A Study of Electric Rope Shovel Digging Effort and Behaviour for Diggability Assessment in Open Pit Mines

by

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Abstract

Improving the drilling and blasting practice in open-pit mines is one of the ways to enhance the economics of a mining operation. Diggability assessment is currently considered as a way to provide feedback on blast quality; however, there is no universally accepted approach to evaluate diggability.

This research focused on the performance monitoring of electric rope shovels in open pit operations for understanding and modeling the influences on the digging as well as for measuring diggability. The effect of digging conditions as well as operator practice and skills on shovel performance was studied. Also, the relationship between digging conditions and vibrations experienced by the machine was investigated.

Based on the knowledge gained through shovel performance monitoring, two approaches (electrical and mechanical) that build upon previous work were developed to first isolate the dig phase and then to calculate a diggability index per pass. The diggability was defined as the resistance of materials to digging and was estimated based on the energy analysis of shovels during digging. It was found that the proposed index is able to distinguish between different digging conditions. Additionally, it was found that there is a relationship between the amount of vibration experienced by the machine and the digging conditions. A classification approach was developed and presented to compare the digging productivity of different shovel operators.

The proposed diggability index has been deployed on a fleet of shovels at a mine and the diggability values are recorded on a real-time basis in a SQL database.
Preface

This dissertation entitled “A Study of Electric Rope Shovels Digging Effort and Behaviour for Diggability Assessment in Open Pit Mines” is submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy (PhD) at the University of British Columbia. The research described herein is original and independent work by the author, Mohammad Babaei Khorzoughi, and was conducted under the supervision of Dr. Hall in the Department of Mining Engineering.


A version of Chapter 4 was published in Minerals Journal [Babaei Khorzoughi, M. and Hall, R. (2016), A Study of Digging Productivity of an Electric Rope Shovel for Different Operators, Special Issue on Frontiers of Surface Mining Research, Minerals, MDPI,Vol.6 , Issue 2, pp. 1-17]. I was the lead investigator responsible for all major areas of problem definition, methodology development, field data collection, data analysis and manuscript composition. Dr. Hall assisted with initial formulation of the problem and contributed to manuscript edits.

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Finally, it should be noted that all the raw data has been collected by the author through several field trials conducted during the research. Elkview Mine operations engineering department, Teck ART and Teck IS+T Operational Technology group assisted with machine instrumentation and field trial arrangements.
Table of Contents

Abstract ............................................................................................................................................ ii
Preface ............................................................................................................................................. iii
Table of Contents ............................................................................................................................... v
List of Tables ..................................................................................................................................... vii
List of Figures ..................................................................................................................................... viii
List of Abbreviations ......................................................................................................................... x
Acknowledgments .............................................................................................................................. xi
Dedication .......................................................................................................................................... xiii
1. Introduction .................................................................................................................................... 1
   1.1. Problem Description ............................................................................................................... 1
   1.2. Research Objectives ............................................................................................................. 3
   1.3. The Case Study: Elkview Steelmaking Coal Mine ................................................................. 4
   1.4. Thesis Outline ....................................................................................................................... 9
   1.5. A Note Concerning the Unit of Measurements ..................................................................... 10
2. Literature Review .......................................................................................................................... 11
   2.1. Loading Equipment Performance Studies ........................................................................... 12
   2.2. Effect of Operator ................................................................................................................ 38
   2.3. Summary .............................................................................................................................. 40
3. Methodology .................................................................................................................................. 45
   3.1. Machine Instrumentation ..................................................................................................... 46
   3.2. Field Trials .......................................................................................................................... 54
   3.3. Post-Blast Evaluation .......................................................................................................... 57
   3.4. Data Pre-Processing ............................................................................................................ 59
   3.5. Dig Cycle Identification ....................................................................................................... 61
   3.6. Operator Influence on Shovel Digging Productivity ............................................................. 72
   3.7. Diggability Assessment ....................................................................................................... 86
4. Effect of Operator on Shovel Performance ................................................................................... 97
   4.1. Productivity Analysis .......................................................................................................... 98
   4.2. Clustering of Shovel Cycles ................................................................................................ 102
   4.3. Operator Digging Practice ................................................................................................... 108
5. Effect of Digging Conditions on Shovel Performance ................................................................. 117
5.1. Time Studies .................................................................................................................. 117
5.2. Vibration Data Analysis .............................................................................................. 123
5.3. Effect of Digging Conditions on Sensor Data .............................................................. 132
5.4. Dig Force Analysis ...................................................................................................... 137
5.5. Electrical Power Analysis ........................................................................................... 140

6. Algorithm Evaluation .................................................................................................... 143
   6.1. Background ................................................................................................................ 143
   6.2. Dig Cycle Isolation Algorithms Evaluation ............................................................... 143
   6.3. Diggability Index Evaluation: Validation & Verification .............................................. 145
   6.4. Diggability Classification .......................................................................................... 159

7. Conclusion and Future Work ......................................................................................... 165
   7.1. Research Conclusions ............................................................................................. 166
   7.2. Research Novel Contribution .................................................................................. 168
   7.3. Future Work ............................................................................................................. 170

References .......................................................................................................................... 175

Appendix I – Rock Mass Diggability Classification ................................................................ 186
Appendix II – P&H4100XPB Shovel Specifications ............................................................... 193
# List of Tables

Table 2.1. Diggability index classification, after Mol et al. (1987) ................................................................. 15
Table 2.2. DI classification (after Hendricks, 1990) ................................................................. 17
Table 2.3. Variability analysis of different performance indicators for 440 cycles of one shift (after Patnayak and Tannant, 2005) ................................................................. 18
Table 2.4. Diggability classification based on fill factor (after P&H MinePro Services, 2003) .......... 26
Table 2.5. Cycle time for shovels (after Giltner and Koski, 2010) ......................................................... 28
Table 2.6. Diggability assessment studies .................................................................................. 35
Table 3.1. Vibration data recording signals .......................................................................... 42
Table 3.2. On-board shovel signals ....................................................................................... 48
Table 3.3. Sensor data ........................................................................................................... 50
Table 3.4. Summary of field trials during Phase I ................................................................. 52
Table 3.5. Blast parameters .................................................................................................. 58
Table 3.6. Digging conditions assessment .............................................................................. 59
Table 4.1. Key Shovel Performance Indicators .................................................................... 80
Table 4.2. Equivalent digging energy classification ................................................................. 90
Table 4.3. Crowd and hoist speed values ............................................................................. 100
Table 4.4. Operator rating system ....................................................................................... 104
Table 4.5. N values for Operators A and B ....................................................................... 113
Table 5.1. Cases A & B ........................................................................................................ 115
Table 5.2. Time value statistics .......................................................................................... 116
Table 5.3. t-test summary .................................................................................................. 118
Table 5.4. Different KPIs for easy and difficult digging conditions ............................................. 121
Table 6.1. Summary of diggability values .............................................................................. 122
Table 6.2. Summary of dig time and loading rate values ....................................................... 124
Table 6.3. Summary of diggability results .......................................................................... 135
Table A1.1. Diggability index rating (after Scoble and Muftuoglu, 1984) .......... 148
Table A1.2. Diggability classification (after Scoble and Muftuoglu, 1984) .............. 151
Table A1.3. Rock classification schemes for excavation purposes (after Hadjigeorgiou and Poulin, 1998) .. 157
Table A1.4. Excavating index rating (after Hadjigeorgiou and Poulin, 1998) .............. 159
Table A1.5. Excavating classification (after Hadjigeorgiou and Poulin, 1998) ..................... 163

