry's slow adoption of technology (Bartos, 2007; Bellamy & Pravica, 2011).

The initial purpose of automation in the mining industry was to protect the health and safety of mine workers, but it was also considered for improvement in productivity by minimizing human error and eliminating poor driving behaviors of tired and/or distracted workers (Dudley & McAree, 2013; Parreira, 2013). In addition, the reduction in loss time due to shift change, breaks etc. was viewed as how automation could improve productivity.

Complexities related to the automation of loading units have encouraged researchers to aim for different levels of automation. Roberts et al. (2002) suggested the following steps toward automation:

- Manual operation: The operator physically presents in the operator cab and performs the operation.
- In-sight tele-operation: The operator is located in the vicinity of machine, and performs all tasks using a remote control.

- Tele-remote operation: The operator controls the machine from a remote location using a remote control and video and audio feedbacks.
- Assisted tele-remote operation: the machine control system performs many tasks, and the operator intervenes via tele-remote control as needed.
- Fully autonomous: The machine operators autonomously.

Operator assistance technologies such as path planning and navigation (Gustafson, 2011; Larsson, 2011) and collision detection and avoidance (Larsson et al., 2010a) have been developed mainly for Load-Haul-Dump (LHD) units by researchers. Dunbabin and Corke (2006) in an effort to automate the digging cycle of an electric rope shovel, proposed techniques to detect and avert dipper stall and the on-line estimation of dipper fill factor. At the time of writing this thesis, there are several operator assistance systems offered by electric rope shovel manufactures that mainly prevent inadvertent mishandling of the machine (*Making Mining Automation a Reality Caterpillar*, 2020; *Operator Assist Technology Komatsu Mining Corp.*, 2020).

Automation in mining has had many applications ranging from an automated valve to a full fleet of autonomous haulage trucks. Increased production hours, lower employee and associated costs , increased fuel efficiency and extended major component lives are among the main benefits reported by researchers (Bellamy & Pravica, 2011; Fiscor, 2018; Glover, 2016). The higher productivity and reduced costs might make some previously uneconomical mines profitable.

2.4 Simulation of The Mining Systems

Generally, simulation defined as the process of creating a model of a real system to understand its performance and evaluate the outcome of various imposed strategies for the operation of the system (J.R. Sturgul, 1999). A system can be continuous or discrete in nature; in a continuous system parameters change continuously with respect to time (Salama et al, 2014). Whereas in a discrete system the changes occur only at a countable number of points in time and are generally triggered by events (Ali, 2016).

On the basis of the system which a simulation model is representing, it can be categorized into either a continuous or a discrete event simulation model. A discrete event simulation models a system operation as a discrete sequence of events. Each event marks a change of state in the system, and it is assumed that there are no other changes between events (MacDougall, 1987). Additionally, a system with one or more random variables is called stochastic, and a system with no random variable is known as a deterministic (L. Kelton, 1982).

Discrete events simulation models have been proved as a tool for the purpose of the analysis and design of systems that consist of chronological sequences of events such as mining haulage system (Ali, 2016). The ability to model a system with different levels of detail and complexity is one of the main advantages of simulation. In contrast, the model's dependency on statistical data is a major disadvantage (Tarshizi, 2012).

2.4.1 Mining haulage system simulation

Simulation was used in mining as early as the 1960s by Rist to solve mining hauling problem (Brown et al., 1988). Also, O'Neil and Manula (1966) utilized computer simulation for an open pit truck haulage system. Since then, simulation has been used by researchers and professionals to solve problems such as truck fleet sizing, dispatch, and allocation (Ataeepour & Baafi, 1999; Awuah-Offei et al., 2003; Bonates & Lizotte, 1988; Forsman et al., 1993; Mena et al., 2013; Moradi Afrapoli et al., 2019; Sturgul & Harrison, 1987), short-, medium-, and long-term mine planning, scheduling and optimization (Fioroni et al., 2008; Upadhyay, 2016), and efficiency improvement (Tarshizi et al., 2015; Cervantes et al., 2019) . Simulation was also used to develop early commercialized fleet management computer software such as TALPAC by Runge Mining and FPC by Caterpillar Inc.

Upadhyay and Askari-Nasab (2018) presented a simulation-based optimization framework to capture uncertainties in short-term mine planning and make mine planning more proactive. Also, Dindarloo et al. (2015) suggest a discrete event simulation framework guideline for truck-shovel mining system equipment selection and sizing.

As an alternative, researchers used a queueing theory approach to study different aspects of the mining haulage system such as truck-shovel sizing (Kappas & Yegulalp, 1991; Kesimal, 1998; May, 2013). Moradi Afrapoli (2019) argued that mining operations cannot be considered Markovian as different activities involved in an operation can follow different distributions. They enhanced the discrete event simulation modeling approach by replacing deterministic variables with stochastic ones. His work also integrates the processing plant operation and fleet management system with the mine simulation model which enhances the modeling accuracy. The simulation model was used as a part of the development of a truck dispatching decision-making model.

2.4.2 Simulation Tools

Computer hardware and software advancements influenced the development of simulation software and helped the industry to introduce faster and more flexible software with better user-friendly interfaces (Sturgul & Li, 1997).

Greberg and Sundqvist (2011) classified simulation software into four categories:

- general purpose languages, such as C++ and VBA.
- simulation languages, such as SIMAN, SLAM, and GPSS.
- general purpose simulation software packages, such as Arena.
- mining software packages such as Haulsim.

While the first two categories offer higher flexibility in term of application, they need developers with good programming skills. Arena is a general purpose simulation software that is widely tested and tried at commercial and academic levels in mining (Parreira, 2013; Shelswell et al., 2013; Vasquez Coronado, 2014).

2.5 Summary, Discussion and Conclusions

The literature review revealed shortcomings as well as opportunities for future work related to the mining industry focused on the shovel operator's performance. The following points summarize the literature review findings:

- While the influence of the operator on the energy efficiency of a shovel is well investigated, how operators loading practices are different and the extent to which they are affecting shovel and mine productivity needs to be investigated.
- Despite studies that collectively have helped professionals to better understand the nature of variation among rope shovel operators' performance, the sources and impacts of these variations remain to be quantified, and the extent to which they influence overall mine production needs to be evaluated.
- Most of shovel performance studies only focus on production and that is primarily production per truck. There is a need for a process to evaluate shovel operator performance to identify key factors that affect productivity and develop strategies to use this information to enhance operator performance.
- Based on the literature review there appears to be a lack of a comprehensive approach that includes multiple variables to assess operator performance and provide them with feedback. The current approach is to evaluate operators on a single KPI such as truck final payload ratio.
- In the absence of details on specific activities (i.e., individual pass payload, dig, swing, and return times), the conventional approach to model shovels with DES is to obtain truck load

information from the truck onboard monitoring system and use shovel bucket capacity to estimate the number of passes required to load the truck. The mean loading cycle time is then calculated by dividing total loading time data obtained from dispatch software by the estimated number of passes. However, it is believed that this leads a wide range of estimations and assumptions that are made throughout the calculations which reduce the value of the results. Additionally, obtaining loading time from dispatch software ignores other shovel activities such as propel and walk, which could lead to an oversimplified model.

- Data from a shovel onboard monitoring system provides details such as digging, swinging and returning times, each individual pass and total truck load and many other KPIs gathered directly from shovel operation. These details could be used to model shovels more accurately and create an understanding of where improvements can be attained.
- Automation and the extent to which it can improve loading activities by removing HF and HE is yet to be evaluated. The result could not only provide a better understanding of potential achievable improvements but also form a prospected baseline for any future development in the automation section.
- As revealed in the literature review, aviation and nuclear industry have been successful in mitigating the role of HF and HE in their operation and maintenance. The mining industry can learn from this and apply their method to expedite its progress toward enhancing electric rope shovel operator's performance. Techniques such as HEP and PSF can be used to identify all direct or indirect factors and aspects of the shovel operation, and their work environment that are likely to increase the chance of HE. Using the operator behaviour DES sub-module introduced here, their economic aspects could be quantified. The result

would give professionals, researchers, and even managers an exact indicator of the influence of each HF and HE in their job activities. Then, introduced measures in the aviation and nuclear industries such as MAP or MEDA can be modified/adjusted to mitigate the identified electric rope shovel operators' HE and HF. Additionally, the cognitive biases -generally defined as systematic patterns of deviation from the norm or rationality in judgment- and their role in the electric rope shovel operators' deviations from optimum performance could be studied using different methodologies introduced in aviation and nuclear industries.

3. CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter explains the theoretical framework and components of the analysis part of the thesis. The chapter introduces the conceptual theoretical frameworks, statistical and mathematical methods, and connections between them to achieve the main objectives of the thesis.

Section 3.2 focuses on studying shovel operator practices and investigates the nature and extent of differences among them. In an effort to better assess operator performance, the opportunity to implement the new findings in a comprehensive operator performance assessment KPI that could capture variation among operators and reflect their overall performance is explored.

Section 3.3 explains the operator and the discrete event simulation application and introduces methodology to evaluate the introduced measures to enhance the performance and production of an electric rope shovel. This section also introduces shovel automation scenarios that will be evaluated to study the extent to which autonomous and operator-assisted loading units could help reduce the influence of HF and HE and thus improve different aspects of a mining operation. Four different levels of automation ranging from operator-assisted swing and return to fully autonomous for a shovel are considered.

The last part focuses on the theoretical frameworks of the discrete event simulation model of a truck and shovel surface mining operation and the operator behavior sub-module. The shovel operator sub-module aims to mimic operator loading behavior in a truck and shovel surface mine operation and provides the necessary tools and required information to evaluate different operational scenarios. Finally, the scope of the work, assumptions, model limitations, and verification process are explained.

3.2 Operator Performance Study

3.2.1 Evaluation of operator’s key activities variation

One of the underlying hypotheses of this thesis is that there are significant variations among operator loading practices that affect performance and productivity of the shovel in particular and the mine operation in general. To understand the variation and influence of shovel operators on production the following will be done:

- Perform a statistical evaluation of shovel operator performance.
- Develop a metric to rank the various operators. This will build on existing metrics such as cycle time and production.
- Identify a performance metric(s) to provide to the shovel operator that will allow them to improve their overall performance.
- Evaluate loading practices and develop strategies to improve shovel operator performance under certain scenarios.

3.3 Electric Rope Shovel Operation Enhancement Study

To explore how the knowledge learned and strategies developed can be used by a mine, a simulation model will be developed to assess the following:

- Shovel operators influence on productivity,
- Potential changes in loading practice on productivity, and
- The autonomous shovel scenarios shown in Table 4 on both shovel and mine productivity and performance.

Table 4. Automation scenarios

Automation	Practice		
	Swing and return	Dig	Propel (positioning and movement)
Level 1	Automated	Operator	Operator
Level 2	Automated	Automated	Operator
Level 3	Automated	Automated	Automated
Level 4	Automated*	Automated*	Automated*

*Improved, compared to the base automated scenario

3.4 Mine Simulation Model

To assess different operational scenarios and investigate the role of the shovel operator on shovel, truck, and mine production and performance, a DES model is developed. The following steps are carried out to develop the model:

- For all input parameters, using MATLAB all data points are extracted from the SQL data base, filtered and written into a text .CSV file. Then, ARENA Input Analyzer software is used to calculate and draw their histogram. After examining different fitted distributions, the best fitted distribution is selected based on the sum of square error criteria calculated by the software. The sum of square error is an estimate of the deviation of the random component in the data from the fit. A value closer to zero indicates a better fitted distribution. Arena Input Analyzer considers continuous distributions presented in Table 5.

Table 5. Arena Input Analyzer continuous distributions

Distribution	Arena Input Analyzer Representative
Exponential	EXPO
Normal	NORM
Triangular	TRIA
Uniform	UNIF
Erlang	ERLA
Beta	BETA
Gamma	GAMM
Johnson	JOHN
Log-normal	LOGN
Poisson	POIS
Weibull	WEIB
Continues	CONT

These distributions will later be used by Arena to draw random points from and generate input data for any required activity that follows stochastic behaviour (i.e., trucks' empty and loaded travel times, their backing up and spotting times, and shovels' loading parameters such as number of buckets to load a truck, dig, swing and return times, each bucket load distributions). Appendix A summarizes all distributions that are used throughout this study for each DES scenario.

- A VBA macro written in Arena reads the following parameters before each run and inserts them into the model:
  - road network parameters (i.e., nodes, their coordinates, segments and length and intersections) converted from the .dxf file using MATLAB software,
  - mine production schedule (i.e., material grade and tonnage, their planned load and dump locations, sequence of mining and precedence, and designated shovel),
  - distributions fitted on the historical data of the required parameters (i.e., trucks' empty and loaded travel times, their backing up and spotting times, and shovels' loading parameters such as number of buckets to load a truck, dig, swing and return times, each bucket load distributions).
- The mine DES model is built using ARENA modules (Figure 5). Trucks and shovels are modeled as entity and resources, respectively. ARENA transporter is used to model trucks interactions. Record and write modules are used to save KPIs. A more detailed information on how they work are presented in the section 3.4.1.
- The model is run for a predefined period of time with a specific number of replications to reach the required half-width for the production within a 95% confidence. Half width is used to determine the reliability of the results. It can be interpreted that within the assumed confidence level (i.e., in 95% of repeated runs) the resulted production would be within the average production ±half width. Arena uses a batching algorithm to calculate the half width (D. Kelton et al., 2015).

- Results are written to an MS Excel file and then transferred to MATLAB software for the data analysis steps.

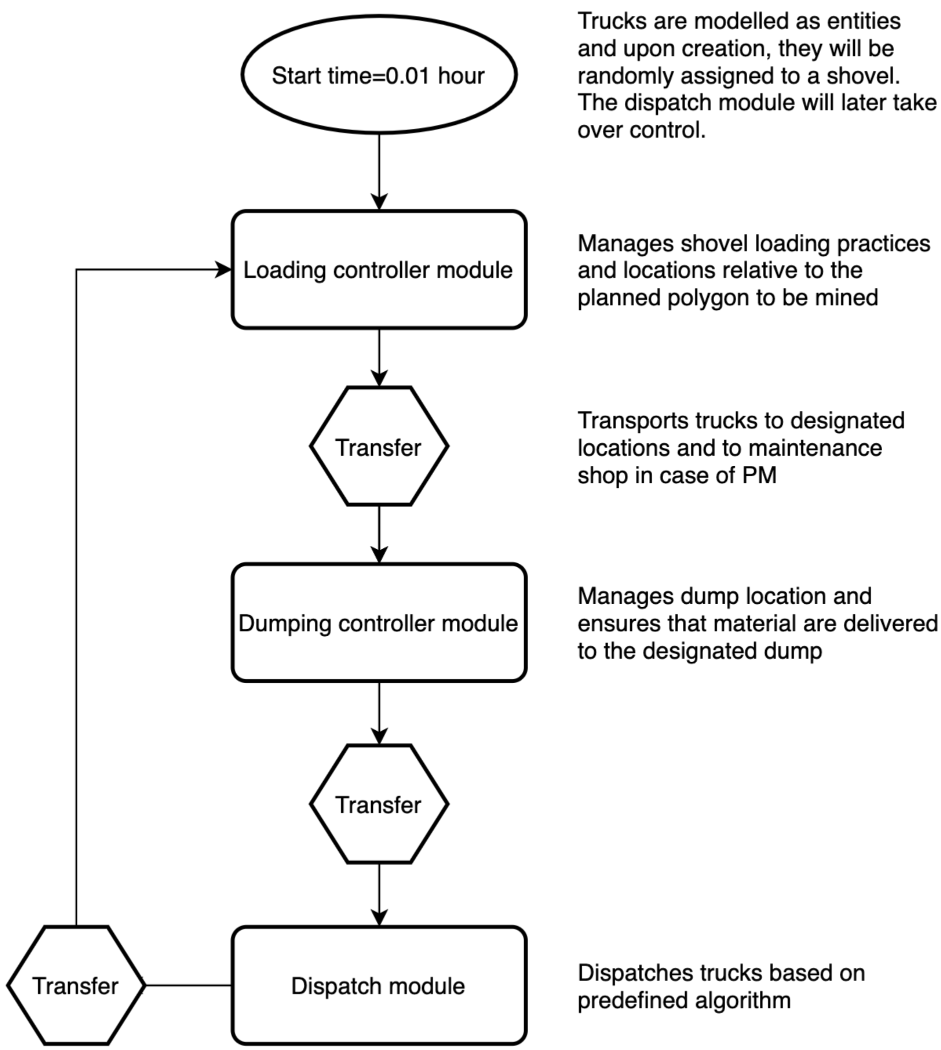

Figure 5. Flow of the mine operation DES

3.4.1 Simulation sub-modules

The following sub-modules form the discrete event simulation model:

Operation initializer: This sub-module initiates the simulation by creating and assigning trucks to a designated shovel for the very first time in the model. It assigns a serial number to each individual truck as an attribute that later is used to track the truck activities. Based on the type of a mine operation this sub-module can lock trucks to a specific polygon. It then allocates a transporter to the truck and dispatches it to its designated shovel.

Loading: Shovels are modeled as resources with a predefined work time schedule. This enables the model to consider operator's shift change and breaks. Shovel as a resource in Arena follows a mean-time-between-failure and mean-time-to-repair random distribution for its failure and repair times. Arena keeps track of their status throughout the run.

Upon a truck arrival at the load location, the loading sub-module takes over its control and checks if its designated shovel is still in the production. If the shovel operator is on a break or the shovel has failed, a new shovel will be assigned to the truck, and the truck will be transferred to its new loading location using the transfer module.

If the shovel is working and available, the loading sub-module puts the truck in the shovel loading queue. When it is the shovels turn, as soon as the previous truck is dispatched the truck starts to spot. The spotting time is calculated using the "spot time" input distribution. Then, the shovel loads the truck [the loading process is executed by the shovel operator sub-module explained in more details in the section 3.4.2], assign its material, then its dump destination based on the material loaded and mine schedule and release it to the transfer module. At this point, the loading sub-module makes the shovel available for the next truck to be loaded.

Additionally, the loading sub-modules keeps track of the mined material from the polygon and transfers the shovel to the next scheduled polygon upon finishing the current one.

Transfer: as its name implies, the transfers sub-module transfers trucks from their current location to their assigned final destination based on the shortest path between them. Based on the truck load status (i.e., loaded or empty) truck travel speed is calculated from the appropriate “truck speed” distribution.

Arena transfer module keeps track of roads and their traffic condition and moves trucks according to the road network geometry. Similar to the real-world, bunching can occur in case a truck travels slower than ones behind it as overpass is not allowed in this model.

Also, at intersections, the transfer sub-module controls and monitors trucks stoppage. In three intersections of the mine a full stop rule is implemented. The transfer sub-module checks if the truck has arrived in one of these intersections and operates those intersections based on the first-come first-serve basis. The truck stoppage distance and time is calculated using the truck previously assigned speed, and the speed will be resumed after the truck passes the intersection.

Dumping: Dump locations are also modeled as resources. This sub-module sends the truck to either the waste or the mill hopper stock-pile location based on the truck assigned load material. Then the truck waits at the queue, and as soon as the dump resource becomes available initiates the dumping procedure.

First, a backing-up time is calculated using the "truck back-up time" input distribution. Then, a dumping time is calculated using the "truck dump time" input distribution and then the truck dumps its load. If more than one dump location is available, the one with smaller queue will be selected. If applicable, the capacity of the hopper is checked after each truck dumps.