vii
List of Figures

Figure 1.1. EVO property location (Elkview Operations, 2010) ................................................................. 5
Figure 1.2. Mining cycle at EVO (Elkview Operations, 2010) ........................................................................ 6
Figure 1.3. Geological cross-section of Natal Phase 2 (Elkview Operations, 2010) ............................................ 6
Figure 1.4. Different shovel activities ........................................................................................................... 7
Figure 1.5. Operator’s Station-Joysticks (modified from P&H operator Manual, 2015) ....................................... 8
Figure 2.1. Monitored signals for easy and difficult digging conditions (modified from Williamson et al. 1983) ....14
Figure 2.2. Example of hoist motors responses for easy and difficult digging conditions (modified from Hendricks, 1990) ........................................................................................................... 18
Figure 2.3. Shovel monitoring data, (after Hunter et al. 1990) ...................................................................... 19
Figure 2.4. Example of digging trajectory and depth of cut (modified from Karpuz et al., 2001) ...................... 21
Figure 2.5. Time normalized digging energy against average depth of cut (Karpuz et al., 2001) .................... 22
Figure 2.6. The output of a linear discriminant set for one loading cycle (after Jessett, 2001) ....................... 24
Figure 2.7. Main effect plots (Data Means) (modified from Clark et al., 2004) ............................................. 31
Figure 3.1. Methodology adopted in this research ....................................................................................... 46
Figure 3.2. Sensor axes orientation ............................................................................................................ 47
Figure 3.3. Overview of vibration data acquisition system ............................................................................ 48
Figure 3.4. USB Camera in the operator cab ............................................................................................... 49
Figure 3.5. Octagon computer installed in the shovel house ........................................................................ 50
Figure 3.6. PTM payload monitoring system ............................................................................................. 51
Figure 3.7. Shovel Schematic (modified from P&H operator manual, 2005) ................................................. 52
Figure 3.8. Shovel dig sequence during field trial #2 (provided by Elkview Operations) ........................... 56
Figure 3.9. Shovel dig sequence during field trial #3 (provided by Elkview Operations) ........................... 56
Figure 3.10. A sample of data retrieved from SQL database ..................................................................... 60
Figure 3.11. A sample of files retrieved from Octagon system ................................................................. 61
Figure 3.12. A complete dig phase (after P&H operators manual, 2005) ................................................... 62
Figure 3.13. A sample of data from PTM sensors for 22 passes ............................................................... 63
Figure 3.14. Identified dig cycles ............................................................................................................... 66
Figure 3.15. A subset of on-board shovel signals for 22 passes ............................................................... 69
Figure 3.16. Identified dig cycles ............................................................................................................... 71
Figure 3.17. A sample of joystick signals ................................................................................................ 75
Figure 3.18. Marked points on the hoist rope ........................................................................................... 77
Figure 3.19. Crowd arm retraction experiment .......................................................................................... 78
Figure 3.20. Hoist rope retraction and crowd arm extension traces during digging for 22 passes .............. 79
Figure 3.21. Schematic representation of a cable shovel .......................................................................... 81
Figure 3.22. An example of digging trajectory ......................................................................................... 82
Figure 3.23. Schematic representation of a cable shovel .......................................................................... 83
Figure 3.24. Crowd and bail angles during a dig cycle .............................................................................. 84
Figure 3.25. Smoothed bail angle signal .................................................................................................... 85
Figure 3.26. Bail angle signal from a gyro sensor ...................................................................................... 85
Figure 3.27. An example of digging trajectory .......................................................................................... 86
Figure 3.28. Digging Forces: Hoist and Crowd Force (after P&H operator manual, 2005) ......................... 90
Figure 3.29. Dipper incremental movement schematic ............................................................................ 93
Figure 4.1. Shovel dig playback during the field trial (Elkview Operations, 2015) ....................................... 98
Figure 4.2. Dig time distribution ............................................................................................................. 99
Figure 4.3. Generated clusters using K-means clustering method ............................................................ 103
Figure 4.4. Result of clustering analysis for comparison of payload and equivalent digging energy ............ 105
Figure 4.5. Result of clustering analysis for comparison of dig time and equivalent digging energy .......... 105
Figure 4.6. Loading rate vs. digging energy for all operators .................................................................. 107
Figure 4.7. Loading rate vs. digging energy for Operator A ......................................................................... 107
Figure 4.8. Hoist joystick reference ........................................................................................................... 109
Figure 4.9. Crowd joystick reference ....................................................................................................... 109
Figure 4.10. Average dig time for different digging energy classes ............................................................. 110
Figure 4.11. Average payload for different digging energy classes ............................................................. 111
Figure 4.12. Digging trajectory for Operators A and B ........................................................................... 112
Figure 5.1. Histogram and boxplot of case A ............................................................................................ 119
Figure 5.2. Histogram and boxplot of case B ............................................................................................ 120
Figure 5.3. Time domain of vibration amplitude of first loading cycle .................................................... 124
Figure 5.4. Frequency domain content of different stages of first loading cycle of a 930 haul truck (A1-axis) .................................................................................................................. 126
Figure 5.5. Frequency domain content of air digging and actual digging (A1-axis) ................................. 127
Figure 5.6. Frequency domain content of two digging cycles from case A and case B (A1-axis) .......... 129
Figure 5.7. Frequency domain of A1-axis vibration during loading of three haul trucks .................. 131
Figure 5.8. A sample set of sensors data for easier digging condition ..................................................... 133
Figure 5.9. A sample set of sensors data for harder digging condition ................................................... 134
Figure 5.10. Instantaneous equivalent power for easier and harder digging conditions ................................ 136
Figure 5.11. Bail force vs. time for two cases of re-handled materials and blasted muck-pile ............. 138
Figure 5.12. F-t curve and the area related to the empty dipper and the crowd arm weight ......... 139
Figure 5.13. Hoist power vs. time for two cases of re-handled materials and blasted muck-pile .......... 141
Figure 5.14. Crowd power vs. time for two cases of re-handled materials and blasted muck-pile ....... 141
Figure 6.1. Video recordings vs. mechanical approach ........................................................................... 144
Figure 6.2. Video recordings vs. electrical approach .............................................................................. 145
Figure 6.3. Dig sequence of P&H4100XPC shovel for the period of March 3-7th (Elkview operations, 2016) .......................................................................................................................................................... 146
Figure 6.4. Distribution of diggability values for re-handle material and run of mine waste ............. 147
Figure 6.5. Diggability Index contour map ............................................................................................... 149
Figure 6.6. Distribution of dig time values for re-handle material and run of mine waste ............. 150
Figure 6.7. Distribution of loading rate values for re-handle material and run of mine waste .......... 150
Figure 6.8. The muck-pile related to case study II .................................................................................... 152
Figure 6.9. Surveyed face related to case study II .................................................................................... 153
Figure 6.10. Averaged diggability index values ....................................................................................... 154
Figure 6.11. Averaged dig time values .................................................................................................... 154
Figure 6.12. Averaged loading rate values .............................................................................................. 155
Figure 6.13. Diggability trial data points (Elkview Internal Report, 2016) ................................................ 156
Figure 6.14. Diggability distributions (modified after Elkview Internal Report, 2016) ......................... 157
Figure 6.15. Distribution of diggability values for re-handle and blasted materials ................................ 158
Figure 6.16. Diggability map for waste .................................................................................................... 160
Figure 6.17. Diggability map for coal ....................................................................................................... 161
Figure 6.18. Diggability histogram for waste ........................................................................................... 162
Figure 6.19. Diggability histogram for coal .............................................................................................. 162
Figure 7.1. Diggability data integration into the ArcMap ........................................................................ 173
Figure A1.1. Rock quality classification system (after Franklin et al., 1971) .......................................... 186
**List of Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>BCM</td>
<td>Banked Cubic Meter</td>
</tr>
<tr>
<td>BI</td>
<td>Blastability Index</td>
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<tr>
<td>COV</td>
<td>Coefficient of Variation</td>
</tr>
<tr>
<td>Deg</td>
<td>Degree</td>
</tr>
<tr>
<td>DI</td>
<td>Diggability Index</td>
</tr>
<tr>
<td>DIG</td>
<td>Digging</td>
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<tr>
<td>DMP</td>
<td>Dumping</td>
</tr>
<tr>
<td>EVO</td>
<td>Elkview Operations</td>
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<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>HI</td>
<td>Hoist Armature Current</td>
</tr>
<tr>
<td>HT</td>
<td>Haul Truck</td>
</tr>
<tr>
<td>HV</td>
<td>Hoist Armature Voltage</td>
</tr>
<tr>
<td>KPI</td>
<td>Key Performance Indicator</td>
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<tr>
<td>OEM</td>
<td>Original Equipment Manufacturer</td>
</tr>
<tr>
<td>OPC</td>
<td>OLE for Process Control</td>
</tr>
<tr>
<td>PE</td>
<td>Potential Energy</td>
</tr>
<tr>
<td>PF</td>
<td>Powder Factor</td>
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<tr>
<td>PLC</td>
<td>Programmable Logic Control</td>
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<tr>
<td>PTM</td>
<td>PulseTerraMetrix</td>
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<tr>
<td>SQL</td>
<td>Structured Query Language</td>
</tr>
<tr>
<td>SR</td>
<td>Sampling Rate</td>
</tr>
<tr>
<td>SWG</td>
<td>Swinging</td>
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<tr>
<td>UCS</td>
<td>Uniaxial Compressive Strength</td>
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My father who always supported me and showed me that nothing can stop a real man; my mother who called me every day to just hear my voice and reminded me to take care of myself.

Last, but certainly not least, my lovely wife, Shirin, who endured me and encouraged me throughout my graduate studies. Without her, I never would have made it through my graduate program. She is an angel, and I am so lucky to have her as my wife forever.
Dedication

To Siamak and Behjat, my parents

And

To Shirin, Love of my life forever
1. Introduction

1.1. Problem Description

With the current cost pressures on mining operations, mines are looking at new ways to improve their operations. Mining operations mainly include two areas: mining and processing. The mining process includes drilling, blasting, loading and hauling and primary crushing (Hustrulid, 1999). Having problems in one stage may lead to inefficiencies in the subsequent stages of the process and therefore affect production. Among the mentioned steps, loading efficiency has a critical role in increasing production and reducing costs as the loading equipment is the source of ore supply (Hustrulid, 1999) or waste removal. For example, according to Scott and McKee (1994), one million dollars can be saved in a surface coal mine with a 1% improvement in digging productivity of a dragline. To achieve efficient loading and subsequently hauling and crushing, efficient blasting is required.

Although blasting is one of the lowest cost items in an open pit mine, it has a critical role in the mining cycle. The cost of drilling and blasting is about 15% of the mining cost (crushing, grinding and processing costs have not been included) compared to the costs of loading and hauling which are up to 60% (Allen et al., 1999). Issues in blasting can add extra cost to a mining operation through wasted explosives, dilution, waste of energy in downstream, need for secondary blasting, damage to equipment, inefficient loading and hauling and inefficient processing (Babaei Khorzoughi, 2013). A poor blast design based on using the wrong type and amount of explosive or improper placement in a blast hole combined with inefficient timing design can lead to poor results and thus significantly reduce the overall productivity of an operation. Therefore, the goal of effective blasting is to achieve a good fragmentation and an acceptable amount of material movement which are shown to be related to diggability (Chung...
and Preece, 1999). The combined impact of such outcomes is more efficient loading as well as lower dilution of the ore and waste products to potentially result in higher productivity and lower cost per tonne (Babaei Khorzoughi, 2013).

To optimise blasting outcomes, it is needed to have quantitative feedback on the outcomes of current blasting practice. Fragmentation analysis, loading equipment performance studies, boulders counting, secondary blasting frequency and crushing performance studies are examples of methods that have been used to assess muck-pile diggability and quality of blast (Brunton et al., 2003; Hendricks, 1990; Jimeno et al., 1995; Koski and Giltner, 2009). However, these methods are mostly impractical due to production loss, high cost, high error\(^1\), subjective results and safety issues (Jimeno et al., 1995). Therefore, many mining operations suffer from the lack of an acceptable and reliable post-blast assessment method to optimise their blasting process. It is believed that a properly measured diggability index as a measure of resistance of materials to being excavated can be used as a robust tool for post-blast evaluation. Additionally, a robust diggability index has to be less prone to measurement errors compared to other methods such as fragmentation measurements in order to be effective. It should be noted that based on the definition of diggability in this research higher values of diggability indicate harder digging conditions.

To enhance the understanding of shovel performance and develop a robust method for assessing diggability, this research focused on the performance monitoring of electric rope shovels in open pit operations. It is believed that this will lead to an approach to use electric rope shovels as a diagnostic tool to assess diggability and therefore blast quality. To achieve this, field studies were conducted at Teck Coal Limited Elkview Operations, British Columbia, Canada.

\(^1\) The error associated with some of mentioned methods such as fragmentation measurement using image analysis has been quantified in the literature (Sanchidrián et al., 2009).
Deployment of a diggability assessment technique is seen as significant to mining operations such as the Elkview mine which spends millions of dollars in blasting annually and does not have any rigorous post-blast evaluation procedure (Elkview Operations, 2014).

1.2. Research Objectives

Electric mining shovels are primarily used as loading equipment in large open pit mining operations around the world. The main hypothesis of this research was that the electric rope shovel can be used as a diagnostic tool to continuously and accurately assess muck-pile digging conditions and so blast quality. As a result, a diggability index was defined based on two independent approaches (electrical and mechanical) to relate shovel digging effort to muck-pile digging conditions independent of the operator practice and machine type. In the past a number of digging studies have been conducted and a few indices have been developed for different purposes, but none of them were widely accepted to continuously and reliably measure diggability in open pit mining operations.