Maintenance: To mimic a preventive maintenance (PM) program for trucks, after the truck dumps its load, this sub-module checks and see if it is time for the truck PM. It does so by checking to see if the truck has exceeded a predefined number of cycles. In general, truck PMs are based on engine run hours, here number of cycles are used and assumed to be a simpler representative of the desired behavior. In order to keep certain number of trucks in the operation, the sub-module checks the number of available trucks in operation and if there are enough of them, the truck will be sent to the shop. If either the number of cycles has not been reached or there is a lack of trucks in operation, the truck will be sent to the dispatch sub-module.

Dispatch: this sub-module assigns the truck to the appropriate shovel. It considers shovel's availability, and the queue at the shovel and compares the shovel production to the planned.

Season change: this sub-module uses a logic-based follow to track season changes and adjust required parameters based on it. It is assumed that there are two major seasons affecting the operation: dry and wet. Truck empty and loaded speeds, spotting and backing times are considered to be influenced by the season.

Data record: this sub-module records operation and production KPIs in specific time intervals (i.e., each cycle and monthly) as well as in a general final report at the end of simulation time.

3.4.2 Operator Sub-module

In addition to the aforementioned sub-modules, in an effort to model the shovel operator's behaviour and loading activities, the operator submodule is developed.

Figure 6 presents the sub-module flow chart. The sub-module uses the number-of-passes-to-load distribution to assign number of buckets to each truck loading task. Then, for each cycle, its specific distribution is used to calculate the bucket load and dig, swing and return times. This will repeat for the assigned number of buckets to the truck.

If the addition of the bucket load to the truck load will cause it to exceed the maximum allowed capacity, that pass load will be discarded. The shovel will be tasked to take an extra pass to reach the minimum allowable load for the truck to be dispatched if it has not yet. This procedure complies with the author's field observation that operators dump their bucket load as soon as the system notifies them about the excessive truck final load considering their current bucket load is added to it. In this situation it is common for the operator to dig another bucket load with less material in it.

After the loading process is completed, a propel time will be calculated from its distribution and added to the total cycle time, and the end of a loading cycle will be marked. A write module will record all the statistics in a .csv file for further analysis.

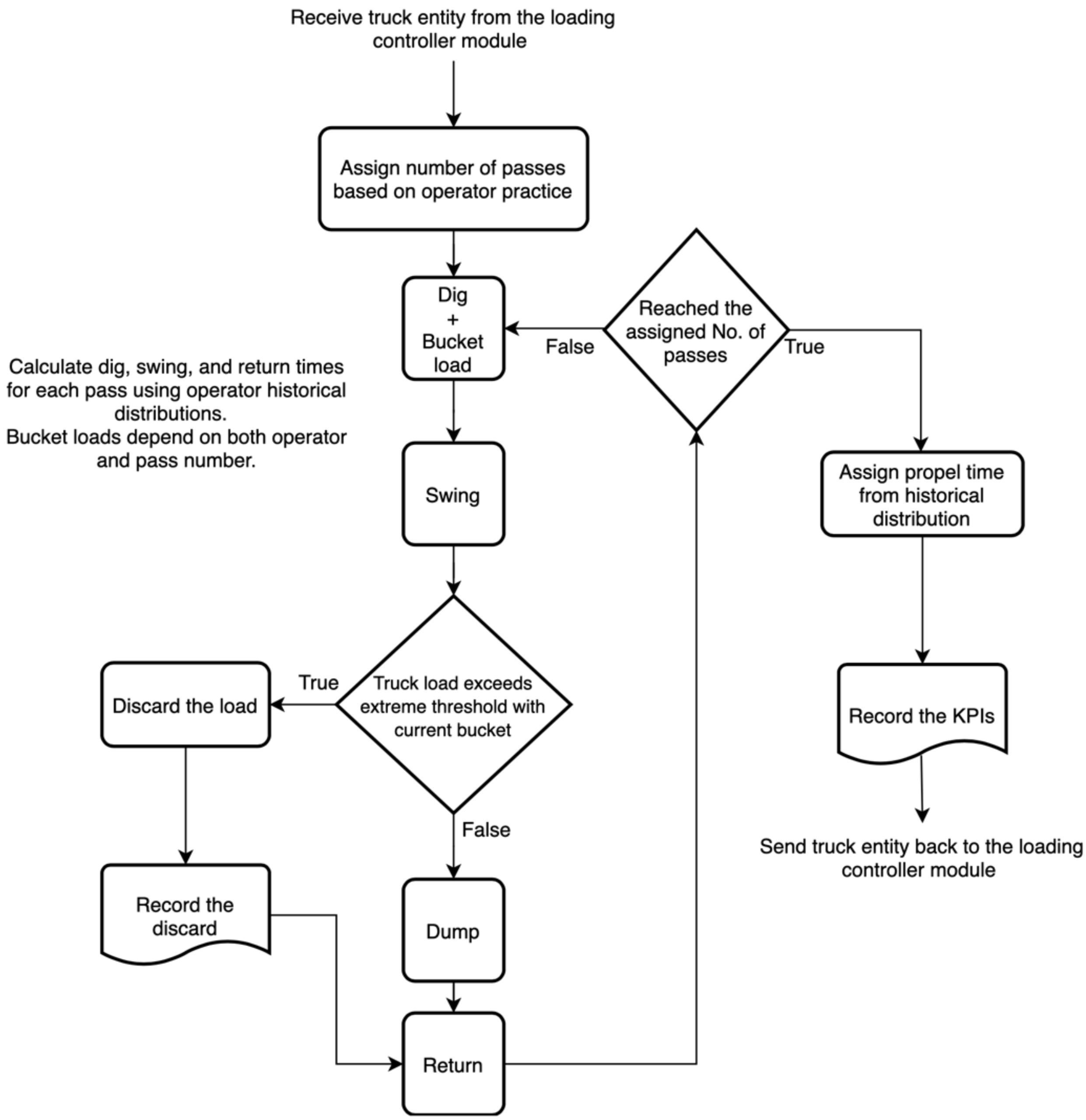

Figure 6. Electric rope shovel simulation sub-module

3.4.3 Mine Simulation Model inputs

The mine simulation model uses the following parameters:

- Mine schedule: dig and dump locations (IDs and coordinates), total tonnage of material, the average grade, and destinations in each block. Shovel number assigned, precedence, and sequence for each shovel.
- Shovel fleet: shovel IDs, availability, number of buckets to load a truck, each bucket load, dig, swing and return times, propel times.
- Truck fleet: truck IDs, availability, number of trucks, capacities, backing, spot and dump times, average empty and loaded speeds.
- General inputs: processing plant maximum throughput rate, road network and associated nodes.

3.4.4 DES model general assumptions

The Following assumptions are made by the DES model:

- Processing plant throughput stays constant during the simulation period.
- Grade of material and their density within a polygon stays constant during its mine.
- Truck driver practice influence is assumed to be reflected in their activity's distributions.
- Mine road reconstruction, maintenance and reconfiguration are not considered.
- All shovels follow the same mean time to failure and mean time to repair statistics.
- All trucks follow the same preventive maintenance plan and check-up statistics.
- No plan or schedule change are considered during the simulation period.
- When applicable, for the shovel operator one half hour required for shift change, and two half hour coffee breaks are considered during a 12-hours shift.
- Truck operators shift change and breaks are ignored.
- Truck refueling lost time is ignored.
- Truck loaded speeds are not correlated with the truck load weight.
- As the focus of this study is on the loading unit and their operator and to limit the influence of the processing plant, it is assumed that there is no down time for the processing plant and also stockpile and mill hopper capacity is assumed to be unlimited.

3.4.5 DES model verification

Before results of the developed simulation model can be used and interpreted, the model needs to be verified and if applicable, validated. Here, as simulation is being used to explore new proposed operational scenarios based on historical data from two different operations, and in absence of the full historical data from the case studies, a full validation assessment of the model is not presented.

In order to verify the model, the first step is to visually monitor the model and make sure it reflects the mine operation using the Arena simulation visualization capability. Afterward, the operational KPIs below for the truck and shovel fleets are investigated against data used to develop the model:

- Trucks:
    - Empty and loaded speeds
    - Backing, spotting, and dumping times
    - Load tonnages
- Shovels:
    - Dig, swing, and return times
    - Pass bucket load
    - Propel times

Additionally, shovel loaded tonnages and delivered materials to the dump locations are used to verify the model.

In order to verify the operator sub-module, the shovel production (i.e., truck final load) statistics are compared with the historical data.

3.4.6 Scope and limitations of the model

The scope of the developed discrete event simulation model is limited to the evaluation of operators' performance and their direct and indirect influences on the shovel, truck and mine production and performance. The model developed here includes many critical objective and constraints of an open pit surface mine operation that are essential to reach the goal of this study, yet compared to a real-world operation, there are other aspects that needs to be considered to make the model more accurate. Such as but not limited to a more sophisticated dispatching algorithm, age and condition of both shovel and trucks, truck re-fueling, processing plant capacity, capacity changes and failure, mine road map changes and re-routes, real-mine dispatch algorithm and system being used. Time, technical and budget prevented this research for from including these in the model.

4. CHAPTER 4: SHOVEL OPERATOR PERFORMANCE STUDY

4.1 Introduction

This chapter presents the performed statistical analysis, implementation of the developed methodology and simulation model and their results.

Section 4.2 introduces the case study data (i.e., shovel health and payload monitoring system dataset) and performed data pre-processing tasks.

In the Section 4.3 the statistical analysis of the operator influences on the key components of the shovel operating cycle results are presented. The results from this analysis lead to an evaluation method in the section 4.4 that could be used to capture differences among operators. This developed method is implemented and used to perform an analysis on the fleet of the operators from the shovel dataset case study and identify best and worst operators.

Section 4.5 uses simulation to explore the extent to which shovel operator can influence shovel, truck and mine operation and how those identified best, and worst operators are influencing operational KPIs. First, the mine operation case study data from an open pit mining is introduced and performed data preprocessing tasks are explained. Then, operator behavior sub-module is implemented in a mine discrete event simulation model and verified. Statistics from the identified best and worst operators in section 4.4 are used in the developed simulation model and their influences on shovel, truck and mine productivity and performance are examined.

Section 4.6 discussed the results.

4.2 The case study dataset

4.2.1 Shovel health and payload monitoring dataset

For this research eighteen months' worth of data from the PTMRS system installed in an open pit surface coal mine in Canada is used to carry out the statistical analysis of loading unit operators' performance.

The operation is employing 3 P&H4100 shovel that have PTMRS installed, and a fleet of 300 tonnes Komatsu haul trucks. The mine operates 24 hours with two 12-hour shifts. The shovel monitoring system database includes 364,655 loading cycle records from 31 operators for a period of 18-months. For the purpose of confidentiality, operator names were replaced by numbers during the data transfer stage. Also, GPS records related to load and dump locations were removed.

For each record, the database includes the following parameters:

- Record time
- Shift time
- Record type (pass/truck)
- Load type (load/discard)
- Operator ID
- Shovel crew
- Propel time
- Digging time

- Swing angle and time
- Return angle and time
- Idle time
- Bucket payload, and the truck final load
- Bucket carry back
- Truck ID
- Truck Capacity
- Shovel position
- Equivalent dig energy
- Maximum dig force
- Diggability index

4.2.2 Data pre-processing

Before any analysis is performed, it is critical to remove outliers. Based on inputs from the PTMRS system experts, mine operational staff and professionals, the following rules are applied, and corresponded records are removed:

- Record that the truck load exceeds 130% of truck capacity.
- Record that the truck load is below 75% of truck capacity.
- Records that the truck load cycle time exceeds 300 seconds.
- Records that either the shovel swing or the return time exceeds 60 seconds.
- Records that the shovel dig time exceeds 120 seconds.

- Records that the shovel propel time exceeds 60 seconds.

Table 6 presents information regarding the number of valid measurements for each individual operator after removing outliers.

Table 6. No. of valid measurements after removing outlier

	Valid Records	
	%	number
OP01	90%	1541
OP02	92%	2286
OP03	97%	3376
OP04	94%	3450
OP05	95%	25014
OP06	97%	5399
OP07	98%	33577
OP08	96%	31963
OP09	99%	31587
OP10	87%	25780
OP11	91%	29299
OP12	94%	27214
OP13	93%	26145
OP14	95%	14107
OP15	91%	1181
OP16	96%	5864
OP17	98%	1132
OP18	96%	8095
OP19	95%	3950
OP20	91%	1361
OP21	92%	1544
OP22	96%	4440
OP23	99%	2010
OP24	85%	1203
OP25	97%	7039
OP26	87%	2727

4.3 Statistical analysis of operator's key activities variation

The first step is to study key loading segments and examine whether a meaningful statistically difference can be established between operators. An analysis of variance (ANOVA) is performed to examine this hypothesis (alpha = 0.05).

The ANOVA takes into account sample size, means, and standard deviations in comparing two or more independent groups (Bailey, 2008). The null hypothesis for ANOVA is that the mean (average value of the dependent variable) is the same for all groups of variables. Upon rejection of it, it can be concluded that there is a statistically significance among those test groups.

The 26 operators with at least 1,000 records were used for subsequent analyses. The operator performance variables selected as KPIs were truck load factor (TLF) (i.e., truck load/truck capacity), loading cycle time, and number of passes to load the truck. Results of the ANOVA performed on a randomly selected sample group of 1,000 records from each operator log (Table 7) demonstrated that mean TLF, cycle time, and number of passes differed among the 26 operators ($0.001 < p < 0.001$) as illustrated in KPI box plots (Figure 7 and Figure 8).

Table 7. ANOVA results on 1,000 key KPI records from each of 26 electric rope shovel operators

Statistic	Truck load factor	Cycle time	No. passes
The mean square within group variation (error)	0.007	1539.1	0.14
The mean square between group variation	0.94	99363.4	4.05
F-statistic[1]	135.85	64.56	29.56
p-value[2]	0.001	< 0.0001	< 0.0001

[1] F-statistic represent the significance of the component in the ANOVA analysis (ratio of the mean squared variations).
[2] P-value represents the probability of the F-statistic to take a value greater than the calculated test statistic, a small p-value suggest rejection of the null hypothesis.

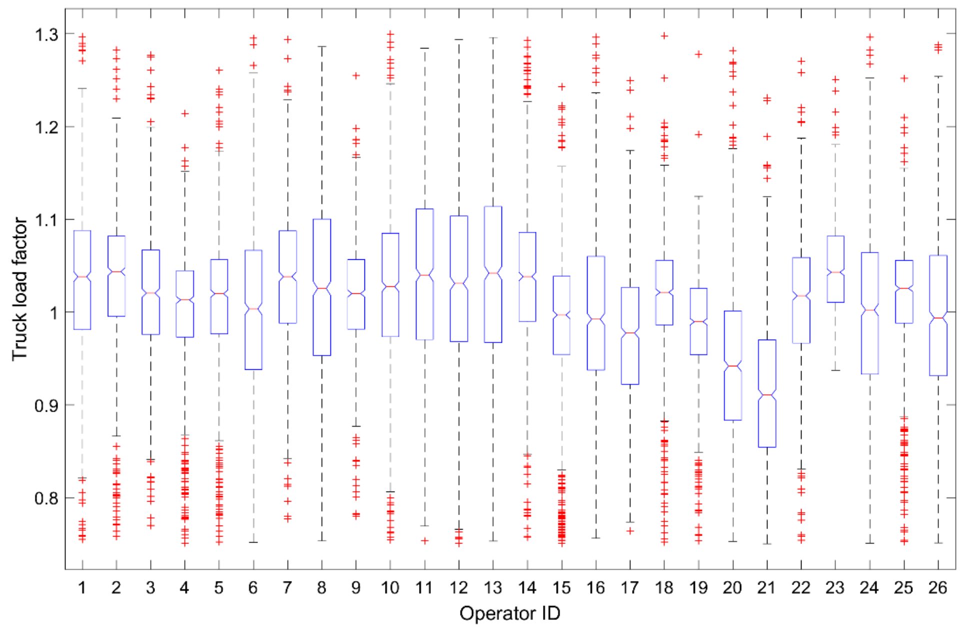

Figure 7. Truck load factor box plot[3]

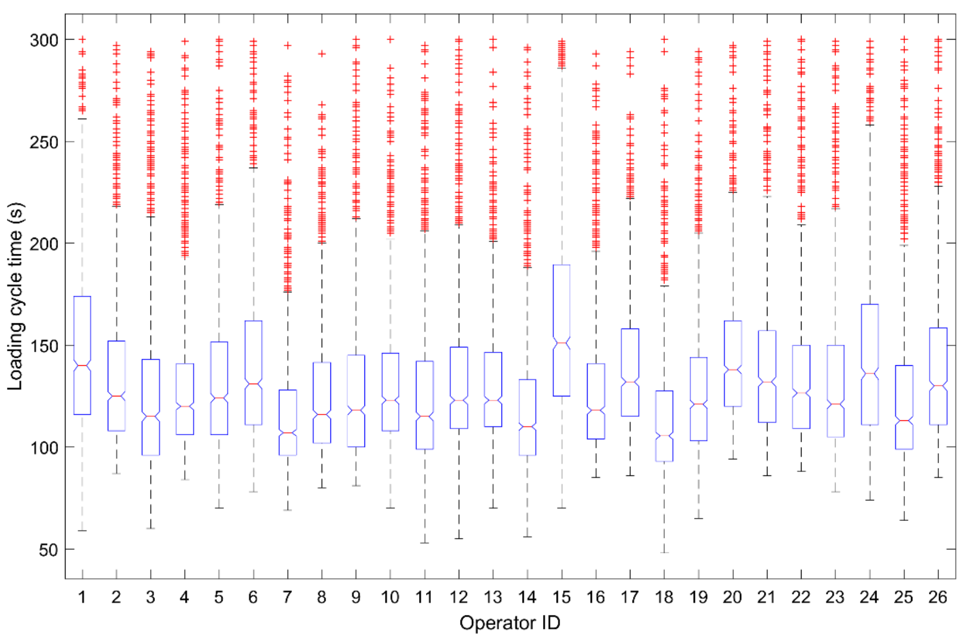

Figure 8. Truck loading cycle time box plot

[3] Bottom and top of box plot represent 25th and 75th percentile, respectively. The red line is the sample median. Red marks are representing values beyond the 1.5 times the interquartile range from the 25th or the 75th percentile.

A closer look at both figures reveals some correlations between TLF and cycle times. For instance, operator 15 has a lower-than-average TLF with higher-than-average cycle times. This is the opposite for operator 7 which has lower cycle times and slightly higher TLF. While this can be generally linked to the operator's experience, it also emphasises the importance of considering all aspects of a loading practice for evaluation purposes.

To further investigate those variations, an ANOVA analysis is performed on the operators' dig, swing and return times. Table 8 presents the result. As expected, not only operators have differences in their overall cycle times, but also in its components (i.e., dig, swing and return).

Table 8. ANOVA results on 1,000 loading time records from each of 26 electric rope shovel operators

Statistic	Dig time	Swing time	Return time
The mean square within group variation (error)	105.2	27.9	32.9
The mean square between group variation	11858.2	4236.1	3743.8
F-statistic	112.7	151.4	113.6
p-value	< 0.0001	< 0.0001	< 0.0001

Figure 9, Figure 10, and Figure 11 present the box plot of dig, swing and return times for the fleet, respectively. The variations among the operators can be visually observed.