In support of the aforementioned research hypothesis the following objectives were pursued:

- Undertake a thorough literature review of past diggability and shovel performance studies
- Develop a method to isolate the digging part of each loading cycle
- Build upon past studies to understand the effect of shovel operators on machine performance and to normalize diggability for operator practice
- Determine different key shovel performance indicators and study the influence of operators and digging conditions on them
- Study vibrations experienced by the shovel boom and understand the relationship between vibrations and digging conditions
• Build upon past studies to define a robust diggability index which can reflect muck-pile digging conditions and can be easily measured
• Develop a diggability algorithm that uses data from factory on board shovel sensors and from aftermarket specialized sensors – Electrical & Mechanical – to estimate the proposed diggability index per pass on a real-time or near real-time basis
• Establish an approach for visualizing and communicating diggability values collected from shovels

The approach adopted for this research is field based using a coal mine open pit operation which will be introduced next.

1.3. The Case Study: Elkview Steelmaking Coal Mine

1.3.1. Elkview Operations

Elkview steelmaking coal operation (EVO) is located in 3 kilometers east of Sparwood in south-east British Columbia, Canada (Figure 1.1). The Elkview property includes 20+ mineable coal seams which range in rank from high to low volatile bituminous. These seams vary from less than one to greater than fifteen meters thick. The current annual production capacity of the mine is about 6.7 million tonnes of hard coking coal (Elkview Operations, 2016).
At the Elkview mine, waste rock and coal are mined through conventional drill and blast and truck and shovel/loader techniques. Figure 1.2 presents the mining cycle: 1) drilling and blasting, 2) waste rock removal, 3) cleaning of coal seams with dozers and backhoes, and 4) loading of coal. The coal is hauled via haul trucks to the breaker area where it is loaded onto an overland conveyor belt that transport the raw coal to the process plant. The waste material is also hauled to the waste dumps (Elkview Operations, 2010). EVO’s current fleet of shovels consists of 6 P&H electric rope shovels. Also, the current truck fleet consists of 41 Komatsu 930Es and 11 Komatsu 830Es (Elkview Operations, 2015).
The field trials of the research were mainly conducted in the Natal pit-Phase 2 (N2). The geological cross sections of N2 is shown in Figures 1.3. This figure locates coal seams, faults, re-handling and waste materials.
1.3.2. Shovel Operation

The fleet of shovels at EVO consists of P&H electric rope shovels. For an electric rope shovel a normal and productive cycle includes: digging, swinging, waiting (usually for the first pass), dumping and returning back to the face. In terms of diggability assessment, digging is the most important part as the dipper is directly engaged in the bank. The digging component is a combination of hoist and crowd actions. Figure 1.4 shows different shovel motions.

![Shovel Motion Diagram](image_url)

Figure 1.4. Different shovel activities

The shovel’s functions are mainly accomplished by on-board hoist, crowd and swing motors. The objective of the hoist motor is to fill the dipper to its nominal capacity in an optimum (minimum) time while the crowd system is responsible to provide a thrust on the dipper for optimum penetration of the dipper into the bank. According to Jessett (2001), the crowd system provides a force normal to the digging trajectory. The shovel swing motion is also accomplished
by two/three swing motors. The swing of dipper from face to dump position and then from haul truck to face usually accounts for the largest portion of the loading cycle time. An efficient swinging practice may significantly reduce cycle time and therefore increase productivity.

The shovel operator controls all work motions of the shovel using two joystick controllers attached to the operator’s seat. The left hand joystick affords crowd/retraction motion and the signal horn when the shovel is in the crowd mode. The right hand joystick affords hoist and swing motions and the dipper trip. The control unit responds to operator’s commands through joysticks movements and then motors adjust volts and amps as desired by the operator (P&H Mining, 2006). Figure 1.5 shows operator’s station as well as joysticks.

![Operator’s Station-Joysticks](image)

Figure 1.5. Operator’s Station-Joysticks (modified from P&H operator Manual, 2015)
1.4. Thesis Outline

The state of the art on diggability and performance monitoring of shovels is presented in Chapter 2. It focuses on the review of loading equipment based diggability assessment methods. These methods are classified into the three groups: shovel instrumentation, loading equipment performance monitoring and numerical and dynamic modeling.

The methodology adapted for instrumenting shovels, collecting data, analysis and developing the algorithms for diggability assessment is presented in Chapter 3. Dig time isolation, digging trajectory definition, vibration analysis theory and diggability index calculations are given in this chapter. Also, several key shovel performance indicators are being defined and a clustering analysis is introduced for data analysis purposes.

In Chapter 4, the effect of operators on shovel performance is investigated. The results of productivity analysis and clustering analysis are given. A classification for shovel operators digging performance is also presented.

In Chapter 5, the effect of digging conditions on shovel performance is presented. In particular the relationship between digging conditions and vibrations, sensors data, dig force and electrical power is investigated.

In Chapter 6, dig cycle isolation algorithms as well as the developed diggability index are evaluated. Four case studies are used to validate the diggability index. The current practice at Elkview mine to visualize and communicate diggability data as well as a classification for diggability are given in this chapter.

Finally, Chapter 7 contains a brief summary of the research outcomes and contributions, and future research and development possibilities.
1.5. A Note Concerning the Unit of Measurements

Metric units of measurement are used throughout the thesis. However, some sensors used have been programmed in a way to have Imperial units of measurement. Additionally, some key shovel performance indicators measured by the commercially available payload monitoring system on-board the shovels have different units of measurement such as “tons” for “payload” and “tons×deg” for energy. The units are clearly stated for each parameter throughout the thesis.
2. Literature Review

Over the past 40 years, a number of digging studies have been conducted and several diggability indices have been developed (Hendricks, 1990; Mol et al., 1987; Patnayak and Tannant, 2005; Williamson et al., 1983). Early investigations on diggability were related to intact rock or in-situ rock mass characterization mainly for equipment selection purposes (Franklin et al., 1971; Hadjigeorgiou and Poulin, 1998; Kirsten, 1982; Scoble and Muftuoglu, 1984). However, since the early 80s with the availability of microprocessor technology and instrumentation of mining shovels, researchers have tried to introduce diggability as an index which could be related to the loading equipment performance as it interacts with the muck-pile (Hendricks et al., 1990; Karpuz et al., 1992; Patnayak, 2006). In addition, a few attempts have been made in the past decade to study loading equipment digging effort and behaviour through analytical and numerical modeling (Awuah-Offei and Frimpong, 2007; Chung and Katasabanis, 2008; Stavropoulou, 2013).

Shovel performance monitoring has been used in the past as a tool to assess diggability based on key shovel performance indicators (KPIs). Cycle and dig time measurements (Allen, 1999; Brandt and Evans, 1998; Brunton et al., 2003; Doktan, 2001; Onederra et al., 2004), dipper fill factor and number of bucket passes (Brandt and Evans, 1998; Brunton et al., 2003; Segarra et al., 2010), dipper payload and power/energy consumption during digging (Hendricks, 1990; Karpuz et al., 2001; Patnayak, 2006) are examples of parameters that have been measured in the past to monitor shovel performance.

As mentioned in Section 1.2 the goal of this research is to use electric rope shovels as a tool for diggability assessment. Therefore, this review mainly focuses on diggability evaluation for
electric shovel operations. Also, a short review of rock mass diggability classifications is presented in Appendix I.

2.1. Loading Equipment Performance Studies

The performance of mining equipment such as electrical cable shovels may vary with the diggability characteristics of the muck-pile, operator practice and machine type. Using loading equipment performance for assessing muck-pile conditions is based on the assumption that the digging rate (productivity) is inversely proportional to the muck-pile coarseness and is directly proportional to the looseness (Jimeno et al., 1995). Previous research attempts have shown that loading equipment productivity declines as average particle size distribution increases (Osanloo and Hekmat, 2005; Singh and Narendrula, 2007). However, in addition to muck-pile conditions, operator proficiency and skills play a significant role in productivity of loading equipment (Hendricks, 1990; Jessett, 2001; Onederra et al., 2004; Patnayak et al., 2008; Awuah – Offei and Summers, 2010; Vukotic, 2013; Abdi Oskouei and Awuah-Offei, 2014; 2015); therefore, it is important to understand this parameter to isolate the effect of variation in muck-pile digging conditions on the shovel digging behaviour and effort.

Past studies presented in the literature are mainly grouped into three categories: shovel instrumentation, productivity monitoring and numerical and dynamic modeling. Research in these three areas is presented next.

2.1.1. Diggability Assessment through Shovel Instrumentation

In the past studies, crowd, hoist and swing motor responses have been used to assess diggability of blasted and in-situ materials through shovel instrumentation. Williamson et al. (1983) conducted the first performance monitoring study to assess blast efficiency in an iron ore mine in
Australia by monitoring of DC motors in a P&H 1900 and a P&H 2100 electric shovel. Crowd armature voltage and current, swing armature voltage, hoist brake relay, crowd propel transfer relay and dipper trip were recorded during the shovel operation. Williamson et al. (1983) used the crowd motor voltage signal to derive a diggability index which was the ratio of change in the voltage and the area under the signal trace. This diggability index is given by:

\[
Diggability \ Index = \frac{\sum |\delta V|}{\int_{t_1}^{t_2} V \, dt}
\]  

(2.1)

where \(V\) is voltage, \(t_1\) and \(t_2\) are start and end of the digging respectively and \(\delta V\) is change in voltage values. The estimated diggability index values were found to vary from 1 to 10 with higher values representing harder digging conditions.

In this study the swing voltage signal was used to determine different activities and to isolate the dig cycle. Swing voltage was assumed to be static over the digging cycle. Figure 2.1 illustrates an example of their analysis including the crowd and swing motors responses for easy and hard digging conditions.
Figure 2.1. Monitored signals for easy and difficult digging conditions (modified from Williamson et al. 1983)

As Figure 2.1 demonstrates, crowd voltages as well as current become more ragged in harder digging conditions. In spite of the fact that Williamson et al. (1983) used crowd voltage to assess diggability, they concluded that crowd power does not correlate well with actual digging conditions.

Mol et al. (1987) reported performance monitoring of P&H2300 electric shovels used for blasted overburden removal at an open cut coal mine in Australia. They measured crowd armature voltage and current, swing armature voltage, hoist armature voltage and current, dipper trip and crowd/propel relays. Similar to Williamson et al. (1983), in this study the swing motor was used to determine dig cycle, and crowd motor responses (volts and amps) were used to assess material diggability. Finally, a combination of crowd voltage, crowd current and dig time was used to derive a diggability metric. For different dig time intervals different definitions were proposed to
estimate the diggability index. Estimated values were found to vary from 0 to 10. Table 2.1 presents diggability classification based on the proposed diggability index.

<table>
<thead>
<tr>
<th>Index Value</th>
<th>Digging Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;1.0</td>
<td>Extremely easy</td>
</tr>
<tr>
<td>1.0-2.0</td>
<td>Very easy</td>
</tr>
<tr>
<td>2.0-4.0</td>
<td>Easy</td>
</tr>
<tr>
<td>4.0-6.0</td>
<td>Normal</td>
</tr>
<tr>
<td>6.0-8.0</td>
<td>Difficult</td>
</tr>
<tr>
<td>8.0-9.0</td>
<td>Very Difficult</td>
</tr>
<tr>
<td>&gt;9.0</td>
<td>Extremely Difficult</td>
</tr>
</tbody>
</table>

In the study performed by Hendricks (1990), a P&H 2800XP shovel was monitored while loading blasted material in a coal mine in Canada. He used crowd armature voltage and current, hoist rope position and crowd arm extension signals to identify different shovel activities (digging, swinging and dumping). In contrast to Williamson et al. (1983) and Mol et al. (1987), he showed that swing voltage was not useful to determine dig cycle, and concluded that crowd motor responses were not sensitive to different digging conditions (from easy to very difficult). He stated that digging action primarily is accomplished by hoist motors, and that the crowd motor only assists to maintain a suitable depth of dipper penetration into the bank.

A post blast analysis was performed to quantify muck-pile conditions by using photographic methods. Moreover, shovel activities were identified through video tape records. To isolate the dig cycle from other activities, Hendricks (1990) used hoist rope position and crowd arm
extension as well as hoist field current. The proposed algorithm was based on some if-then rules. Hendricks identified the beginning of digging when the hoist rope extension and crowd arm retraction are at a maximum and he identified end of digging when the crowd arm extension is at a maximum. However, Jessett (2001) in part of his study showed that this is a rigid procedure which may result in erroneous conclusions since in normal digging operation operators may follow different tactics.

Hendricks (1990) showed that crowd motor responses are not strongly related to digging conditions and he used hoist voltage and current signals to estimate muck-pile diggability. The established diggability index by Hendricks (1990) is given by:

\[
DI = \frac{\sum_{i=1}^{n} |HV_{i+1} - HV_i|}{\sum_{i=1}^{n} |SR \times HV_i|} \times \frac{\sum_{i=1}^{n} |HI_{i+1} - HI_i|}{\sum_{i=1}^{n} |SR \times HI_i|}
\]  

(2.2)

where:

- \( n \) = number of readings taken during the dig cycle
- \( DI \) = Diggability Index
- \( HV \) = hoist armature voltage
- \( HI \) = hoist armature current
- \( SR \) = sampling rate

Equation 2.2 was used to determine the raggedness in hoist armature voltage and current signals. It was shown that in difficult digging conditions the DI is high while in easy digging conditions it is low. Table 2.2 shows the diggability classification proposed by Hendricks (1990) based on the DI values.
Table 2.2. DI classification (after Hendricks, 1990)

<table>
<thead>
<tr>
<th>Digging Condition</th>
<th>DI range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy Digging</td>
<td>0.4-0.8</td>
</tr>
<tr>
<td>Average Digging</td>
<td>0.8-1.2</td>
</tr>
<tr>
<td>Difficult Digging</td>
<td>1.2-1.6</td>
</tr>
</tbody>
</table>

It was also indicated that using average current and voltage values could be misleading. In difficult digging conditions, the hoist current average would be low compared to an easy digging condition because of high raggedness of the signal. Figure 2.2 compares examples of hoist current and voltage signals for easy and hard digging conditions. Hendricks (1990) concluded that using the average value for calculating power consumption gives a lower value for difficult digging conditions which is not expected. Additionally, he considered the influence of digging trajectory on diggability assessment. It was shown that the digging trajectory represented by a cut ratio (a ratio of crowd to hoist motion during the digging) has a significant influence on the motors responses and so DI values. But due to the presence of complicating factors such as variation in muck-pile characteristics through its height, the accurate distance between shovel and muck-pile and variations in muck-pile profile during different cycles, he was unable to normalize diggability index on the basis of digging trajectory or operating practice.
Hunter et al. (1990) developed a cost reporting system to optimize blast and therefore to achieve minimum mining cost. By closely monitoring each blast and subsequent operations, it is possible to measure the effect of blasting on cost. Production variables, current operation costs and survey data were collected in this study. An image analysis system was also used to measure size distribution of dumps in the passing haul truck box, and a shovel monitoring system was employed to assess diggability. Finally, maintenance and reliability information was collected to estimate maintenance cost under different digging conditions.