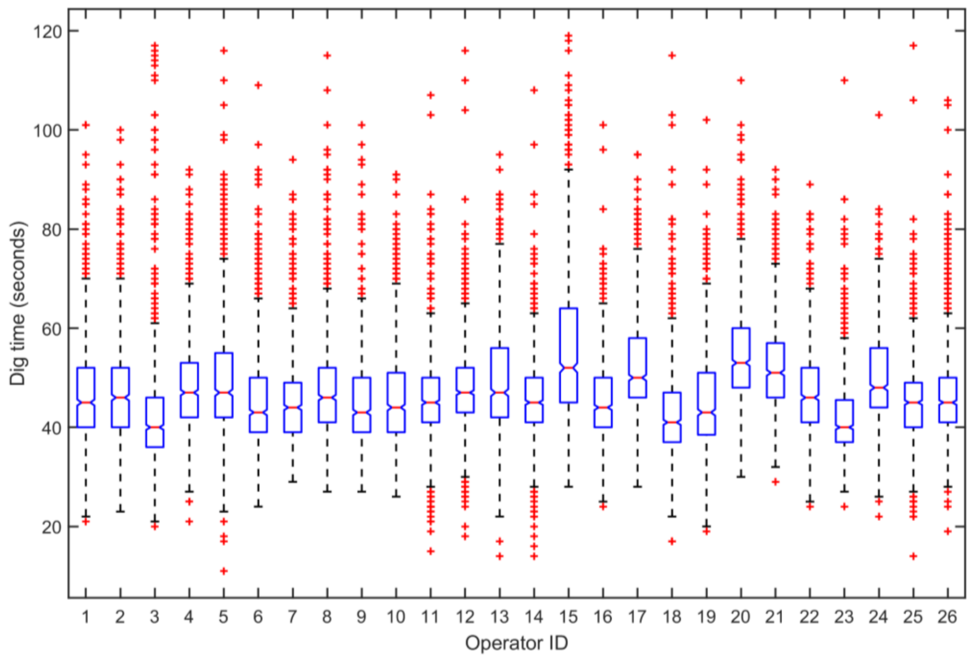

Figure 9. Dig time box plot

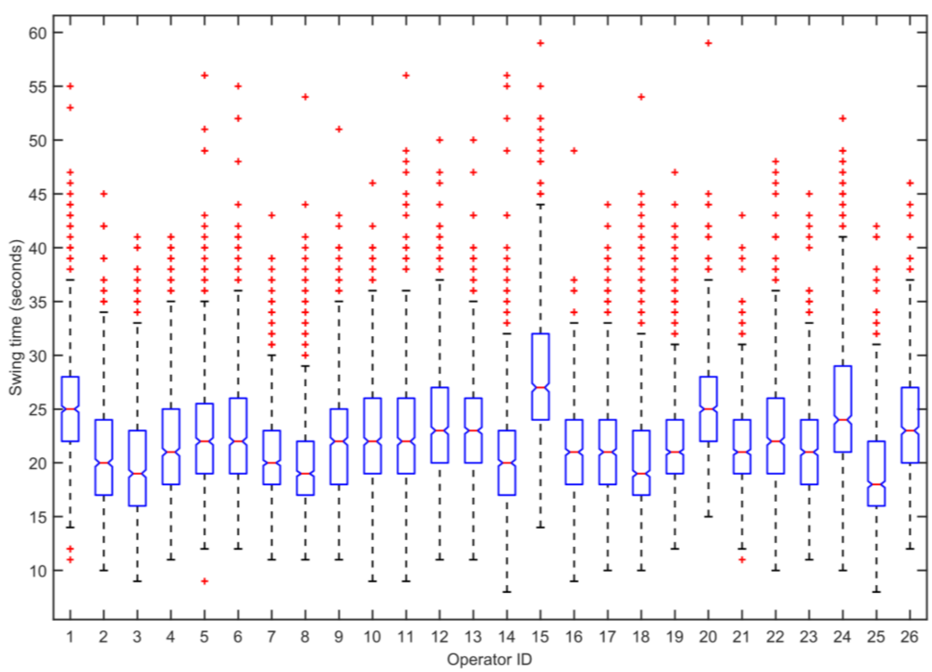

Figure 10. Swing time box plot

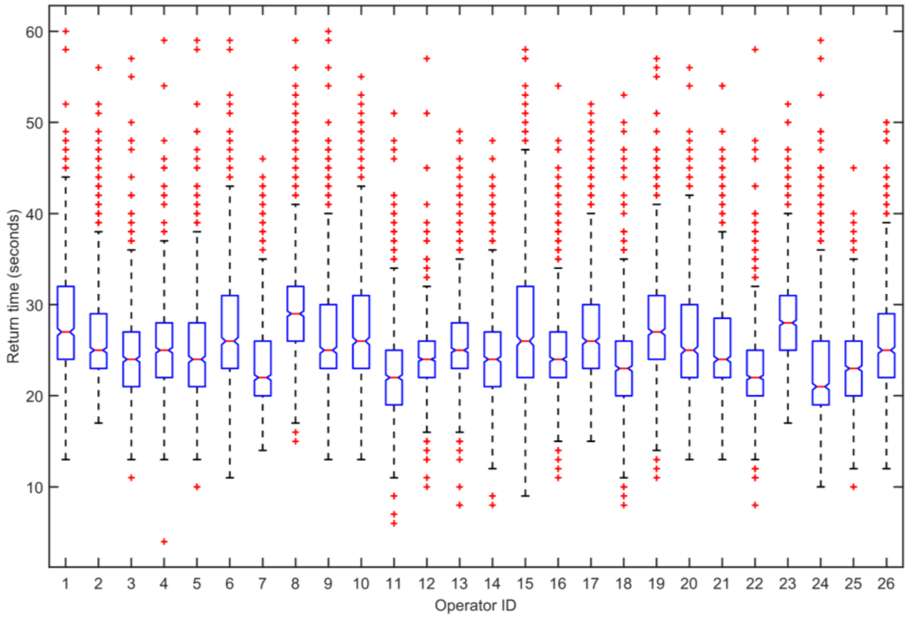

Figure 11. Return time box plot

4.4 Operator relative score

Traditionally, individual operator performance is evaluated based on mean truck payload (Shakti, 2015). In the section 4.3 of this study, it was identified that operators have differences in their dig, swing and return times, bucket load and number of buckets to load a truck. Hence, it is worth investigating whether those previously identified parameters could be added to an equation to enhance the comparison of operators' performance.

Here, statistically identified KPIs where there were significant variations among operators are used to calculate operator relative score (ORS) using proposed equation 4.1:

$$ORS_i = \sum_k R_i \qquad (4.1)$$

where ORS_i is operator i relative score, R_i is the operator rank in the fleet in that KPI category, and k is the KPI category.

In each KPI category, operators are ranked based on their performance. For each operator, the ORS is then calculated by summing their rank in all categories. The purpose of this step is to find operators located at each extreme by combining all factors affecting the operation outcome.

The final shovel production depends on a linear combination of loading times and bucket load (i.e., truck load divided by the loading cycle time). Hence, the ORS considers equal weight for loading times, number of buckets to load and bucket load.

To further evaluate their influence on operational KPIs, the practices of the best and worst ranked operators (BRO and WRO, respectively) are used as inputs to the simulation model. Since ORS is the sum of operator rank in each category, a lower score represents better overall practices. Table 9 presents the result.

Table 9. The ORS analysis result

	Valid Records		TFL		Swing time		Return time		Dig time		No. of passes		ORS	
	%	number	mean	rank	mean	rank	mean	rank	mean	rank	mean	rank	score	rank
OP01	90%	1541	1.03	6	25.6	25	28.3	23	47.4	14	3.2	20	88	7
OP02	92%	2286	1.04	3	20.7	5	26.4	16	47.6	17	3.1	5	46	20
OP03	97%	3376	1.02	11	20.1	3	25.1	10	46.6	12	3.1	6	42	22
OP04	94%	3450	1.00	18	21.9	13	25.7	13	48.4	19	3.1	7	70	12
OP05	95%	25014	1.01	15	22.4	15	25.1	11	50.5	22	3.2	19	82	8
OP06	97%	5399	1.00	17	23.4	20	27.7	21	45.9	7	3.2	17	82	8
OP07	98%	33577	1.03	5	21.0	7	24.1	6	45.4	4	3.1	4	26	25
OP08	96%	31963	1.02	10	19.8	2	29.7	26	47.5	16	3.1	13	67	14
OP09	99%	31587	1.02	12	22.4	14	27.2	18	46.4	10	3.2	16	70	12
OP10	87%	25780	1.03	9	22.4	16	27.5	20	46.5	11	3.3	24	80	10
OP11	91%	29299	1.03	8	23.2	18	22.8	1	46.0	9	3.1	14	50	19
OP12	94%	27214	1.03	7	23.7	21	24.2	7	47.5	15	3.0	1	51	17
OP13	93%	26145	1.04	2	23.2	17	25.6	12	49.2	20	3.1	11	62	15
OP14	95%	14107	1.04	4	20.7	6	24.3	8	46.0	8	3.1	3	29	24
OP15	91%	1181	0.99	23	28.5	26	28.6	25	58.2	26	3.3	25	125	1
OP16	96%	5864	1.00	19	21.2	8	25.1	9	45.4	3	3.1	12	51	17
OP17	98%	1132	0.98	24	21.4	9	27.5	19	52.8	24	3.2	15	91	6
OP18	96%	8095	1.02	14	20.5	4	23.7	5	43.5	2	3.1	9	34	23
OP19	95%	3950	0.99	22	21.7	12	27.9	22	45.6	5	3.2	18	79	11
OP20	91%	1361	0.94	25	25.1	23	26.7	17	55.4	25	3.3	23	113	2
OP21	92%	1544	0.91	26	21.5	11	25.8	14	52.6	23	3.2	22	96	4
OP22	96%	4440	1.01	16	23.3	19	23.3	2	47.1	13	3.1	8	58	16
OP23	99%	2010	1.05	1	21.5	10	28.5	24	42.2	1	3.1	10	46	20
OP24	85%	1203	0.99	20	25.6	24	23.4	4	50.1	21	3.4	26	95	5
OP25	97%	7039	1.02	13	19.2	1	23.3	3	45.7	6	3.1	2	25	26
OP26	87%	2727	0.99	21	24.0	22	26.1	15	48.3	18	3.2	21	97	3
Fleet		median	1.02		22.1		25.8		47.2		3.1			
		mean	1.01		22.5		25.9		48.0		3.2			

Table 10 shows the WRO (with an overall ORS of 125) and BRO (with an overall ORS of 25) statistics compared to the overall group. One could argue that the WRO fewer number of records (1181 records compared to operators with more than 25,000 records) can be an indication that the operator is either novice or still under training and hence their poor performance. The author does not have access to the operators' profile and cannot confirm the status of any operator in this study.

Nevertheless, the ORS is intentionally designed to only identify operators loading performance based on their actual work and exclude the effect of external parameters that do not necessarily influence the shovel production such operator age, experience etc. It was considered critical to make sure that the ORS is not biased based on operator's status, age, years of experience etc. and it only reports their performance. Its only purpose is to flag anomalies for management so that they can look into what is causing the good or poor score.

Table 10. Mean (± standard deviation) values for five key performance indicators and shovel operator relative score (ORS); WRO: worst-ranked operator; BRO: best-ranked operator

	Truck load factor (%)		Dig time (s)		Swing time (s)		Return time (s)		No. passes	
	Mean±SD	Rank	Mean±SD	Rank	Mean±SD	Rank	Mean±SD	Rank	Mean±SD	Rank
WRO	99±9	23	58.2±18.3	26	28.5±7.0	26	28.6±8.7	25	3.3±0.6	25
BRO	102±7	13	45.6±10.2	6	19.2±5.2	1	23.3±4.7	3	3.0±0.3	2
Group median	101±8		47.2±10.7		22.1±5.4		25.8±6.1		3.1±0.4	
Group mean	101±8		48.0±11.3		22.5±5.4		25.9±6.1		3.2±0.4	

The BRO tended to load trucks slightly above capacity with smaller standard deviation than the WRO. This is generally accepted as a good practice as long as overloading is not excessive. Mean dig, swing, and return times were 22, 33, and 19% lower, respectively, for the BRO than the WRO, indicating more energy-efficient operating practices. Furthermore, the BRO took fewer passes to load a truck with significantly smaller variation, which also indicates more efficient loading practices.

Dig time is directly linked to shovel power consumption (Hendricks, 1989; Patnayak & Tannant, 2005). The same can be said for swing and return times because the more time a shovel spends in rotation, the more energy it uses. Machine positioning and digging strategies such as angle of attack to the bank and amount of hoist and crowd are among the parameters controlled by operators and will determine operator cycle times.

Figure 12 and Table 11 present statistics and a histogram of both operator KPIs and clearly demonstrates better operation by the BRO with lower variability. Skewedness in a histogram is often linked to the presence of a lower or upper bound on the data. As both the truck load and their loading times are physical phenomena with some limitations. To reach their best result operators will need to shift their average close to those boundaries as much as possible. This could generally result in a distribution that is skewed toward the activity's boundary. Hence, the skewness in the BRO's activity distributions could be seen as their effort towards optimum loading. Using the same logic, it could be argued the variability for WRO's activities statistics might be directly linked to their inexperience.

Table 11. Worst ranked operator and best ranked operator loading key performance indicators

	Dig cycle time (second)		Swing cycle time (seconds)		Return cycle time (seconds)	
	WRO	BRO	WRO	BRO	WRO	BRO
Mean	17.7	15.1	8.5	6.9	8.7	7.6
Standard deviation	6.7	4.16	2.9	2.5	2.7	2.3

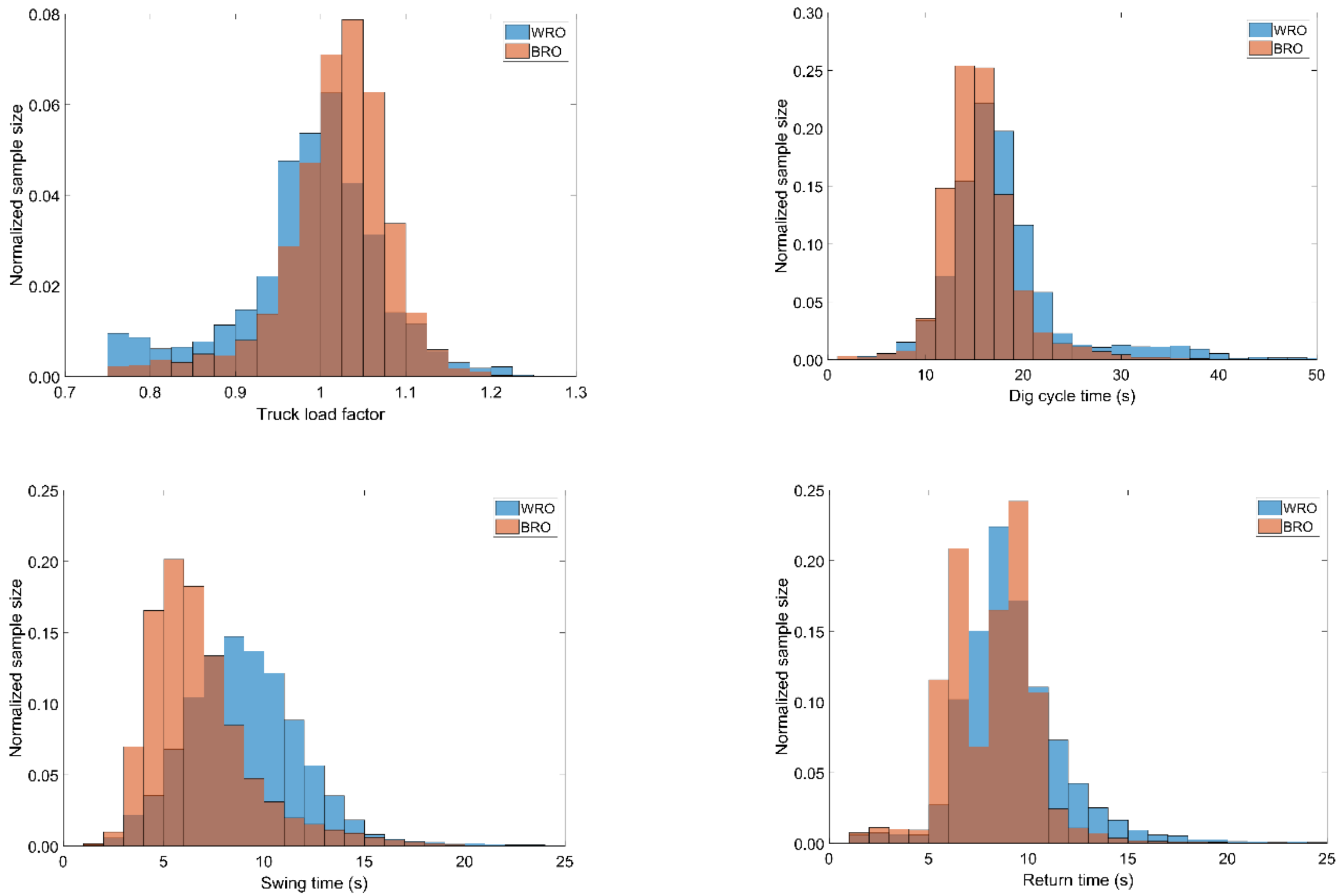

Figure 12. Comparative normalized histogram of worst-ranked operator (WRO) and best-ranked operator (BRO) key performance indicators: a) truck load factor, b) dig time, c) swing time, and d) return time, Dark brown indicates where WRO and BRO overlap.

Figure 13 and Table 12 present a comparison histogram of the BRO and the WRO swing and return angles. The BRO has smaller swing and return angles. This generally can be achieved through better machine positioning. A good position of the shovel relative to the bank not only gives trucks better maneuverability and allows them to spot faster and closer to the shovel, but also minimizes the shovel's need to make minor adjust to its position during a loading cycle.

The BRO also has a larger number of return angles with values less than 10 degrees. Based on the author field visits and first-hand experience one explanation could be that in situations allowed by the relative distance of the truck from the bank, the operator starts to lower the bucket as soon as the material is dumped into the truck. This results in a close to 45 degree drop of the bucket, faster transition to the dig mode and hence smaller angle of return measured by the system.

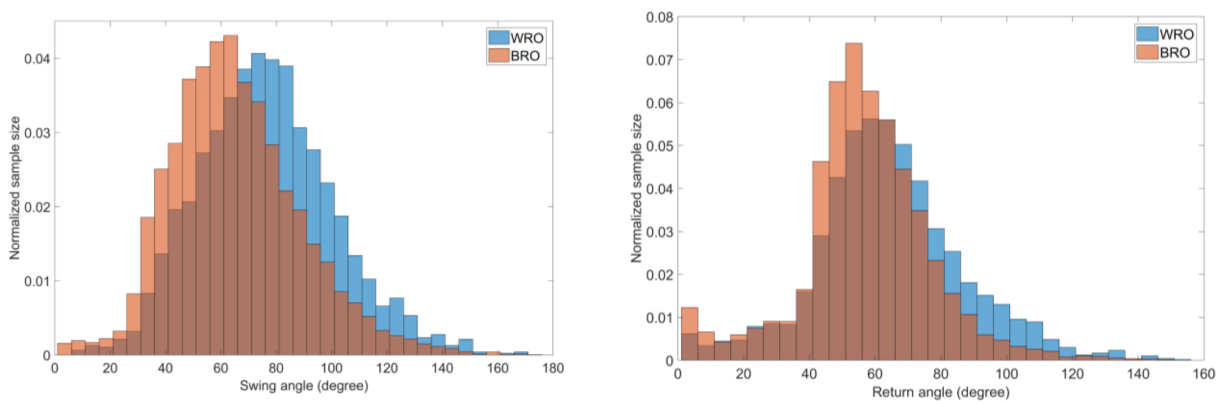

Figure 13. BRO and WRO swing and return angles comparison

Table 12. WRO and BRO swing and return angles

	Swing angle (degree)		Return angle (degree)	
	WRO	BRO	WRO	BRO
Mean	76	69	64	57
Standard deviation	24	21	23	19

An operator's digging strategy is also another critical aspect of the shovel operation. As mentioned before, this greatly impact dig time. More importantly, bucket load and the amount of energy used to dig the material are also influenced. Figure 14 compares both operators' maximum dig force, which is the maximum amount of force operator used to dig the material during a truck loading cycle measured and recorded by the shovel health and payload monitoring system. It can be seen that the BRO performed considerably more consistent throughout their job.

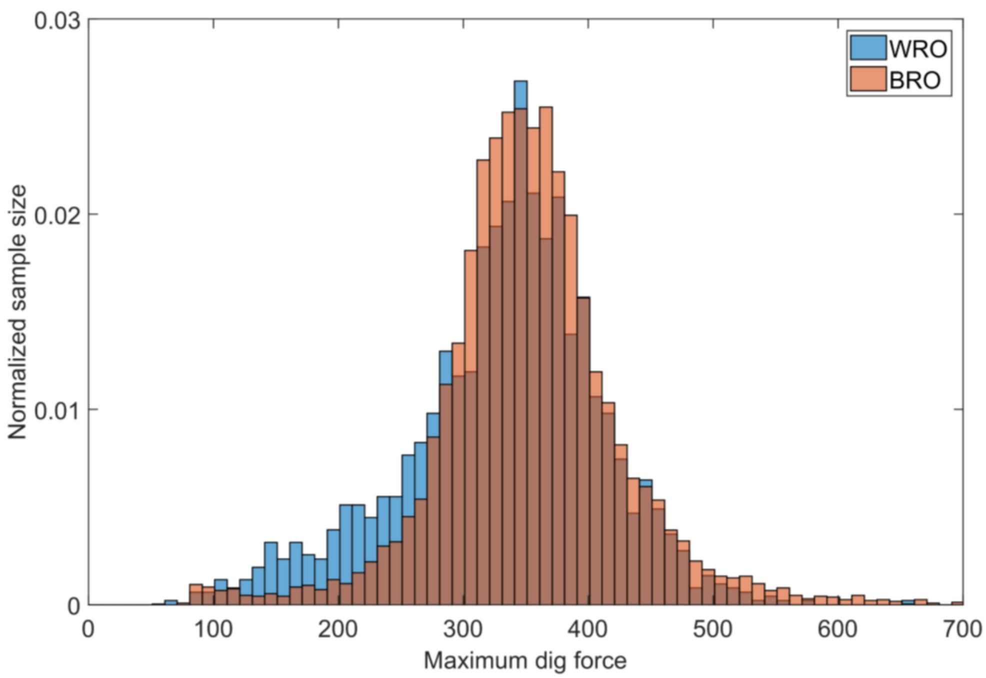

Figure 14. BRO and WRO maximum dig force comparison

In addition to the dig strategy, maximum force is a function of dig condition. Figure 15 and Table 13 show both operators dig condition (diggability) and average bucket load (i.e., truck final load / number of passes to load the truck). As discussed in the section 1.3, diggability is designed to reflect many aspects of the dig condition such as rock fragmentation, the material characteristics and hardness of the rock. A higher diggability number indicates a less favorable dig condition. The KPI is also developed to eliminate the influence of the operator experience and digging strategies.

It can be seen that in general the WRO work condition was better than the BRO. As diggability provides feedback on the general dig condition, it can also be argued that the effect of seasons on operational parameters is inherently reflected in the diggability index.

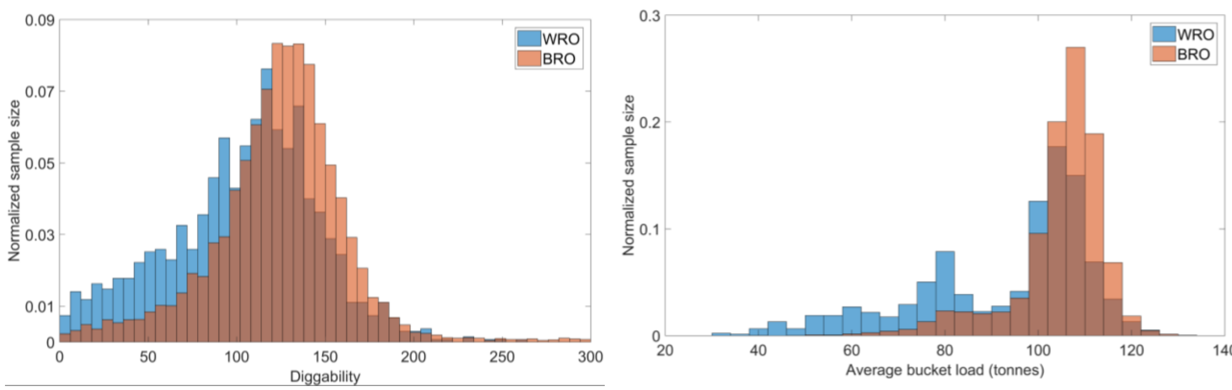

Figure 15. BRO and WRO dig condition and bucket load comparison

Table 13. WRO and BRO dig condition and Bucket load comparison

	Diggability		Average bucket load (tonnes)	
	WRO	BRO	WRO	BRO
Mean	104	124	90	105
Standard deviation	42	43	25	18

As shown in Figure 15 and Table 13, WRO bucket load has greater variance compared to the BRO. This links to another aspect of the operation, the operator loading strategy. Figure 16 shows the number of passes to load a truck for each operator. It is clear that overall BRO tends to load trucks with fewer bucket loads (95% of the time with only three passes). Whether this is a direct result of the operator's confidence in their operation that has also led to the higher bucket tonnage, and/or the result of the operator's experience needs more study.

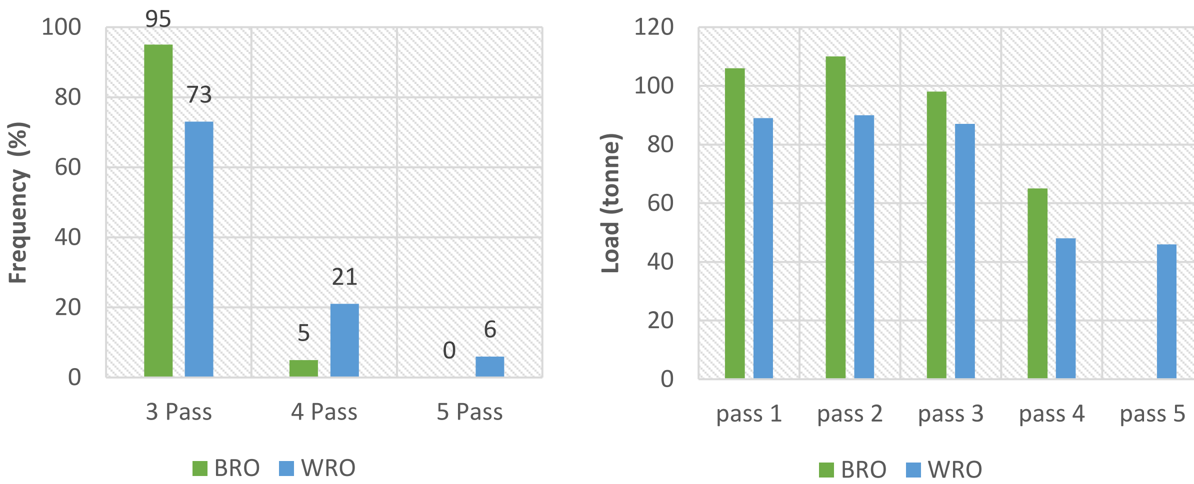

Figure 16. The BRO and WRO comparative load statistics

It is not clear if the extra passes with lower bucket loads used by the WRO are the operator's loading habit or a result of them trying to reach truck target load. This needs further field study, yet it shows the significance of operators' differences. In the next section the significance of these influences on the shovel and mine production and performance are investigated.

4.5 Shovel Operator Influence Evaluation

4.5.1 Mine operation data

To assess the impact of variability in the shovel operator performance a simulation model is built. This model is also used to evaluate proposed enhancement shovel operation. The model is built using data from an existing mine.

These data include road network, production schedule, loading and dumping locations, and KPIs related to the truck fleet operation. Although the mine operational dataset contains minimum information required to model the shovel fleet operation, it lacks many details necessary to model the shovel operator behaviour. Hence, throughout this research, the information related to the shovel operation are replaced with the one obtained from the shovel health and payload monitoring system.

Gol-E-Gohar is an open-pit surface iron mine located in Iran. Its material handling system comprises trucks and shovels. The mine employs five shovels, three for waste and two for ore. There are three destinations for materials, two processing plants and one waste dump. Figure 17 shows the general mine network.

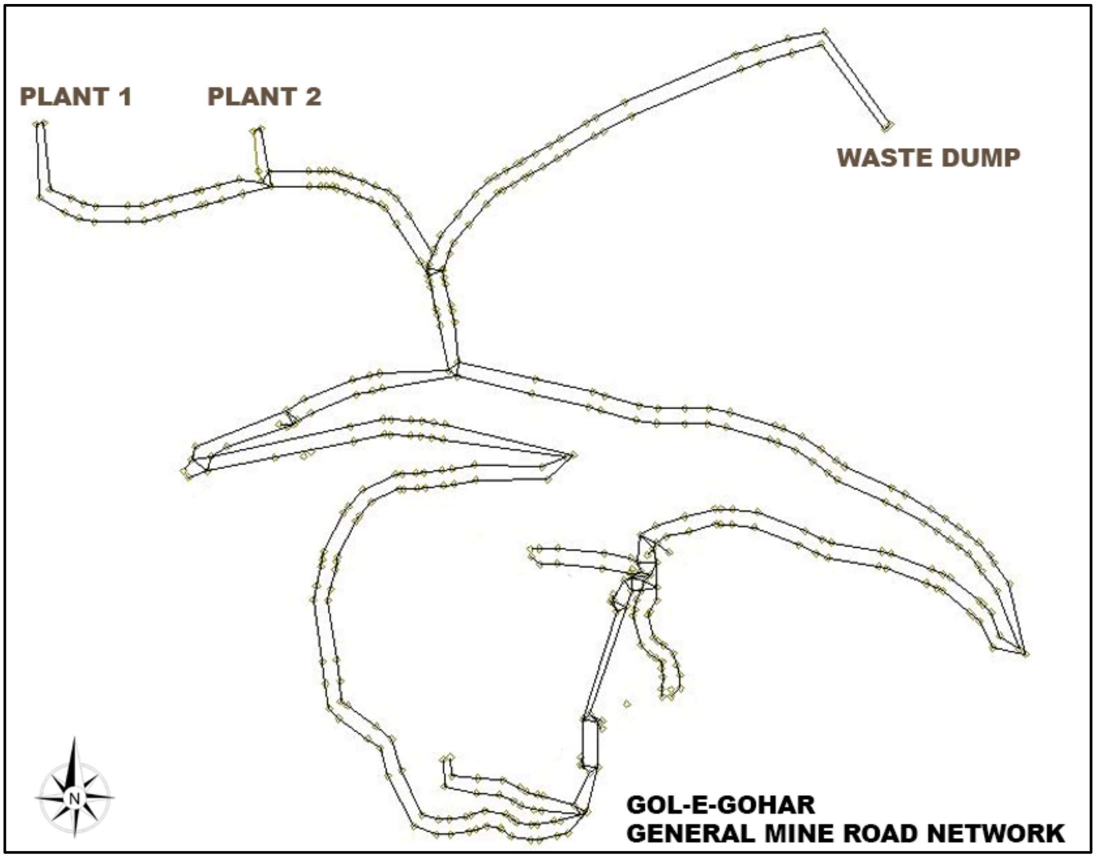

Figure 17. Mine network and dump locations

A fleet of Caterpillar 793C trucks hauls materials to two plant crushers and a waste dump based on a prescheduled plan. As mentioned before, the shovel health and payload monitoring data set include information for the fleet of shovels loading 300 tonnes trucks. For the fleet of trucks, the 793C speeds are assumed to be representative of the 300 tonnes truck speeds. Table 14 contains truck fleet input parameters.

Table 14. Truck input parameters

	Mean	Standard deviation	Distribution
Empty speed (km/h)	35.7	10.7	NORM (35.7, 10.7)
Loaded speed (km/h)	18.8	7.52	5 + LOGN (18.8, 7.52)
Spotting time (s)	37	27.1	1 + LOGN (37.8, 39.1)
Backing time (s)	15.6	10.9	1 + LOGN (14.8, 11.5)
Dumping time (s)	47.9	21.2	NORM (47.9, 21.2)

The mine yearly schedule is borrowed from Upadhyay (2016). It is only used as a reference to determine loading and dumping assignments. Table 15 presents an example of the mine schedule that covers the 10 first sequences of mining.

Table 15. Mine schedule for the first 10 sequences

No	*x*	*y*	*z*	*Tonnage*	*Dump ID*	*Period*	*Dig Location Nodes*						*Shovel*	*Seq*
1	101734	600173	1610	636,600	1	1	384	428	429	430	431	229	1	1
2	101823	600201	1610	553,500	1	1	384	432	433	434	435	229	1	2
3	101916	600232	1610	651,420	1	2	384	500	501	502	503	229	1	3
4	101745	600127	1595	553,500	1	3	378	560	561	562	563	213	1	4
5	101882	600170	1595	520,050	2	4	378	616	617	618	619	213	1	5
6	101922	600253	1595	594,450	2	5	378	680	681	682	683	213	1	6
7	101912	600335	1595	763,440	1	6	378	744	745	746	747	213	1	7
8	101833	600354	1595	570,600	2	7	378	796	797	798	799	213	1	8
9	101886	600439	1595	631,800	2	8	378	852	853	854	855	213	1	9
10	102001	600401	1595	634,920	2	9	378	896	897	898	899	213	1	10

4.5.1.1 Data pre-processing

Before any analysis is performed, it is critical to remove outliers. The following rules are applied, and corresponded records are removed:

- Record that is negative.
- Record that truck speed exceeds 55 km per hour.
- Records that truck spot time exceeds 180 seconds.
- Records that truck dump time exceeds 120 seconds.

4.5.2 Simulation scenario development

In an attempt to capture and quantify the role of HF and assess the influence of operator's practices and skills on the shovel, truck, and mine production and performance, statistics from best and worst rated operators are used in the developed rope shovel operator behaviour simulation sub-module and the mine operation DES model.

For both WRO and BRO DES models, all of the mine general operational input data are kept the same and only the operator behaviour simulation sub-module input parameters are changed. This provides the opportunity to solely focus on the operator role and limit the influence of other aspects of an operation.

The following sections describe the DES model input parameters for each case study in more details and explains assumptions that are made during scenario development as well as the DES limitations.

4.5.2.1 Mine operation DES general input data

In order to only include the role of operators and their influences on the shovel and mine operational performance, the following input parameters for the mine operation DES model are considered to stay the same for all scenarios:

- Mine schedule
- Road network

- Load/dump locations
- Trucks empty and loaded speeds
- Trucks spotting times
- Trucks backing time
- Shovel failures, borrowed from Samanta et al. (2001)
- Shovel operators shift change/break times (half an-hour shift change, and two half an-hour breaks for a 12-hours shift.)

Table 16 presents a summary of the mine operation general DES input statistics.

Table 16. Operators influence DES model general distribution inputs

Parameter	Mean	Standard deviation	Distribution
Empty speed (km/h)	35.7	10.7	NORM (35.7, 10.7)
Loaded speed (km/h)	18.8	7.52	5 + LOGN (18.8, 7.52)
Spotting time (s)	37	27.1	1 + LOGN (37.8, 39.1)
Backing time (s)	15.6	10.9	1 + LOGN (14.8, 11.5)
Dumping time (s)	47.9	21.2	NORM (47.9, 21.2)
Shovel MTBF (h)	WEIB (130,0.76)		
Shovel MTTR (h)	LOGN (11.39,14.73)		

Truck fleet size and their availability can play a significant role in shovel production and utilization. A match factor introduced by Burt and Caccetta (2014) is initially used to calculate the required truck fleet size. Moradi Afrapoli et al. (2019a) discussed limitations in using a match factor. Since the main focus of this study is the loading aspect of the operation, scenarios 1, 2, and 3 are considered for fleet sizes of 20, 40, and 60 trucks, respectively. The 60 trucks fleet size is found to be the scenario with a close to optimum truck-shovel match through a trial-and-error process. The 40 and 20 trucks fleets are selected to study under-truck situations.

The discrete event simulation model was set up to run for thirty 12-h shifts to represent a month's worth of work and to run for 25 iterations to meet the required half-width for the production within a 95% confidence interval.

4.5.2.2 BRO and WRO behaviour DES model inputs

To study the role of an operator in a mine operation and compare their results, BRO and WRO loading practices' statistics are used separately as the input for the DES operator behaviour sub-module.

The developed shovel sub-module uses the "operator number of passes to load" distribution to assign the number of buckets to each truck. Then for each pass, the specific distribution is used to calculate the bucket load. This is repeated for the number of buckets assigned to the truck. If the total load of a truck exceeded the extreme threshold (i.e., 1.3 × capacity), that bucket load is considered a discard load.

Table 17 and Table 18 list the mean, standard deviation and the best-fit distributions for operator input parameters for the loading sub-module.

Table 17. BRO input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	15.2	4.21	POIS (15.2)
Swinging time (s)	6.3	2.6	0.5 + LOGN (5.8, 2.65)
Returning time (s)	7.67	2.33	0.5 + GAMM (0.907, 7.9)
Bucket load (Pass 1)	109	16	11 + 129 * BETA (10.5, 3.49)
Bucket load (Pass 2)	108	14.2	11 + 128 * BETA (12.7, 4.25)
Bucket load (Pass 3)	97.1	15.7	11 + WEIB (92.1, 6.58)
Bucket load (Pass 4)	65.1	20.8	17 + WEIB (54, 2.43)
Number of buckets	DISC (0.95,3,1,4)		

Table 18. WRO input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	95.3	21.4	11 + 126 * BETA (4.76, 2.43)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Bucket load (Pass 3)	92.6	20.5	18 + 116 * BETA (4.09, 2.27)
Bucket load (Pass 4)	50.9	23.1	11 + WEIB (42.1, 1.74)
Bucket load (Pass 5)	46.6	25.4	11 + WEIB (39.6, 1.64)
Number of buckets	DISC (0.73,3,0.94,4,1,5)		

4.5.2.3 Note on the use of data from different sources for the DES modeling

As discussed in the literature review, simulation has been proven to be useful in defining, emulating, and studying hypothetical scenarios that are otherwise hard, expensive or sometimes impossible to execute in the real-world. It is common to use historical data from one system to create a simulation model to estimate the performance of a different or new system (Sturgul & Harrison, 1987).