In this study, a prototype monitoring system was used to monitor a P&H2100 shovel for diggability assessment. The system included a set of rotary transducers and a central computer along with an operator console. The operator manually recorded the end of loading a haul truck and downtimes. A tilt sensor was mounted on the boom to record boom jacking and vibrations. Thus, crowd current and voltage, vertical and horizontal tilt signals and crowd, hoist and swing
positions were recorded at 0.1 second intervals. An example of data collected over a 200 second period is illustrated by Figure 2.3.

Figure 2.3. Shovel monitoring data, (after Hunter et al. 1990)

Load time per truck, time per dig cycle, waiting time for truck, downtime, diggability index, boom vibration index and swing angle are examples of estimated indices from this study. Diggability index was based on the Williamson et al. (1983)’s diggability index and boom vibration index was based on the longitudinal tilt signal and was defined as the number of peaks above a given threshold during loading of one haul truck. Hunter et al. (1990) concluded that tilt signals are the direct measure of loading severity on the boom’s mechanical structure and could be related to digging conditions and operator characteristics. In the proposed vibration index, mechanisms of excitation, operator proficiency and variations in muck-pile digging conditions were not considered which might cause various inaccuracies. In addition to shovel monitoring data and fragmentation analysis, maintenance operation data and costs were collected. It was
shown that failure of a shovel’s major components such as boom, dipper handle and crowd gear box is directly affected by digging conditions. Finally, based on the collected data, the mining cost imposed by blasting results was calculated which included primary and secondary drilling and blasting cost, loading cost, hauling cost and crushing costs. It was concluded that the proposed system could be used to optimize blasting based on the estimated mining cost.

Karpuz et al. (1992) presented performance monitoring of the P&H 2100BL electric shovels in Turkey surface coal mines. They compared cycle time, dig time, dipper fill factor and power on the main drive A.C. motor for four rock types with and without blasting under different depth of cut classifications. As a result, the influence of depth of cut and blasting on shovel performance was revealed. In this study, the average power of digging, energy consumption of digging and specific digging energy values were calculated to detect relative changes in the diggability of rock units and to examine effect of depth of cut. It was shown that large depth of cuts will result in higher power consumption. Karpuz et al. (1992) concluded that based on their results from different dig cycles, the specific digging energy which depends on power consumption, digging time and amount of excavated material was the best indicator which could reflect influence of depth of cut as well as ground characteristics. To measure power, a system was developed comprising mainly of a wattmeter and a data logger.

Similarly, in another paper, Karpuz et al. (2001) presented a quantitative determination of depth of cut and its relationship with performance parameters by monitoring dipper motion over digging activities. Depth of cut is one of the operational parameters which significantly affects parameters such as dig time, fill factor and dig energy that could be used in the diggability studies. Depth of cut was defined as the shortest distance between the initial face profile and the
digging trajectory. An example of the typical motion trajectory of the dipper in the x-y space during the digging is illustrated by Figure 2.4.

![Diagram of dipper motion trajectory](image)

**Figure 2.4. Example of digging trajectory and depth of cut (modified from Karpuz et al., 2001)**

They concluded that a low depth of cut value may result in a dipper which is not full at the end of the dig cycle. This would increase the dig time significantly. Alternatively, a high value of depth of cut may cause higher consumption of energy to fill the dipper.

In this study the dipper position was determined by using crowd angle and length. These parameters were measured using electrical transducers. Similar to the other research, in addition to performance parameters, a video tape of shovel activities was recorded at the same time. Also, before initiating the monitoring, excavation face properties were recorded including rock type, fracturing, weathering, and blast parameters such as blasting quality, block dimensions and swell factor. The post-blast quality was assessed by employing image analysis techniques. Consequently, based on the several monitored dig cycle data, they concluded that energy consumption while digging per unit of time (time normalized digging energy) is strongly correlated with depth of cut as illustrated in Figure 2.5. Additionally, based on the results of
different tests it was concluded that normalized digging energy is also strongly correlated with rock digging characteristics.

Figure 2.5. Time normalized digging energy against average depth of cut (Karpuz et al., 2001)

Kumar et al. (2000) reported performance monitoring of electric mining shovels using microprocessor technology in surface coal mines. The hoist and crowd motor responses were recorded under two different digging conditions—soft and hard—for up to four digging cycles. They concluded that hoist motor voltage and current are more sensitive to digging characteristics of muck-pile than crowd motor responses. Similar to Hendricks (1990) and contrary to Williamson et al. (1983) and Mol et al. (1987), they introduced the hoist current signal as representative of the actual work done during digging. Also, they noted that besides crowd and hoist motor responses, shovel performance is a function of dipper position from the toe in the bank and muck-pile characteristics. In addition to this, they also studied the harmonic spectrum of voltages and concluded that an increase in the difficulty of digging resulted in a rise in the harmonic voltages.

Jessett (2001), in his thesis presented a tool for performance monitoring of electric rope shovels. The data was collected from a P&H 5700 shovel operating in the Hunter Valley, NSW,
Australia. The data were recorded at the rate of 100Hz and included the stress state of the boom and boom suspension rope, boom dynamics, the main operator commands and analogue electrical signal from the shovel’s primary drive systems. To record the stress state and boom dynamics, he used eight accelerometers mounted to the boom as well as sixteen strain gauges fitted to the boom and boom support ropes. Statistically comparing measured data for different operators, Jessett (2001) concluded that operator style affects shovel productivity. However, the variation in muck-pile digging conditions was not considered in comparing different operators’ performance.

As part of this research, a framework was developed to monitor different shovel activities based on the electrical signals of the drive systems. To develop this framework, first, using a self-organizing algorithm, it was shown that a structure exists in the sampled data from a shovel’s electric drives, and data makes different clusters for different shovel activities. Then, employing Fisher’s linear discriminant functions in a hypothesis testing strategy, an algorithm was presented and tested to track different shovel activities (digging, swinging, dumping, returning to dig and waiting for haul truck) and to detect events that result in significant duty loading. These events include: Swing-During-Dig, Hoist Stall and Jacked Boom. It was shown that on average, 30% of loading cycles include swing during digging. Figure 2.6 shows an example of a linear discriminant set’s output for one loading cycle of the shovel. Jessett (2001) concluded that using this approach, shovel activities could be monitored with an accuracy of about 90%.
Similar to Jessett (2001), Joseph and Hansen (2002) introduced an algorithm to isolate different shovel activities. They recorded hoist motor current and voltage, swing motor current and voltage and dipper trip current and voltage. Then to isolate different shovel activities over a loading pass, variation in the hoist power consumption was used. These activities include dipper trip, dipper rebound, swinging to face, positioning the dipper, preparing to dig, digging in face and hoist drum braking.