The goal of assessing different operator's influences on a shovel and mine production and performance can be considered as an example of such an application. While the data for the general operation of the iron ore mine including load and dump locations, haul road network, truck empty and loaded speeds, and mine schedule is available, the addition of detailed data related to the operators practices from the coal mine helped to setup the simulation. This allowed further study of the influence of operators' practices on many aspects of a mining operation.

4.5.2.4 Assumptions and limitations

In addition to the simulation general limitations and assumptions discussed in the section 3.4.6, combining data from the two sources involves the assumption that the operators' practices stay the same for the new operation. For this study, iron and coal over-burden could have significant differences in their density that would be anticipated to influence how operators operate and their production. As the goal of this research is to investigate the role of electric rope shovel operators, it could be argued that the result of the comparison of operator's outcome is a valid indication of the extent to which operator's behaviour could influence shovel and mine performance and production. However, the actual results presented in this thesis are not indicative of real production numbers for the iron mine; they illustrate the influence of shovel operators on overall production and led to an enhanced understanding of the truck shovel effect on production which facilitated the development of strategies to mitigate the operator's influence.

Also, the shovel health and payload monitoring system data set include information from the operation that the crusher has a greater capacity than what the material handling system can provide. The operation uses the stockpile and blending process to feed the crusher. Hence, the capacity of the dump locations is assumed to be unlimited in the simulation.

4.5.3 Verification of the simulation model

The discrete event simulation model based on the five shovels operating at a surface mine is first inspected to ensure it properly represented the mine operation. Arena has the option to run the simulation model in an animation mode. This provides the user with an ability to check how well the system and its components are working, track the path components need to follow and monitor resources' KPIs. The initial verification step involves visual inspection of the model components behaviour such as truck movements (i.e., source/destination, path and speed of travel), shovel/dump resources activities and status throughout a pilot run.

Then, the shovel and truck operation characteristics are verified by comparing against data used as the model input. Quantile-quantile plot (Q-Q plot) is used to compare the DES model results against either the input data set directly or their representative distribution. For instance, Figure 18 present the Q-Q plots of trucks empty speeds against the standard normal distribution and it can be seen that the resulted truck speeds from the DES model reasonably follows the expected normal distribution of the input data set.

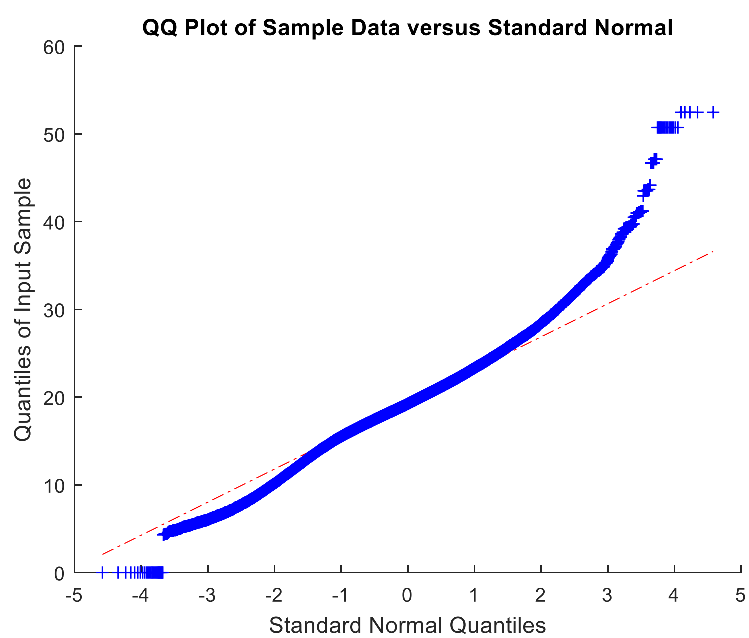

Figure 18. Q-Q plot of trucks empty speeds

Furthermore, shovel-loaded tonnages and delivered materials to the dump locations are used to verify the model (Figure 19). All loaded materials are delivered to their designated dump locations.

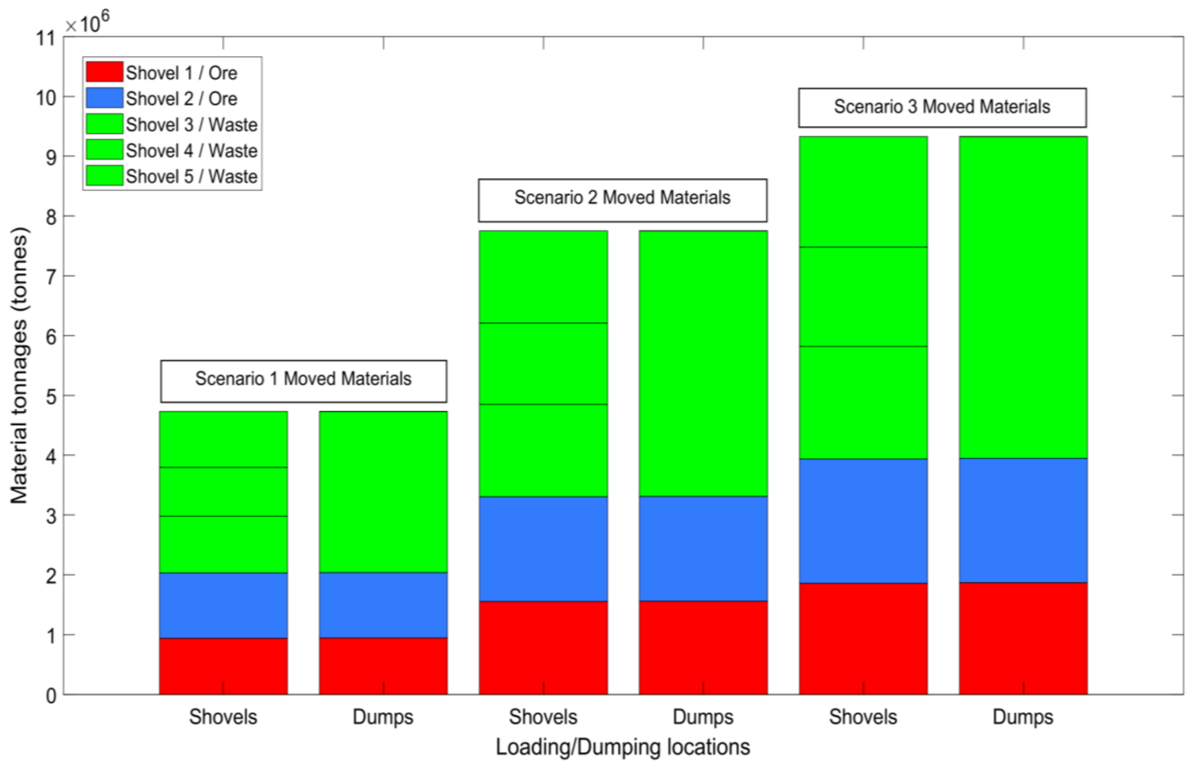

Figure 19. Worst-ranked (WRO) operator discrete event simulation model material handling summary for fleet sizes of 20, 40, and 60 trucks (scenarios 1, 2, and 3, respectively)

To verify the proposed shovel operator sub-module, mean modeled and measured TLFs are compared and are similar (Table 19).

Table 19. Mean (±standard deviation) truck load for the worst- and best-ranked operators

	Measured (from historical database)	Model Scenario 2
Worst-ranked operator	0.99±0.09	0.99±0.12
Best-ranked operator	1.02±0.07	1.04±0.08

4.5.4 Operators influence evaluation results

All truck fleet operational parameters (i.e., speed capacity and dispatch algorithm) are the same for both the WRO and BRO, thus it is only their loading practices that could be considered as the main contributors to the observed differences. In all three scenarios, the BRO has higher production than the WRO (Figure 20). Despite a 50% difference in truck fleet size moving from scenarios 2 to 3, the WRO achieves only 6.9% higher production than BRO had achieved in scenario 2. This highlights the influence of operator performance on overall production and optimal fleet size for truck and shovel operations.

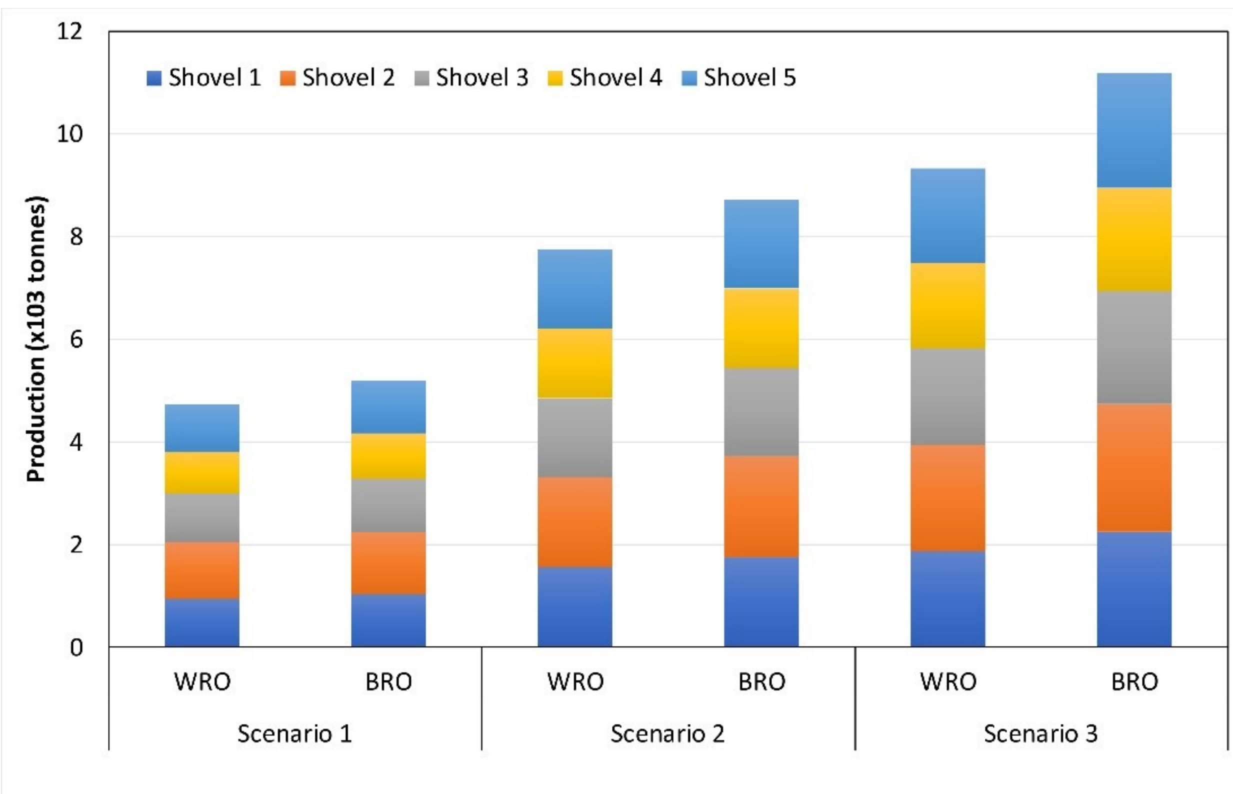

Figure 20. Total shovel production for worst-ranked operator (WRO) and best-ranked operator (BRO) for fleet sizes of 20, 40, and 60 trucks (scenarios 1, 2, and 3, respectively)

As mentioned above, truck fleet size and truck availability affect utilization and productivity of the shovel fleet. Increasing the number of trucks (i.e., higher truck availability) results in larger production gaps between the WRO and BRO. Whereas there is only a 9.5% difference in production between the two operators in scenario 1, it increases to 12.5 and 19.9% in scenarios 2 and 3, respectively. This emphasizes the role of shovel operators as the truck fleet size and utilization is optimized.

Given that a 20% difference in mine production is significant, it is worth further assessing sources for these differences. Table 20 shows production, total number of trucks loaded, and mean truck load (i.e., total production divided by the total number of trucks loaded). As a cross check, Table 20 reasonably agrees with earlier mean truck loads derived directly from simulation statistics (refer to Table 19). The relatively small difference (approximately 0.3%) between WRO and BRO mean truck load in all three scenarios suggests that the difference in total production could be attributed to operator loading cycle time. Loading cycle time appears to play a greater role in mine productivity and efficiency than assumed in traditional operator assessment systems.

Table 20. Production key performance indicators

	Scenario 1		Scenario 2		Scenario 3	
Operator	WRO	BRO	WRO	BRO	WRO	BRO
Total number of trucks loaded	15,984	16,538	26,217	27,829	31,504	35,737
Total production ($\times 10^6$ tonnes)	4.73	5.18	7.75	8.72	9.33	11.19
BRO production (% higher than WRO)	9.5		12.5		19.9	
Mean truck load (tonnes/truck)	295.9	313.2	295.6	313.3	296.1	313.1
BRO truck load (% higher than WRO)	5.8		6.0		5.7	

In addition to their influence on production, loading cycle times could affect other aspects of a mining operation. Although the number of trucks in the queue is similar between the WRO and BRO in the scenarios 1, 2, and 3 (Figure 21), the wait time in the queue is 21.9, 20.7, and 41.5%

shorter for the BRO than the WRO, respectively. Minimizing the wait time not only improves productivity and reduces operational costs, but also could be a significant opportunity to reduce diesel emissions (CO, CO_2, NO_x, unburnt hydrocarbons, and particulate matter) during truck idling.

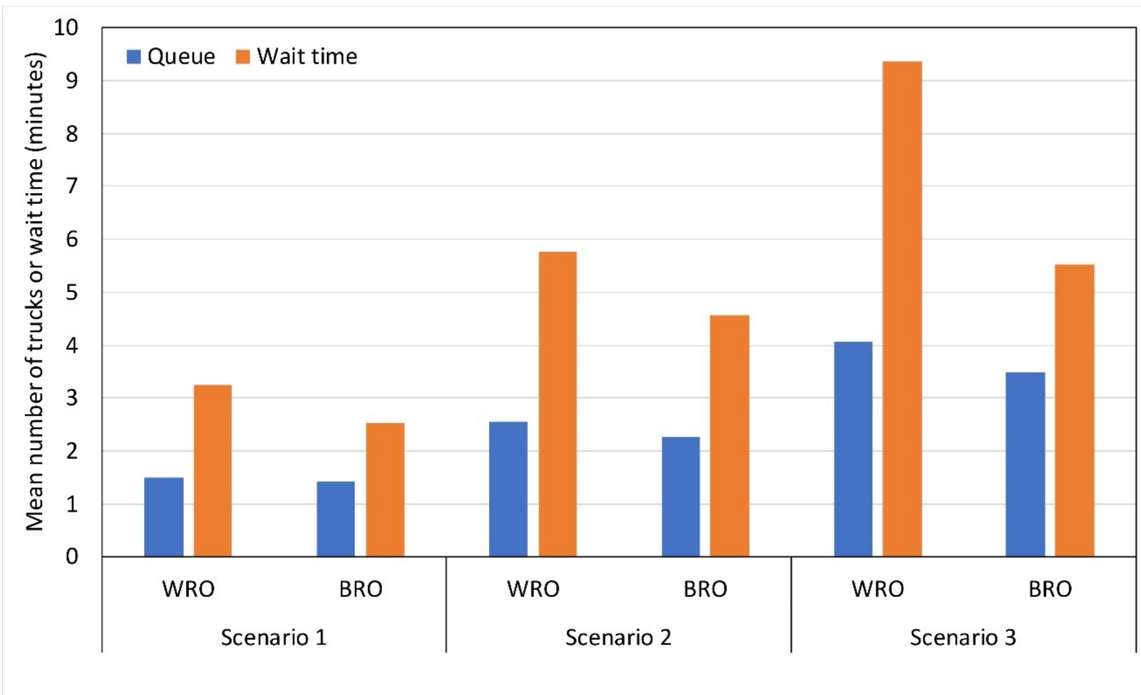

Figure 21. Mean number of trucks and wait time in queue at shovel loading locations in three discrete event simulation modelling scenarios; WRO: worst-ranked operator, BRO: best-ranked operator

4.6 Discussion

This chapter first studied whether a statistically meaningful variation can be observed among electric rope shovel operators' practices. Dig, swing and return times, bucket load and number of buckets to load a truck are found to have differences among operators. The extent of those identified differences suggests further studies are necessary to identify and better understand the HFs involved.

The ORS is developed as an evaluation method that in addition to the traditional "truck average load", considers newly discovered aspects of an electric rope shovel operation into the evaluation process. Application of the ORS on the shovel health monitoring system database proves that the KPI is able to capture operator's performance and reflects different aspects of their practices on the final production and performance.

Based on the fact that there is a linear relationship between the shovel hourly production and the shovel loading components, the ORS puts equal weight on each component's importance. Whether assigning different weights could improve the KPI's ability to distinguish operator's skill and performance needs further study.

Using the developed operator behavior sub-module and mine operation DES model, it is shown that operators have significant impact not only on the shovel production but also on the mine production and performance. Trucks queueing is also shown to be greatly influenced by the efficiency of the shovel operator.

It could be argued that the extent to which operators influences operations could be different from operation to operation, yet the operator behavior DES sub-module collectively with the methodology introduced in this research can be deployed to evaluate many previously unknown impacts of electric rope shovel operators on both the shovel and the mine operation, production and performance.

5. CHAPTER 5: ROPE SHOVEL OPERATOR PERFORMANCE IMPROVEMENT

5.1 Introduction

This chapter tries to leverage the knowledge gained from Chapter 4 and introduce measures that could be implemented to improve electric rope shovel performance and production.

Two approaches are introduced subsequently to help an operator improve their loading practices and enhance shovel and mine overall productivity. The first approach is designed as a dynamic means to integrate truck fleet utilization and availability into the way a shovel operates. It is intended to provide a shovel operator with the required flexibility in situations that truck final load can be compromised in an exchange for a reduction in the truck waiting time in the queue. This approach is evaluated using the developed simulation model and results are presented.

The next measure presented here is a KPI intended to capture the significance of the loading cycle time and combines it with the truck final load to provide an operator with an easier to interpret feedback of their loading practices.

Finally, section 5.4 proposes a methodology to explore how and to what extent automation can help eliminate HF and improve the loading activity and what are the implications for the truck and mine overall productivity and performance. Different scenarios are introduced here, and anticipated improvements that can be achieved through them are evaluated using the developed simulation model.

5.2 Dynamic Target Loading

The final load of a truck is the primary KPI to signal the end of a load cycle. Also, its value divided by the truck capacity which forms the TLF is used to evaluate a shovel operator performance throughout their work. The closer an operator loads trucks to their nominal capacity (i.e., truck load ratio = 100%) the better their performance is based on current practices.

Mining operations generally follow 10:10:20 rule suggested by truck manufacturers that dictates no more than 10% of truck loads must exceed 110% of their capacity and none should exceed 120% (Thompson et al., 2019). To comply with this rule, a common practice in mining is to define under, normal, over and extreme thresholds for the truck final loads. Those thresholds also being used as guideline to the operator and adherence to them is considered as a performance criterion. Figure 22 present a typical threshold chart for the truck final load.

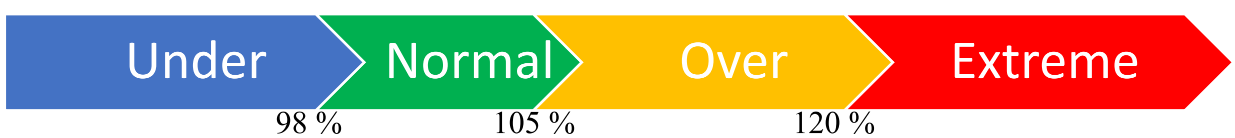

Figure 22. A typical thresholds chart for truck final load ration

This is generally a good approach as it not only encourages operators to load trucks within their optimum capacity and thus maximizes the production, and it also reduces truck exposure to excessive loads which can lead to failures. On the other hand, reaching the narrow target normal threshold could be challenging in some situations for an experienced operator and it could be even more difficult for an inexperienced operator. This often leads to an operator loading the truck with extra correction pass called trim passes.

While in some situations trim passes are necessary to meet the normal target load of the truck, they add extra times to the loading cycle. This quickly becomes an issue when there are trucks in queue waiting to be loaded. Based on the findings in Chapter 4, it is envisioned that in this situation, the negative influence of the lost time on the overall mine production outweighs the gain from loading the truck closer to its nominal capacity.

As an alternative, the concept of dynamic target loading (DTL) is proposed here. The main idea is to improve shovels production by providing operators with a more flexible target truck final load in situations where the number of trucks in the queue are high. Figure 23 presents an example of the proposed approach.

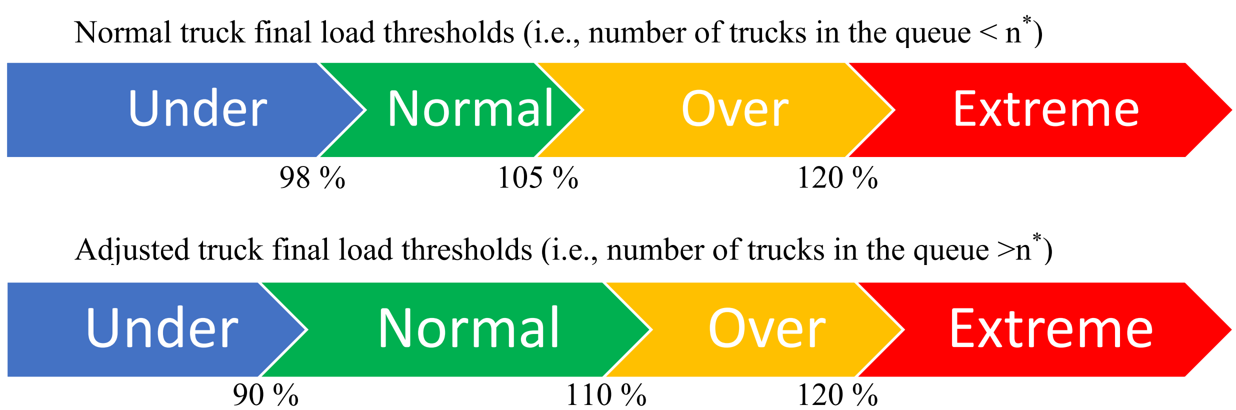

Figure 23. Proposed dynamic target load thresholds *(n: experimental number)*

In combination with targeted training, the approach could be used to help operators aim for fewer number of passes with higher bucket loads, and reduction of trim passes that will result in reduced loading cycle times. Using the discrete event simulation model, the proposed approach is evaluated.

5.2.1 DTL simulation scenario development

To assess the potential extent to which DTL can improve shovel, truck, and mine production and performance, the following three operational scenarios are considered here:

- The first scenario uses statistics from the worst rated operator and will be the benchmark for this evaluation.
- The second scenario investigates whether the shovel and the mine production can be improved by implementing the DTL mechanism.
- And finally, the third scenario is developed to study DTL long-term implications. It evaluates the extent to which DTL can improve the operator and the mine performance and production in long-term when accompanied by proper operator training programs.

The following sections discuss these three scenarios in more details.

5.2.1.1 General mine DES operation data inputs

In order to exclusively study the result of changes in each scenario, the following input parameters for the mine general operation DES model are considered to stay the same for all scenarios:

- Mine schedule,
- Road network,
- Load/dump locations,
- Trucks empty and loaded speeds,
- Trucks spotting times,

- Trucks backing time,
- Shovel failures, borrowed from Samanta et al. (2001)
- Shovel operators shift change/break times (half an-hour shift change, and two half an-hour breaks for a 12-hours shift.)

Table 21 present the summary of input statistics for these scenarios.

Table 21. DTL evaluation DES model general distribution inputs

Parameter	Mean	Standard deviation	Distribution
Empty speed (km/h)	35.7	10.7	NORM (35.7, 10.7)
Loaded speed (km/h)	18.8	7.52	5 + LOGN (18.8, 7.52)
Spotting time (s)	37	27.1	1 + LOGN (37.8, 39.1)
Backing time (s)	15.6	10.9	1 + LOGN (14.8, 11.5)
Dumping time (s)	47.9	21.2	NORM (47.9, 21.2)
Shovel MTBF (h)	WEIB (130,0.76)		
Shovel MTTR (h)	LOGN (11.39,14.73)		

As the main focus of this study is the loading aspect of the operation, a fleet size of 60 trucks is used as it is the optimum truck-shovel match determined through a trial-and-error process.

The discrete event simulation model is set up to run for thirty 12-h shifts to represent a month worth of activity and 25 iterations to meet the required half-width for the production within a 95% confidence interval.

5.2.1.2 Benchmark scenario

In order to identify and quantify the extent to which DTL can improve an operator performance and mine operation production, the first scenario uses WRO loading statistics as the input for the DES operator behaviour sub-module and establishes a benchmark Table 22.

The shovel sub-module developed to capture operator behaviour used the operator number of passes to load distribution to assign the number of buckets to each truck. Then for each pass, the specific distribution was used to calculate the bucket load. This is repeated for the number of buckets assigned to the truck. If the total load of a truck exceeded the extreme threshold (i.e., 1.3 × capacity), that bucket load is considered a discard load.

Table 22. DTL study first scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	95.3	21.4	11 + 126 * BETA (4.76, 2.43)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Bucket load (Pass 3)	92.6	20.5	18 + 116 * BETA (4.09, 2.27)
Bucket load (Pass 4)	50.9	23.1	11 + WEIB (42.1, 1.74)
Bucket load (Pass 5)	46.6	25.4	11 + WEIB (39.6, 1.64)
Number of buckets	DISC (0.73,3,0.94,4,1,5)		

5.2.1.3 DTL scenario input parameters

The second scenario uses the same statistics except when the number of trucks in the loading queue are greater than two the number of passes to load the truck will be fixed at three. Additionally, as the operator is not trying to reach a narrow target threshold, it is reasonable to assume that they will aim to maximise their bucket loads. Hence, the bucket load is also fixed with the operator's highest average bucket load. Table 23 lists the mean, standard deviation and the best-fit distributions for operator input parameters for the second scenario.

Table 23. Second scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Number of buckets (Second)	FIXED (3)		

5.2.1.4 DTL third scenario (long-term implications)

The last scenario explores the potential gain from the possibility of improving the operator's loading behaviour due to the use of the DTL and training operators as needed. The idea is that given the broader target load and limited number of passes to load a truck, an operator could aim for their bucket maximum load. It is expected that in the long-term this could teach operators how to increase their overall bucket load. As well, if operators are being scored using the ORS they could be identified for additional training.

For this scenario, in addition to the fixed number of buckets in the second scenario, the bucket load is also replaced with the BRO statistics (recall from previous section that BRO has higher bucket loads with smaller number of passes to load a truck).

Table 24 lists the mean, standard deviation and the best-fit distributions for operator input parameters for the third case study scenarios.

Table 24. Third scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	109	16	11 + 129 * BETA (10.5, 3.49)
Bucket load (Pass 2)	108	14.2	11 + 128 * BETA (12.7, 4.25)
Bucket load (Pass 3)	97.1	15.7	11 + WEIB (92.1, 6.58)
Bucket load (Pass 4)	65.1	20.8	17 + WEIB (54, 2.43)
Number of buckets	FIXED (3)		

5.2.1.5 Assumptions and limitations

It should be noted that although it is envisioned that DTL could improve all aspects of an operator loading practices (i.e., dig, swing and return times and machine positioning), in this study the model only assumes bucket loads are influenced and other aspects of the operator loading practices remain the same as before.

Also, the shovel health and payload monitoring system dataset include information from the operation that the crusher has a greater capacity than what the material handling system can provide. The operation uses the stockpile and blending process to feed the crusher. Hence, the capacity of the dump locations is assumed to be unlimited in the simulation.

5.2.2 DTL improvement evaluation

Figure 24 shows the total production for the three DES scenarios. Despite the general belief that a truck should be loaded no less than its nominal capacity, it can be seen that after limiting the number of passes to load the truck in the second scenario a slight overall production gain has been achieved.

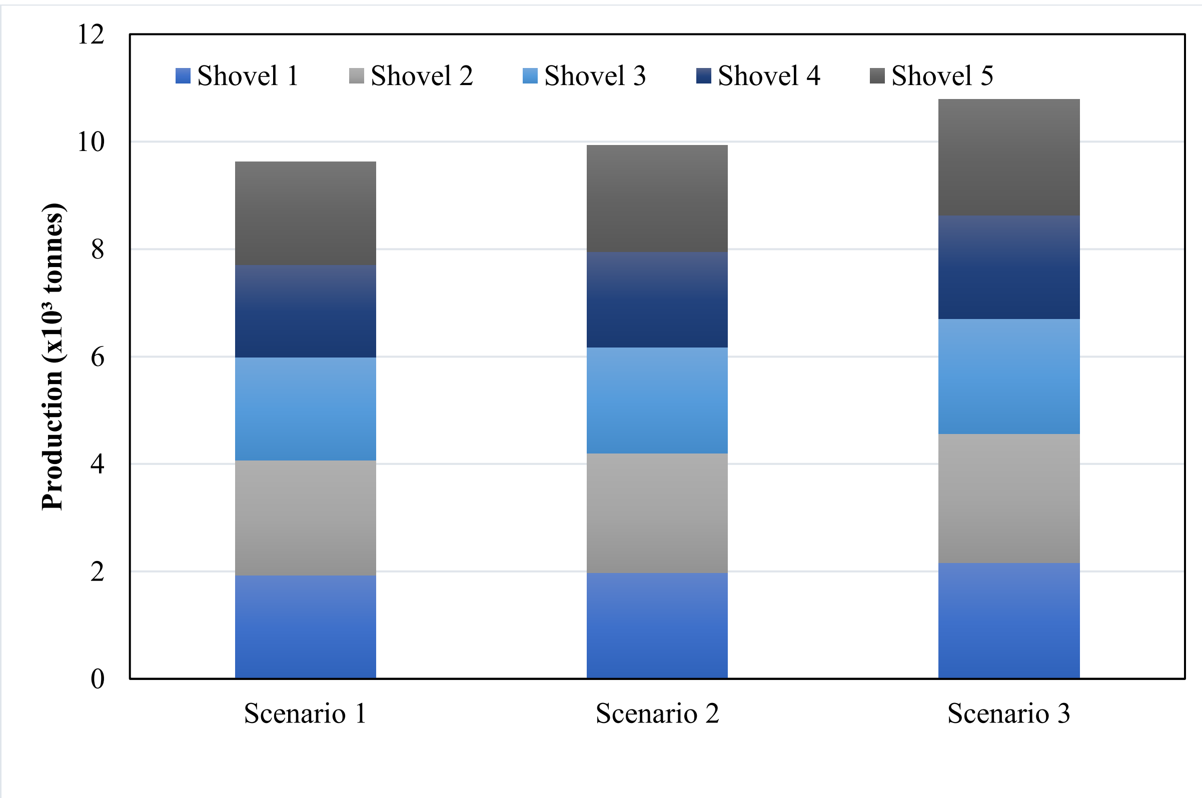

Figure 24. Total shovel production of DTL scenarios

To better understand the source of the production gain, operational KPIs for the three scenarios are presented in Table 25. It can be observed that while average truck load has dropped in the second and third scenarios, the decreased loading times has helped the shovels to load more trucks and thus the total production to increase (3.8% in the second and 12.1% in the third scenarios compared to the first scenario).

Table 25. DTL scenarios operational KPIs

Case	Loading time (s)	Truck load (tons)	Scheduled utilization (%)	No. loaded trucks
	Mean±std	Mean±std	Fleet average	Total
Scenario 1	116±22	296±41	85	32597
Scenario 2	108±15.7	291±36	83.8	34204
Scenario 3	108±15.5	314±26	84.2	34373

Figure 25 also shows the influence of the applied strategy on the truck fleet KPIs. As anticipated before, it can be observed that both average trucks wait times and number of them in queue decreases in the second and third scenarios. As discussed before, minimizing the wait time not only improves productivity and reduces operational costs, but also could be seen as a significant opportunity to reduce diesel emissions (CO, CO_2, NO_x, unburnt hydrocarbons, and particulate matter) during truck idling.

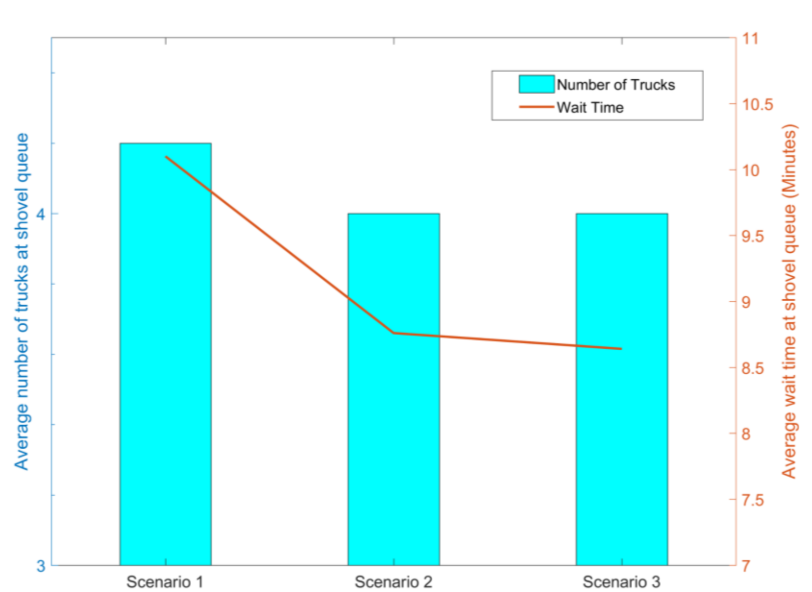

Figure 25. Trucks average wait time and numbers in queue for DTL scenarios

5.3 Projected Hourly Production

A loading task has two main aspects, truck final payload and cycle time (total time to load a truck). However, as it was discovered in previous sections of this study, the magnitude of each one's influence on the shovel's production is not equal. Figure 26 presents a hypothetical example range of a P&H4100 cycle times, truck payloads and expected resulting hourly production. The graph clearly illustrates the more prominent role of cycle times in production compared to the truck final load.

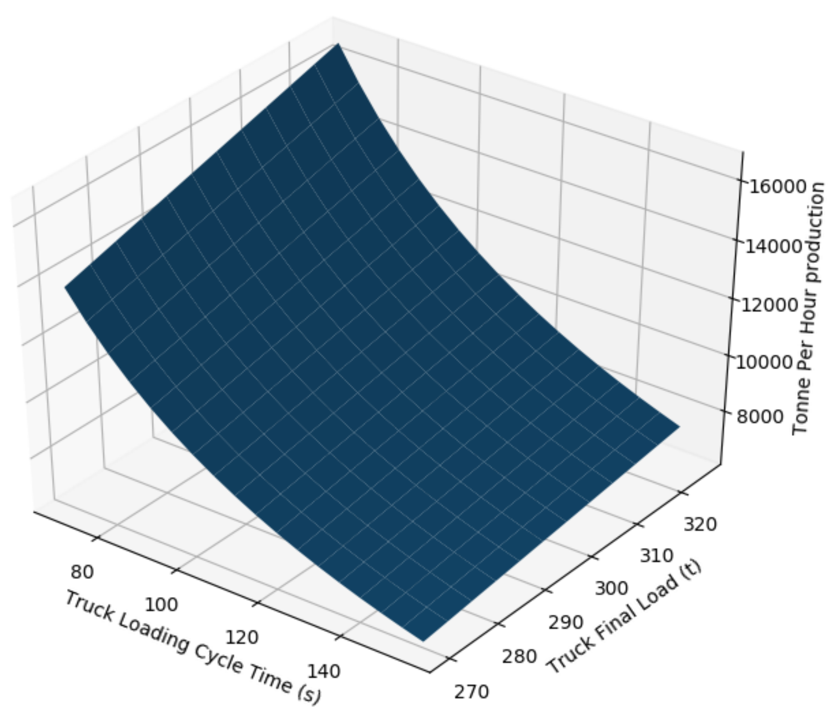

Figure 26. Example of a P&H4100 loading cycle time, truck final load and resulting hourly production

Currently, truck final payload and its load cycle time are presented as separate KPIs to the rope shovel operator. While these provide the operator basic feedback on their loading activity, it can be argued that the overall picture (i.e., the resulted total production) is missing. The significance of the cycle time role also suggests that in contrast to the traditional approach that mainly considers truck load as a KPI to evaluate shovel operator loading performance, in order to better assess their performance outcome, it is necessary to take into account a combination of both truck load and cycle time instead.

Thus, the KPI Projected Hourly Production (PHP), that includes both TFL and CT is suggested in equation 5.1:

$$PHP = \frac{TFL}{CT} \times AF_j \qquad (5.1)$$

Where TFL is the truck final load and CT is the total time took to load the truck. AF_j is an adjustment factor derived from the operational data specific to the operation and truck type j. It can be calculated using equation 5.2:

$$AF_j = 100 \times \left(\frac{TC_j \times MAL_j}{Min_{Fleet}(CT)}\right)^{-1} \qquad (5.2)$$

TC_j and $Min_{Fleet}(CT)$ are the truck capacity and the recorded lowest cycle time to load a truck type j at a particular mine. MAL_j is the maximum allowable load for the truck type j. The PHP higher values indicate better performance amongst operators.

PHP estimates the loading activity performance as a combination of time and load. Hence, it provides the operator with a more tangible feedback that will allow them to understand how well they are doing compared to what is possible. Having this feedback operators can adjust their loading to focus on maximum hourly production versus loading each individual truck to its optimum capacity.

Also, compared to the traditional "ton per hour" (TPH), PHP only considers shovel productive time. This removes the impact of truck availability and makes PHP a suitable KPI to study only the shovel operator performance independent from external sources.

5.3.1 PHP example

To better illustrate the application of the PHP, the following example is presented. The current operation has a fleet of trucks with the $TC_j = 300\, tonnes$, and for the first 6-months of the operation the minimum recorded time to load a truck within the acceptable thresholds (95% to 110% of the truck capacity) is $Min_{Fleet}(CT) = 96\, seconds$. The MAL_j is 110% of the truck capacity or 1.1.

Table 26 presents calculations for three different scenarios from the WRO loading practices from the shovel health and payload monitoring database. Scenario A is the WRO that loaded a truck slightly higher than its 100% capacity as required from the mine operation. In scenario B, the operator improved their CT but achieved slightly lower TFL. While the classic evaluation process that only considers the TFL could conclude that in the second scenario the operator did a worse job, the PHP has reflected the achieved improvement.