Most of the studies presented so far were based on the digging of broken rocks. Patnayak (2006) monitored the performance of P&H4100 series shovels in an oil sand operation. He used a set of recorded data including date and time, hoist armature voltage and current, hoist field current, crowd armature voltage and current, crowd field current, and swing voltage and current for eight different shovels including two models: TS and BOSS. The data sampling rate was 1Hz.
cycle time, digging energy and digging power were used as the key shovel performance indicators. As addressed by several researchers, digging trajectory has an important role in assessing material diggability (Hendricks, 1990; Karpuz et al., 2001). Patnayak (2006) showed that average hoist power (Equation 2.3) is less sensitive to digging trajectory and could be a useful metric to assess muck-pile diggability though he did not have any data to quantify variations in digging trajectory. Table 2.3 compares the variability between different performance indicators. The coefficient of variation values confirm that hoist power has the lowest variability.

\[
\text{Average Hoist Power} = \frac{\sum_{i=1}^{n} \text{Hoist Energy for Individual Dig Cycle}}{\sum_{i=1}^{n} \text{Dig Time for Individual Dig Cycle}}
\]  

(2.3)

where \( n \) is the number of dig cycles. Hoist power energy for individual dig cycle is also given by:

\[
\text{Hoist Power} = \frac{0.5 \sum_{i=1}^{n} |HV_{i+1} \times HI_{i+1} + HV_{i} \times HI_{i}|}{\text{Dig Time}}
\]  

(2.4)

where:

\( HV \) = hoist armature voltage

\( HI \) = hoist armature current
Table 2.3. Variability analysis of different performance indicators for 440 cycles of one shift  
(after Patnayak and Tannant, 2005)

<table>
<thead>
<tr>
<th></th>
<th>Dig Cycle</th>
<th>Hoist Energy</th>
<th>Hoist Power</th>
<th>Crowd Energy</th>
<th>Crowd Power</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time (s)</td>
<td>(KJ)</td>
<td>(KW)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum</td>
<td>6</td>
<td>70</td>
<td>12</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>24</td>
<td>28210</td>
<td>1450</td>
<td>8500</td>
<td>657</td>
</tr>
<tr>
<td>Range</td>
<td>18</td>
<td>28141</td>
<td>1438</td>
<td>8500</td>
<td>657</td>
</tr>
<tr>
<td>Mean</td>
<td>12</td>
<td>11599</td>
<td>963</td>
<td>2928</td>
<td>246</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>4</td>
<td>5011</td>
<td>262</td>
<td>2044</td>
<td>168</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>36</td>
<td>43</td>
<td>27</td>
<td>70</td>
<td>68</td>
</tr>
</tbody>
</table>

He also monitored key shovel performance indicators over different digging conditions to find the relationship between his KPIs and material diggability. For example, he postulated that digging time in similar operating conditions (trajectory and operator) could be used as a diggability metric. In the difficult digging conditions the digging time would be expected to be longer than easy digging conditions. However, it was shown that dig time between individual dig cycles in the same operating condition could vary due to the different digging height, depth of dipper penetration into the bank and digging trajectory. Therefore, he concluded that dig time is not a good indicator alone to assess diggability.

During this study, besides performance data, digital video recordings of different operating shovels were taken to identify different activities (especially dig cycle). By comparing these
video records with performance data, it was concluded that in contrast to previous research, swing voltage is less sensitive to different shovel activities. Finally, Patnayak (2006) used hoist and crowd motor responses to isolate the dig cycle based on several if-then rules. However, the developed algorithm to isolate dig cycle was site specific.

2.1.2. Shovel Performance Study

In addition to the diggability studies through shovel instrumentation, some attempts have been made to relate shovel productivity to muck-pile digging conditions. As a result, some indicators such as dipper fill factor, dig time, cycle time, mucking rate and payload were evaluated in the past. Hawkes et al. (1995) presented a review of available methods of monitoring of equipment productivity operating in mines. According to Hawkes et al. (1995), the complete assessment of mining process of a surface coal mine involves determination of KPIs in the process, a methodology for recording and assessing the data and determination of suitable measurements.

In this study, methods for shovel monitoring were also discussed. Based on the work published by Williamson et al. (1983) and Kennedy (1995), Hawkes et al. (1995) named the principal requirement of shovel monitoring system: “minimal rock handling, minimal interruption to production, accuracy and reproducibility of results, relatively low cost, suitability for routine use, real time data output, minimal subjective input, data quality to reflect true shovel performance and resulting size parameters which can be related to a blast design model’’ [Hawkes et al., (1995), p.129].

As a case study, they conducted a manual time and motion study for a truck/shovel operation in a coal mine in Australia. They aimed to find the relationship between powder factor and size of blast and shovel productivity; however, the quality of collected data was poor. Therefore, no
correlation was evident. They concluded that shovel monitoring should be controlled and well understood to draw precise conclusion on the success of any blast practices.

A document published by P&H MinePro Services (2003) defines the diggability as the ease of excavation in the working face which is a function of material hardness, weight, density, grain size, moisture content, fragmentation and several other factors. In this document fill factor was reported as a diggability metric which shows how easily materials flow into the dipper. Fill factor is defined as:

\[
\text{Fill Factor} = \frac{\text{Loose Volume per Load}}{\text{Dipper Rated Volume}}
\]

(2.5)

It is important to consider that fill factor could vary by different dipper designs and machine conditions as well as operator practice and skills. A shovel with a custom designed dipper operating in well-fragmented and loosened enough materials can achieve fill factors of 100 to 120% and more (MinePro Services, 2003). Table 2.4 shows the material diggability classification based on the dipper fill factor for electric rope and hydraulic shovels presented by P&H MinePro Services (2003).

Table 2.4. Diggability classification based on fill factor (after P&H MinePro Services, 2003)

<table>
<thead>
<tr>
<th>Material Diggability</th>
<th>Approximate Dipper Fill Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Electric Rope Shovel</td>
</tr>
<tr>
<td>Easy Digging</td>
<td>1.05-1.20</td>
</tr>
<tr>
<td>Medium Digging</td>
<td>1.00-1.15</td>
</tr>
<tr>
<td>Hard Digging</td>
<td>0.90-1.00</td>
</tr>
<tr>
<td>Very Hard Digging</td>
<td>0.85-0.95</td>
</tr>
</tbody>
</table>
Onederra et al. (2004) presented outcomes of a comprehensive study called Shot to Shovel. In this study the influences of muck-pile characteristics and operator skills on shovel productivity was investigated using a Drill and Blast Information Management system, High Precision GPS and the Modular Mining Inc.’s Dispatch System. Although the data was collected from a hydraulic shovel, because of its importance this study is included here.

During the course of the project a set of performance data was collected including number of bucket passes, dig, swing, dump and return time. The results showed a high degree of variability in all of the loading cycle components, especially dig time. They believed this can be explained by variation in muck-pile characteristics and different digging tactics. To examine the impact of muck-pile characteristics on shovel performance, they monitored fragmentation, muck-pile shape, swell and looseness. They chose these parameters because of their ease of measurement and their reported impacts on loading equipment productivity. To assess fragmentation, Onederra et al. (2004) employed Split Desktop image processing system and the photographs were taken of the truck box when it was full.