Table 26. PHP application example

Scenario	TFL_i (tonnes)	CT_i (Seconds)	TC_j (tonnes)	MAL_j	Min_{fleet} CT (Seconds)	AF_j	PHP	Expected hourly production* (tonnes)
A	302	143	300	1.1	96	29	61	7602
B	297	129	300	1.1	96	29	66	8288
C	270	105	300	1.1	96	29	74	9257

*Expected hourly production is calculated using following formula: $\frac{3600}{CT} * TFL$

As observed earlier in the section 3.2.1, an inexperienced operator tends to load trucks to their capacity using an extra pass called trim pass. In the third scenario it is assumed that the operator has cut the trim pass and used only three passes to load the truck.

Although the truck final load is lower in scenario C, the expected hourly production is higher. The PHP correctly reflects that and could be considered as a tool to educate operators toward operation excellence.

It should also be noted that similar to DTL, PHP becomes more valuable in situations where either the number of trucks and shovels are well-matched, or the operation is shovel limited (i.e., number of trucks are higher than needed).

5.4 Semi- and Full-Autonomous Electric Rope Shovel

This section aims to study the extent to which autonomous and operator-assisted loading units could improve different aspects of a mining operation. Four different levels of automation ranging from operator-assisted swing and return to fully autonomous for a shovel are considered and compared against a manual fleet as the benchmark.

Automating the dig, swing, and return part of a loading activity can be seen as the initial steps toward automation of electric rope shovels. Complexities involved in the dig section of a loading activity suggests that their automation could occur separately from swing and return. Thus, here in the first autonomous scenario, a swing and return system is studied. The second scenario evaluates the effect of adding the dig-assisted function to the system.

The third scenario investigates how a fully autonomous shovel can improve the shovel and mine production and performance. Furthermore, as previously noted in an autonomous LHD study (Larsson et al., 2010b), the biggest advantage of automation could be seen in fewer errors and higher consistency. Hence, the fourth scenario explores what benefits could be gain by a hypothetical optimal autonomous electric rope shovel. Table 27 summarizes automation scenarios.

Table 27. Automation scenarios

	Practice		
Automation	Swing and return	Dig	Propel (positioning and movement)
Level 1	Automated	Operator	Operator
Level 2	Automated	Automated	Operator
Level 3	Automated	Automated	Automated
Level 4	Automated*	Automated*	Automated*

*Improved, compared to the base automated scenario

5.4.1 Automation scenario development

5.4.1.1 General mine DES operation data inputs

Following input parameters for the mine operation DES model are considered to stay the same for all scenarios:

- Mine schedule,
- Road network,
- Load/dump locations,
- Trucks empty and loaded speeds,
- Trucks spotting times,
- Trucks backing time,
- Shovel failures, borrowed from Samanta et al. (2001)
- Shovel operators shift change/break times (half an-hour shift change, and two half an-hour breaks for a 12-hours shift.)

Table 28 present the summary of input statistics for these scenarios.

Table 28. Automation DES model general distribution inputs

Parameter	Mean	Standard deviation	Distribution
Empty speed (km/h)	35.7	10.7	NORM (35.7, 10.7)
Loaded speed (km/h)	18.8	7.52	5 + LOGN (18.8, 7.52)
Spotting time (s)	37	27.1	1 + LOGN (37.8, 39.1)
Backing time (s)	15.6	10.9	1 + LOGN (14.8, 11.5)
Dumping time (s)	47.9	21.2	NORM (47.9, 21.2)
Shovel MTBF (h)	WEIB (130,0.76)		
Shovel MTTR (h)	LOGN (11.39,14.73)		

As the main focus of this study is the loading aspect of the operation, a fleet size of 60 trucks is used as it is the optimum truck-shovel match determined through a trial-and-error process.

The discrete event simulation model is set up to run for thirty 24-h shifts to represent a month worth of activity and 25 iterations to meet the required half-width for the production within a 95% confidence interval.

5.4.1.2 Benchmark - manual fleet

In an effort to capture the extent to which operator's HF and HE could be managed by the proposed automation and how mine productivity and operational KPIs are influenced, a fleet of manual shovel is modeled in the simulation as the benchmark.

Table 29 and Table 30 present statistics for the fleet average from the shovel onboard health and payload monitoring system dataset that are used as input to the model.

Table 29. Manual fleet key activity statistics

	Statistics		
Activity	Mean	Standard Deviation	Distribution
Dig time (s)	15.1	4.15	NORM (15.1, 4.15)
Swing time (s)	7.02	2.6	LOGN (7.02, 2.6)
Return time (s)	8.2	2.8	NORM (8.2, 2.8)
Propel time (s)	22.6	14.4	1 + LOGN (21.7, 16)
No. of bucket	3.17	0.41	DISC (3,0.83,0.967,4,1,5)

Table 30. Bucket load statistics for the manual fleet scenario

Pass No.	Load Statistics (tons)		
	Mean	Standard Deviation	Distribution
Pass 1	105	21.8	11 + WEIB (98.4, 4.57)
Pass 2	105	17.8	11 + 129 * BETA (8.85, 3.32)
Pass 3	97.7	18.2	11 + 129 * BETA (7.35, 3.6)
Pass 4	69.2	27.8	11 + 128 * BETA (1.94, 2.33)
Pass 5	80.9	30.1	TRIA (11, 99, 139)

5.4.1.3 Automation level 1 scenario – Automated swing and return

Automating the dig, swing, and return part of a loading activity can be seen as the initial steps toward automation of electric rope shovels. Complexities involved in the dig section of a loading activity suggests that their automation could occur separately from swing and return. Thus, here in the first autonomous scenario, a swing and return ystem is studied. This could also allow for teleoperation of a shovel where the remote operator executes the dig function and then releases the machine to do the swing dump return.

For this scenario it is assumed a shovel with an automated swing and return cycle would be as good as the BRO identified in the Section 4.4. Table 31 and Table 31 present the statistics used for this.

Table 31. Loading statistics inputs for the automation level 1

Activity	Statistics		
	mean	Standard Deviation	Distribution
Dig time (s)	15.1	4.15	NORM (15.1, 4.15)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	22.6	14.4	1 + LOGN (21.7, 16)
No. of buckets	3.17	0.41	DISC (3,0.83,0.967,4,1,5)

Table 32. Bucket load statistics for the automation level 1 scenario

	Load Statistics (tons)		
Pass No.	Mean	Standard Deviation	Distribution
Pass 1	105	21.8	11 + WEIB (98.4, 4.57)
Pass 2	105	17.8	11 + 129 * BETA (8.85, 3.32)
Pass 3	97.7	18.2	11 + 129 * BETA (7.35, 3.6)
Pass 4	69.2	27.8	11 + 128 * BETA (1.94, 2.33)
Pass 5	80.9	30.1	TRIA (11, 99, 139)

Figure 27 compares the best operator's swing times against the average fleet values. It can be seen that the best operator not only spends less time to perform the activities but is also more consistent.

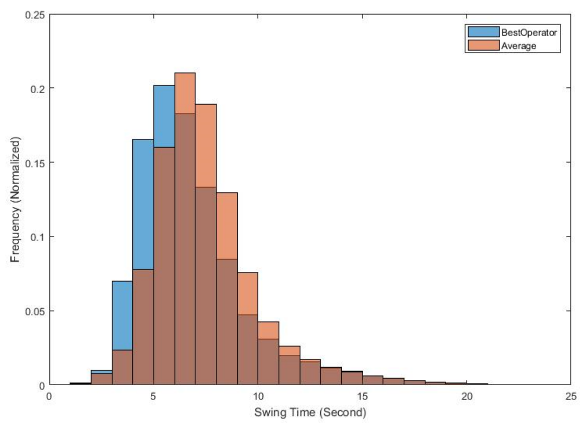

Figure 27. Best operator's swing times vs. fleet average

5.4.1.4 Automation level 2 scenario – Automated swing, return and dig

The second scenario evaluates the effect of adding the dig assist function to the system. It is envisioned that automating the dig part of a loading activity could improve both dig time and bucket loads. Hence, for this scenario statistics for the associated part of loading task (i.e., dig, swing/return) of fleet average in the manual DES model are replaced with the best previously identified practice among operators. Table 33 and Table 34 present the statistics.

Table 33. Loading statistics inputs for the automation level 2

Activity	Statistics		
	mean	Standard Deviation	Distribution
Dig time (s)	13.5	3.3	NORM (13.5, 3.3)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	11.3	8.06	1 + LOGN (10.3, 7.17)
No. of buckets	3.03	0.2	DISC (3,0.97,1,4)

Table 34. Bucket load statistics for the automation level 2 scenario

Pass No.	Load Statistics (tons)		
	Mean	Standard Deviation	Distribution
Pass 1	108	16.2	11 + 129 * BETA (10.5, 3.49)
Pass 2	110	15.8	11 + 128 * BETA (12.7, 4.25)
Pass 3	98.4	16.9	11 + WEIB (92.1, 6.58)
Pass 4	48.9	21.4	17 + WEIB (54, 2.43)

Figure 28 compares the best operator's dig times and truck load against the average fleet values. It can be seen that the best operator tends to load trucks slightly higher than 100% with noticeably better consistency (5% standard deviation compared to the fleet average 9%).

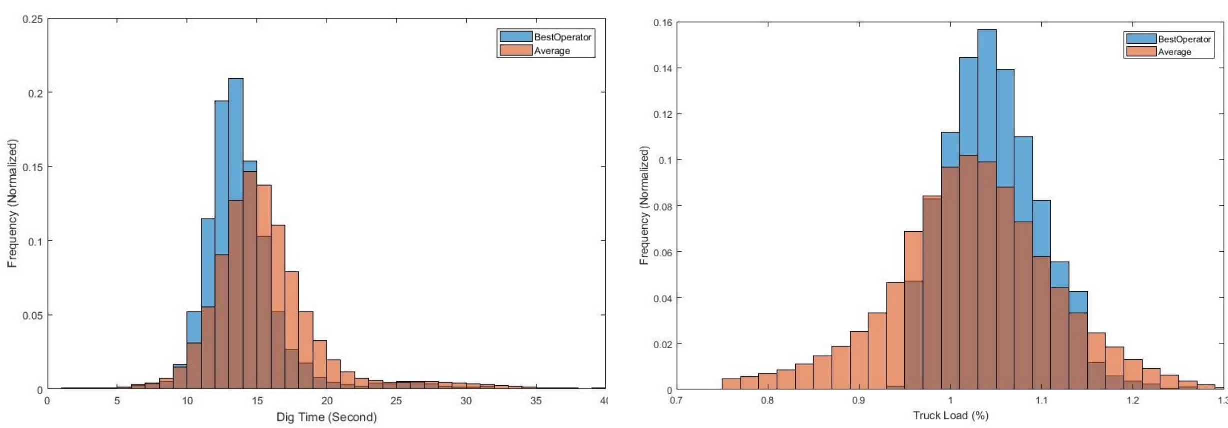

Figure 28. Best operator's dig time and truck load vs. fleet average

5.4.1.5 Automation level 3 scenario – fully autonomous electric rope shovel

It is expected that a full autonomous shovel could load a truck without the need for human intervention. Hence, as argued for the automation scenarios level 1 and 2, for the third autonomous scenario statistics from the best loading practices are used to model a full autonomous shovel.

In addition to improved dig, swing, and return times, it is also assumed that shovels load trucks more consistently [i.e., constant three passes]. Moreover, as no human presence is needed for the operation of a fully automated shovel, break-times are eliminated in this scenario. Table 35 presents input statistics for the third scenario.

Table 35. Loading statistics inputs for the automation level 3

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	13.5	3.3	NORM (13.5, 3.3)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	11.3	8.06	1 + LOGN (10.3, 7.17)
No. of buckets	3	0	FIXD (3)
Bucket load	108	16.2	11 + 129 * BETA (10.5, 3.49)

5.4.1.6 Automation level 4 scenario – improved fully autonomous electric rope shovel

Finally, as previously noted in an autonomous LHD study (Larsson et al., 2010b), the biggest advantage of automation could be seen in fewer errors and higher consistency. Although a significant improvement was reported in their study, here a conservative approach of a scenario with 10% and 50% hypothetical improvements respectively in the average and standard deviation of loading activities is examined (except for the shovel bucket load as the 10% increase would cause it to exceed bucket maximum nominal capacity).

This scenario could be interpreted as an optimistic ideal automation implementation. Table 36 presents this scenario input parameters.

Table 36. Hypothetical improved autonomous shovel key activity statistics

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	12.15	1.65	NORM (12.15,1.65)
Swing time (s)	5.67	1.33	NORM (5.67,1.33)
Return time (s)	6.57	1.2	NORM (6.57,1.2)
Propel time (s)	10.17	4.03	NORM (10.17, 4.03)
Bucket Load (ton)	108.8	8.2	NORM (118.8, 8.2)
No. of bucket (no)	3	N/A	CONST (3)

5.4.1.7 Assumptions and limitations

The shovel health and payload monitoring system data set include information from the operation that the crusher has a greater capacity than what the material handling system can provide. The operation uses the stockpile and blending process to feed the crusher. Hence, the capacity of the dump locations is assumed to be unlimited in the simulation.

5.4.2 Results and evaluation

Table 37 and Figure 29 demonstrate the total production of the shovel fleet during the simulation period and compare automated scenarios with the base (i.e., manual) scenario. While implementing an swing and return system in the first scenario has resulted in 3.6% improvement, it has been the automated dig function in the second scenario that improved production by 8.8%, both compared to the manual case.

This could be directly linked to the fact that in the automated dig scenario trucks are being loaded with more optimum bucket loads, and hence, not only their average final load has lower variability, but also the number of passes required to fill them, and total loading time are decreased on average. Figure 30 shows these changes.

Table 37. Shovel fleet production during the simulation period

	Shovel production (million tons)						
	1	2	3	4	5	Total	% Difference[1]
Manual fleet	4.04	4.33	3.84	3.74	4.01	19.97	0.0%
Scenario 1	4.21	4.51	3.93	3.86	4.19	20.69	+3.6%
Scenario 2	4.41	4.75	4.13	4.05	4.40	21.73	+8.8%
Scenario 3	5.55	5.96	5.02	5.15	5.51	27.19	+36.1%
Scenario 4	5.74	6.16	5.17	5.31	5.70	28.09	+40.6%

[1]Compared to the manual fleet.

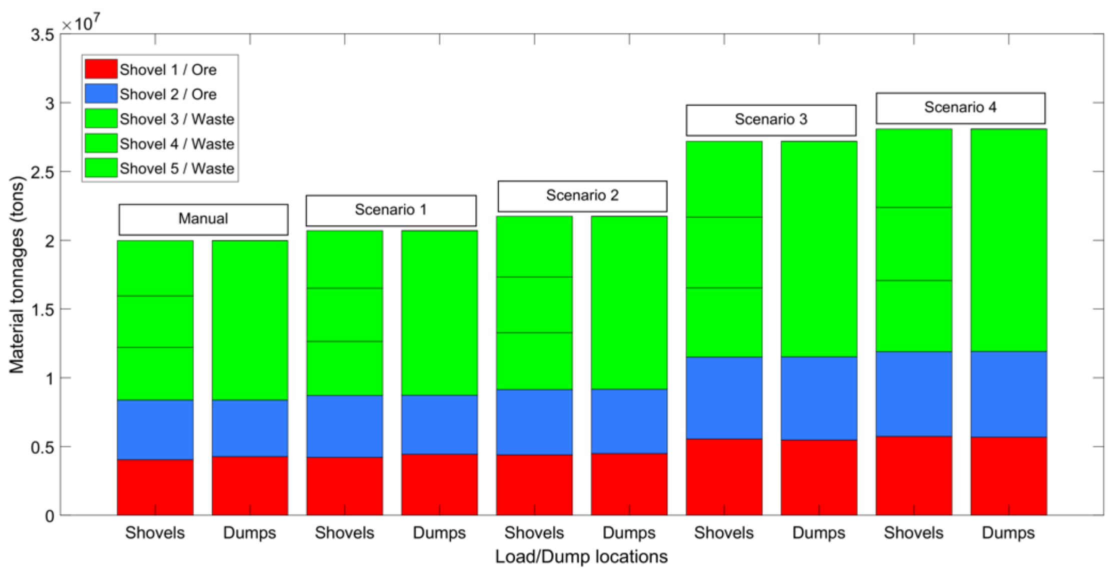

Figure 29. material moved during the simulation period from shovels to dump locations

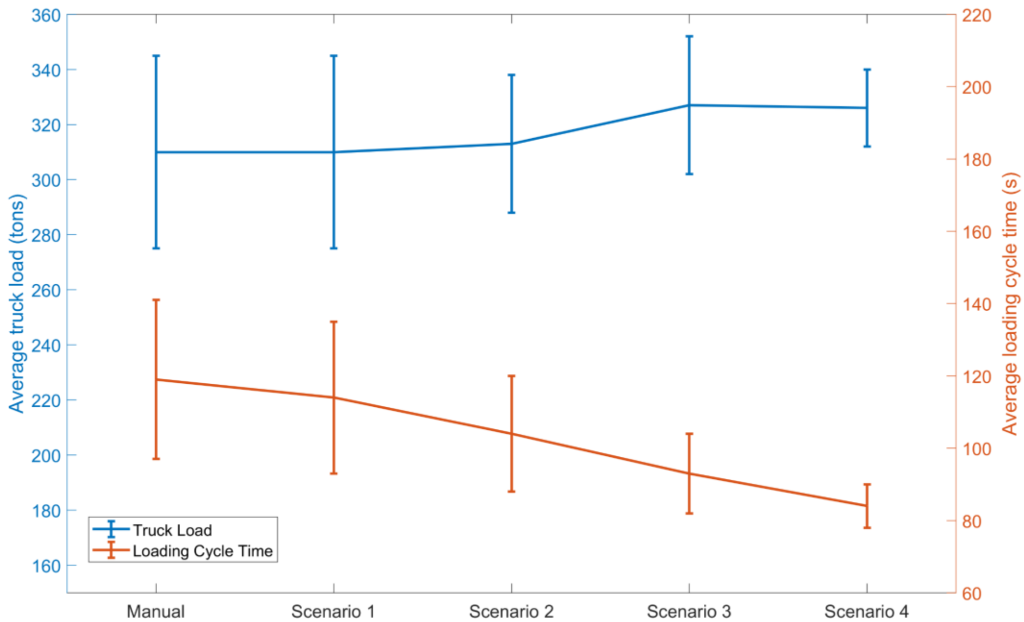

Figure 30. Average and standard deviation of total loading cycle time and truck load

As expected, assuming an automated shovel could perform as good as the BRO in the research resulted in an incredible 36.1% improvement in production. Reduced propel time and number of buckets to load a truck collectively with the higher bucket load could be regarded as the main operational contributors. Also, the elimination of the shift changes and lunch break times (total of 1.5 hour per 12-hour shift including one shift change and two half an hour breaks) has a great role in this achievement. It can be seen from Table 38 that these lost production hours can account for almost half of the automation production gain compared to the manual scenario.

Table 38. Influence of shift change and break times on operational KPIs

Case	Loading time (s)	Truck load (tons)	Scheduled utilization (%)	Production (tons x 10^6)
	Mean±std	Mean±std	Fleet average	Total
Scenario 3	92.6±10.9	326±25	83.4	27.2
Scenario 3 with break time	92.5±10.9	323±24.8	83.6	23.8

In addition to their influence on production, loading cycle times could affect other aspects of operation. Figure 31 presents the average number of trucks and their waiting time in queue. It can be seen that there is a lower wait time for all non-manual scenarios. While all truck fleet operational parameters (i.e., spotting, backing, and dump times, speeds, capacity, and dispatch algorithm) were the same for all scenarios, it is the shovel loading practices that are the main contributor to the decrease in truck wait times.

Additionally, the extra trucks assigned to active shovels when a shovel is out of service either due to operator breaks or shift change could also result in a higher number of trucks in a queue at loading locations in non-autonomous scenarios. Minimizing the wait time not only improves productivity and reduces operational costs, but also could be seen as a significant opportunity to reduce the air pollution caused by truck idling. Additionally, this could enable operations to reduce their active truck fleet size.

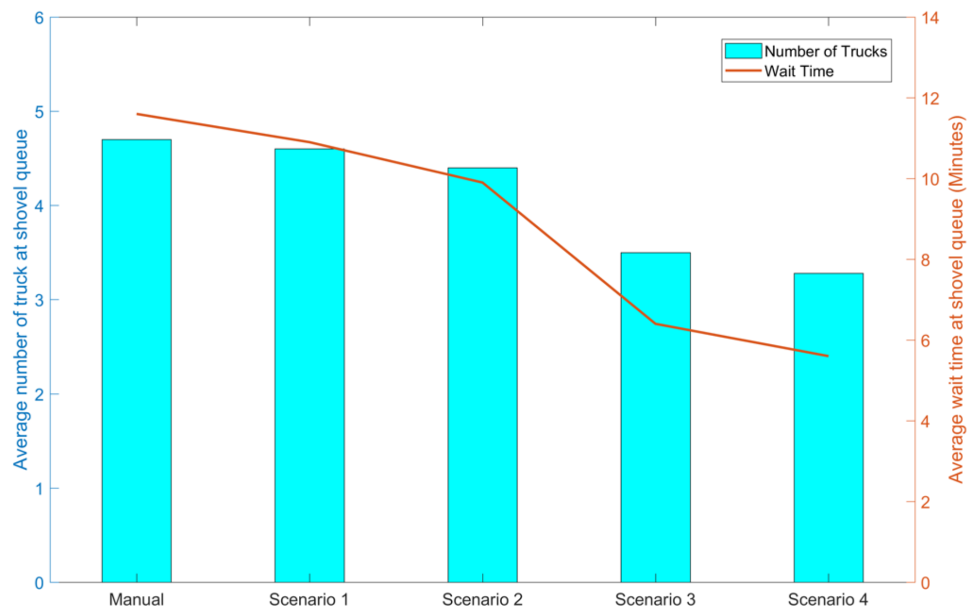

Figure 31. Average number of trucks in queue and their wait time at loading locations

Truck fleet size and availability plays a significant role in a shovel's utilization of availability. As the direct result of decreased loading times and improved efficiency of shovels, trucks have become the bottleneck of the operation. Hence, shovels have to wait for trucks to become available and the average shovel fleet utilization dropped by 10% in the improved autonomous scenario compared to the manual. It could be argued that the autonomous and improved autonomous shovels production would have been even more if the truck fleet size were increased. Furthermore, in case increasing the number of trucks is not an option for the operation, a scenario with fewer shovels can be considered to meet the same level of production.

6. CHAPTER 6: CONCLUSION

6.1 Summary of The Research

Shovels are prominent player in the mining material handling system. Given their importance, this research explored whether detailed data from a shovel health and payload monitoring system with the help of statistical analysis and modeling technics could be used to broaden the existing body of knowledge about their operators and the extent to which HFs are influencing production and performance.

The research presented a detailed assessment of electric rope shovel operator loading practices and how they influenced shovel and mine productivity, as well as truck fleet efficiency. It was observed that mean truck load factor, loading cycle time, and number of passes to load a truck differed among operators.

The ORS system based on these variables was developed to evaluate operators loading practices. The ORS was implemented in a case study and showed that the identified BRO tended to load trucks slightly higher than their nominal capacity in a shorter cycle time and with fewer numbers of passes than the WRO.

In an effort to capture the extent of shovel operator's HF influence on the shovel, truck and mine operation an electric rope shovel operator sub-module was developed and used in a surface mine discrete event simulation model case study. After verification, the simulation was implemented to explore the extent to which operator loading practices influence mining operations.

The result showed that not only shovel and mine production are affected by the operator's practices, but also the number of trucks and their wait time in loading queues. The operator's role became more influential with increasing truck fleet size.

The proposed method used the identified best and worst operators from the ORS evaluation as the input for the developed electric rope shovel operator simulation sub-module in the mine operation discrete event simulation model. It showed the significant influence of the number of passes and cycle time on the mine production. This new knowledge was leveraged to develop the concept of DTL.

The DTL was proposed as a measure to improve shovel and mine production by providing operators with a more flexible target truck final load in situations where the number of trucks in queue are greater than two. The benefits of using DTL were evaluated using the simulation model and it was shown that it could help an operator improve their overall production up to 12.1% by eliminating trim passes and hence reduce loading cycle times.

Based on identified importance of cycle times and in an effort to fill the need for a comprehensive KPI that incorporates more than one measured performance indicator, PHP was introduced. It was designed to capture two important aspects of a loading activity (i.e., load and cycle time) at the same time and reflects operator loading practices and their influences on the shovel production. The KPI provides operators with an active feedback about their loading practices. In the case of connected systems, the KPI could leverage the real-time data from the fleet and updates the results on-the-fly.

Last but not least, this research presented a detailed assessment of different levels of automation for an electric rope shovel. Four hypothetical levels of automation were considered for shovels, and the influence of each proposed level on both shovel and mine productivity were evaluated. It was found that in addition to 40.6% increased mine overall production, wait times at loading locations could also be reduced by up to 20%. The increased production for the autonomous scenarios was almost equally due to elimination of breaks and shift time changes as well as the assumption of more efficient loading using automation technology.

6.2 Conclusions and Discussion

This work demonstrated:

"*That the use of advanced analytics and discrete simulation on real time electric rope shovel data can lead to the identification of and an understanding of the various influences on shovel"*.

Through the use of detailed data on shovel operator performance and discrete event simulation a greater understanding of the impact of the shovel operator on shovel performance and overall mine performance was gained. It identified the main contributors to the variability in shovel operator performance and developed approached to allow operations to improve them. It also provided an estimate of the benefit of various levels of automation on shovel and mine production.

It is envisioned that the proposed operator relative score system can be used by mine professionals to complement other shovel performance measurements. This will help identify operators that need additional training as well as identify where the training should focus. It can also be used to assess the progress of a new and under-training operator and establish a baseline for their preparedness. Additionally, the approach could also help mine operations to re-group their operators based on a calculated rank to achieve specific goals for their crew's production.

The ORS considers a linear relationship between the shovel hourly production and the shovel loading components and puts equal weight on each component's importance. Whether assigning different weights could improve the KPI ability to better distinguish operator's skill and performance needs further study.

The developed shovel's operator behavior sub-module can emulate electric rope shovel operators' behavior. The sub-module enables professionals to study the role of each shovel operator in their overall mine haulage and production system. Yet, there are some aspects of the electric rope shovel operation such as dig pattern and machine energy consumption that can be added to the model to further study any existing relationship between an operator loading strategies and their performance. The simulation sub-module may help identify areas needed and demonstrate the importance of training for shovel operators and predict potential productivity improvements.

In order to mitigate the influence of an electric rope shovel's operator on the shovel and mine operation, DTL and PHP were developed. The DTL was designed to use the inherent potential of the new generation of connected systems in the mining industry and leverages the future interoperability between loading and haulage systems. The DTL shifts the operation optimization from a single unit level (i.e., loading unit) to a system level (i.e., loading and haulage).

The DTL's decision-making algorithm can be expanded to include real-time data from many aspects of a loading and haulage system such as truck's haulage cycle, fuel consumption etc. When integrated with a real-time DES model, the decision-making algorithm could evaluate different operational scenarios and make the best possible decision in real time.

PHP is also introduced to help operators improve their performance. Given the discovered importance of loading cycle times, the enhanced interpretation gained from the proposed PHP could enable an operator to modify their loading tactics and receive on-the-fly feedback that enables them to further optimize their production. PHP leverages the connected systems and by considering best recorded practice for its calculation, it creates a constructive competitive environment between operators that can further help them stay motivated.

While both DTL and PHP try to help an operator optimize their production and performance, their final goal is slightly different, and they also target different aspect of a loading activity. DTL tries to optimize the mine overall production by looking at the loading and haulage systems activities at the same time and puts the priority on the mine production. PHP on the other hand provides operators the necessary feedback they need to adjust their bucket loads and cycle times to enhance their production and performance.

Automation has been seen as the direct measure to reduce and remove HF. It is envisioned that the proposed simulation approach can be used as a decision-making tool by mine professionals and help them assess the extent to which automation could improve their activities.

6.3 Novel Contributions

The research main novel contributions are:

1- The ORS KPI was developed which is a new approach to assess the relative performance of shovel operators. It considers cycle times (i.e., dig, swing and return times), number of passes and truck final load.

2- The knowledge gained through operator performance monitoring and the discrete event simulation modeling revealed that in situations where trucks are waiting in the queue, loading cycle times, which inherently represents both no. of passes and each pass cycle time, outweigh truck final load. DTL as a new approach was proposed to provide the ERS operator with a flexibility in the target truck final load to compensate for over-truck scenarios.

3- Contrary to the common view that mainly associates truck load factor with the operator of an electric rope shovel's performance, analysis of detailed operational data showed that the number of passes and cycle times are as critical. In order to emphasize the importance of cycle times, PHP as a new KPI was developed.

4- Electric rope shovel's operators shown to have substantial variations in their sub-loading activities (i.e., swing, return, and dig times, bucket load and number of buckets to load a truck). These variations were shown to not only influence shovel production, but also other aspects of a mine operation such as number of trucks in queue and their wait times at loading locations.

5- A discrete event simulation sub-module was developed to represent an electric rope shovel operator in a mine loading-haulage simulation model. It models material loading based on each-pass information (i.e., dig, swing, and return times, number of buckets to load, and each bucket load). The sub-module enables a discrete event simulation model to estimate variations in operators loading practices.

6- A methodology to study how electric rope shovel operators are influencing shovel and mine production was suggested. The approach uses the output from the ORS as an input to the developed operator simulation sub-module in an open pit surface mine model to measure the extent to which electric rope shovel operators' HF influences both shovel and mine performance and productivity.

7- A simulation model was created to assess the potential influences of varying levels of automation of electric rope shovel. Results indicated improvement in production due to the elimination of breaks and shift change and more consistent operation. As well the ability to model the efficiency of an automated shovel compared to human operated ones is possible with the model. This approach could be used to put upper and lower bounds on the autonomous shovel performance (i.e., it performs better than human operated or worse). This also allows assessing the economic risk associated with implementing these shovels when they become available.

6.4 Future Work

Based on the research done following future works are suggested:

- Enhancement to the operator simulation sub-module and incorporate the dig, swing and return paths to the model. This could be used to model and study operators' loading practices and its influence on both production and energy consumption. This could also help to study and improve each operators' loading tactics.

- Enhancement to the mine operation DES model such as integrating truck re-fueling mechanism and investigate what influences correlating the truck loaded speed with the amount of load could have on the final result and the DES model overall accuracy.

- Investigate underlying HFs contributing to those identified variations among operators.

- Investigate whether assigning a weight to each sub-category of the ORS could help the KPI to assess operators more accurately.

- Investigate whether other aspects of the operation such truck fuel cost and traveled distance could be added to the DTL decision machine to improve its outcome.

- Evaluate the PHP in the action and study its short-term and long-term influence on operators' loading performance and production.

- Investigate whether the automation technologies could improve overall machine health by preventing human errors (i.e., extra stresses on machine frame, or events such as boom jacks). Also, how trucks could be influenced by the more consistent payloads with better load distribution needs to be studied.

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APPENDIX A

This Appendix summarizes distributions used throughout this research.

Operators influence study

Table 39 presents the common distributions used for all the DES scenarios.

Table 39. Operators influence DES model general distribution inputs

Parameter	Mean	Standard deviation	Distribution
Empty speed (km/h)	35.7	10.7	NORM (35.7, 10.7)
Loaded speed (km/h)	18.8	7.52	5 + LOGN (18.8, 7.52)
Spotting time (s)	37	27.1	1 + LOGN (37.8, 39.1)
Backing time (s)	15.6	10.9	1 + LOGN (14.8, 11.5)
Dumping time (s)	47.9	21.2	NORM (47.9, 21.2)
Shovel MTBF (h)	WEIB (130,0.76)		
Shovel MTTR (h)	LOGN (11.39,14.73)		

Table 40 and Table 41 present distributions for evaluating the BRO and the WRO scenarios, respectively.

Table 40. BRO input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	15.2	4.21	POIS (15.2)
Swinging time (s)	6.3	2.6	0.5 + LOGN (5.8, 2.65)
Returning time (s)	7.67	2.33	0.5 + GAMM (0.907, 7.9)
Bucket load (Pass 1)	109	16	11 + 129 * BETA (10.5, 3.49)
Bucket load (Pass 2)	108	14.2	11 + 128 * BETA (12.7, 4.25)
Bucket load (Pass 3)	97.1	15.7	11 + WEIB (92.1, 6.58)
Bucket load (Pass 4)	65.1	20.8	17 + WEIB (54, 2.43)
Number of buckets	DISC (0.95,3,1,4)		

Table 41. WRO input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	95.3	21.4	11 + 126 * BETA (4.76, 2.43)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Bucket load (Pass 3)	92.6	20.5	18 + 116 * BETA (4.09, 2.27)
Bucket load (Pass 4)	50.9	23.1	11 + WEIB (42.1, 1.74)
Bucket load (Pass 5)	46.6	25.4	11 + WEIB (39.6, 1.64)
Number of buckets	DISC (0.73,3,0.94,4,1,5)		

DTL study

Table 39 presents the common distributions used for all the DES scenarios. Table 42, Table 43, and Table 44 present statistics that were used the operator shovel behaviour sub-module for each scenario.

Table 42. DTL study first scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	95.3	21.4	11 + 126 * BETA (4.76, 2.43)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Bucket load (Pass 3)	92.6	20.5	18 + 116 * BETA (4.09, 2.27)
Bucket load (Pass 4)	50.9	23.1	11 + WEIB (42.1, 1.74)
Bucket load (Pass 5)	46.6	25.4	11 + WEIB (39.6, 1.64)
Number of buckets	DISC (0.73,3,0.94,4,1,5)		

Table 43. DTL second scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 2)	96.8	20.5	11 + 127 * BETA (5.23, 2.6)
Number of buckets (Second)	FIXED (3)		

Table 44. DTL third scenario input parameters

Parameter	Mean	Standard deviation	Distribution
Digging time (s)	17.6	6.7	POIS (17.6)
Swinging time (s)	8.56	2.92	0.5 + LOGN (8.13, 3.39)
Returning time (s)	8.7	2.7	0.5 + GAMM (0.979, 8.4)
Bucket load (Pass 1)	109	16	11 + 129 * BETA (10.5, 3.49)
Bucket load (Pass 2)	108	14.2	11 + 128 * BETA (12.7, 4.25)
Bucket load (Pass 3)	97.1	15.7	11 + WEIB (92.1, 6.58)
Bucket load (Pass 4)	65.1	20.8	17 + WEIB (54, 2.43)
Number of buckets	FIXED (3)		

Semi- and full-autonomous scenarios

Table 39 presents the common distributions that were used for all the DES scenarios. For all other parameters their appropriate distribution from Table 45 through Table 52 were used.

Table 45. Manual fleet key activity statistics

	Statistics		
Activity	Mean	Standard Deviation	Distribution
Dig time (s)	15.1	4.15	NORM (15.1, 4.15)
Swing time (s)	7.02	2.6	LOGN (7.02, 2.6)
Return time (s)	8.2	2.8	NORM (8.2, 2.8)
Propel time (s)	22.6	14.4	1 + LOGN (21.7, 16)
No. of bucket	3.17	0.41	DISC (3,0.83,0.967,4,1,5)

Table 46. Bucket load statistics for the manual fleet scenario

	Load Statistics (tons)		
Pass No.	Mean	Standard Deviation	Distribution
Pass 1	105	21.8	11 + WEIB (98.4, 4.57)
Pass 2	105	17.8	11 + 129 * BETA (8.85, 3.32)
Pass 3	97.7	18.2	11 + 129 * BETA (7.35, 3.6)
Pass 4	69.2	27.8	11 + 128 * BETA (1.94, 2.33)
Pass 5	80.9	30.1	TRIA (11, 99, 139)

Table 47. Loading statistics inputs for the automation level 1

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	15.1	4.15	NORM (15.1, 4.15)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	22.6	14.4	1 + LOGN (21.7, 16)
No. of buckets	3.17	0.41	DISC (3,0.83,0.967,4,1,5)

Table 48. Bucket load statistics for the automation level 1 scenario

	Load Statistics (tons)		
Pass No.	Mean	Standard Deviation	Distribution
Pass 1	105	21.8	11 + WEIB (98.4, 4.57)
Pass 2	105	17.8	11 + 129 * BETA (8.85, 3.32)
Pass 3	97.7	18.2	11 + 129 * BETA (7.35, 3.6)
Pass 4	69.2	27.8	11 + 128 * BETA (1.94, 2.33)
Pass 5	80.9	30.1	TRIA (11, 99, 139)

Table 49. Loading statistics inputs for the automation level 2

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	13.5	3.3	NORM (13.5, 3.3)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	11.3	8.06	1 + LOGN (10.3, 7.17)
No. of buckets	3.03	0.2	DISC (3,0.97,1,4)

Table 50. Bucket load statistics for the automation level 2 scenario

	Load Statistics (tons)		
Pass No.	Mean	Standard Deviation	Distribution
Pass 1	108	16.2	11 + 129 * BETA (10.5, 3.49)
Pass 2	110	15.8	11 + 128 * BETA (12.7, 4.25)
Pass 3	98.4	16.9	11 + WEIB (92.1, 6.58)
Pass 4	48.9	21.4	17 + WEIB (54, 2.43)

Table 51. Loading statistics inputs for the automation level 3

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	13.5	3.3	NORM (13.5, 3.3)
Swing time (s)	6.3	2.66	LOGN (6.3,2.66)
Return time (s)	7.3	2.4	NORM (7.3,2.4)
Propel time (s)	11.3	8.06	1 + LOGN (10.3, 7.17)
No. of buckets	3	0	FIXD (3)
Bucket load	108	16.2	11 + 129 * BETA (10.5, 3.49)

Table 52. Hypothetical improved autonomous shovel key activity statistics

	Statistics		
Activity	mean	Standard Deviation	Distribution
Dig time (s)	12.15	1.65	NORM (12.15,1.65)
Swing time (s)	5.67	1.33	NORM (5.67,1.33)
Return time (s)	6.57	1.2	NORM (6.57,1.2)
Propel time (s)	10.17	4.03	NORM (10.17, 4.03)
Bucket Load (ton)	108.8	8.2	NORM (118.8, 8.2)
No. of bucket (no)	3	N/A	CONST (3)