Using HPGPS, the Modular Mining Inc.’s dispatch system and GIS based software, the profile of the muck-pile was generated. It was shown that muck-pile shape has a direct impact on the diggability. In the lower (flatter) regions of the muck-pile, dig rate was below average. Also, it was observed that dig rate decreases in the corner regions of muck-piles. They stated that this occurred due to loading geometry limitations and/or decreases in material looseness as the burden relief decreases.

Similarly, Clark et al. (2004) investigated the effect of muck-pile characteristics on the
performance of electric rope shovel by using scale model technology to emulate actual field conditions in the laboratory. The modeled machine type in this study was P&H4100XPB and muck-pile independent variables were size distribution, compaction, height and cohesion, but in the presented paper only muck-piles with high oversize size distribution were tested which could affect the results. A dig algorithm was also used to simulate operator performance. Measured dig response included dig energy, dig time and dipper payload. They modeled oversize piles with three compaction degree (loose, compact and very tight) made up of two pile height\(^2\) (37.5ft and 50ft) compared against two cohesions (high cohesion with clay fines and low cohesion with sandy dirt fines). They concluded that muck-pile height does not have any significant effect on shovel productivity. High cohesion material increased the dig time, increased energy consumption and increased the payload. However, compaction was inversely proportional to payload. Figure 2.7 shows a reproduction of their results.

\(^2\) A scale of “1 mm: 1 inch” was used to model piles.
To further investigate the relationship between muck-pile characteristics and loading equipment performance, Segarra et al. (2007) investigated the effects of blasting parameters on loading equipment efficiency. They used mucking rate (amount of rock excavated per unit of time) and mean bucket load (bucket load per pass) as key excavator efficiency indicators for rope shovels and front-end-loaders. During the course of this project, rock characteristics, blasting parameters (drill pattern, explosive energy and charging) and loading equipment performance (truck loading time and number of buckets to fill a truck) were measured in an open pit iron mine. To characterise rock properties, point load test and rock density measurements were carried out for different samples from different benches.

They introduced excavator (rope shovel and front-end-loader) efficiency as a measure of muck-pile diggability which is a function of rock movement and fragmentation. Although there are
several factors such as muck-pile profile, operator proficiency and machine type that may affect the relationship between blasting performance and loading equipment’s productivity, in this study similar to most of the published work only the effect of blast parameters were investigated. Blasthole length, burden at the crest of the block, spacing, stemming, sub-drilling length, mass of explosive, charge length and energy of explosive were recorded during this project.

They concluded that there is no strong correlation between mean bucket load and blasting parameters, whereas there is a positive correlation between mucking rate and explosive energy. Also, it was shown that there is no significant correlation with rock characteristics. Segarra et al. (2007) suggested that mucking rate is a non-monotonic function of the useful work of the explosive per unit volume of rock (specific energy, J/m$^3$).

Based on the results of this work, Segarra et al. (2010) presented a model for prediction of mucking productivity which was defined as bank cubic meters loaded into trucks per hour. This production rate was estimated from the product of maximum production rate and the efficiency of loading equipment. The efficiency of the loading equipment was defined as a function of rock strength, nominal bucket capacity and explosive energy concentration or energy powder factor.

Mechanical rock characteristics, blasting design parameters and loading equipment productivity data were collected from field measurements in 20 blasts at two open pit mines (Iron and Copper). Excavator productivity data includes excavator type (front-end-loader and rope shovel), nominal bucket payload, mass loaded into a truck, passes required to load the truck and truck loading time. All of these data were recorded manually. The gathered data in the field were used to obtain coefficients of the developed model. As a result, production rate was defined as:
\[ Q = Q^0 e^{-bf/B_p} \left[ \frac{\sigma^2}{(E - E^0)^2 + \sigma^2} \right] \]  

(2.6)

where:

- \( Q \) = Production Rate
- \( B_p \) = Nominal Payload of Excavator
- \( Q^0 \) = Maximum Production Rate\(^3\)
- \( \sigma \) = Scale Parameter
- \( k \) = Coefficient
- \( E \) = Energy Concentration (Energy Powder Factor)
- \( f_s \) = Rock Strength Factor
- \( E^0 \) = Energy Concentration at which the excavator’s efficiency is maximum

\( Q^0, k, \sigma \) and \( E^0 \) were determined from data using non-linear least square regression technique.

Rock strength factor was given by:

\[ f_s = 0.0015 \rho_r - 3 + 0.264 I_{s(50)} \]  

(2.7)

Where \( \rho_r \) is rock density (kg/m\(^3\)) and \( I_{s(50)} \) is point load strength. Segarra et al. (2010) concluded that this model explains up to 90% of the variance of the production rates and is statistically significant though it is a site dependent equation.

In an attempt to improve the model presented in Equation 2.6, Sanchidrian et al. (2011) suggested that \( Q^0 \) depends on the dipper capacity and proposed a new model given below:

\[ Q = c_i B^0_M \quad c_2 e^{-bf_s} e^{-\frac{(E - E^0)^2}{2\sigma^2}} \]  

(2.8)

where:

\(^3\) In the presented paper, \( Q^0 \) was calculated in a data-dependent manner while it could be related to factors such as machine type and conditions, dipper capacity and loading technique (single or double sided).
$B_M =$Dipper Payload \hspace{1cm} \sigma =$ Shape Parameter

c$_1$,c$_2$,k=Coefficient \hspace{1cm} E_E =$ Energy Concentration(Energy Powder Factor)

f$_s$=Rock Strength Factor$^4$ \hspace{1cm} E$_e$ =$ Energy Concentration at which the excavator's efficiency is maximum$

Compared to model presented in Equation 2.6, it was concluded that the modified model explains 92% of the variance of the production rate.

Similarly, Koski and Giltner (2007) and Giltner and Koski (2010) reported the outcomes of an audit performed on blasting operations at an iron mine. The main goal of this study was to improve productivity through digging conditions improvement and oversize reduction.

According to this, to assess diggability, seventeen measures of diggability such as photometric fragmentation analysis, digging rates, plugged mill chute frequency, secondary breakage, etc were identified. However, most of these measures were infeasible to use due to cost, inadequate records, safety issues and being too subjective. Hence, dig rate, crusher delay and incident reports were employed for electric shovels and front end loaders. Table 2.5 shows an example of their analysis which compares the cycle times to fill the shovel dipper for different digging conditions and different shovel models.

$^4$ In this work $f_s$ was given by:

\[ f_s = 0.025\rho_r - 50 + 4.4I_{s(50)} \]
Table 2.5. Cycle time for shovels (after Giltner and Koski, 2010)

| Loader Type                  |平均 (s) |正常 |硬质
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>P&amp;H2100电铲</td>
<td>38.7</td>
<td>55.9</td>
<td></td>
</tr>
<tr>
<td>标准偏差 (s)</td>
<td>10.8</td>
<td>17.0</td>
<td></td>
</tr>
<tr>
<td>P&amp;H2800电铲</td>
<td>35.8</td>
<td>46.2</td>
<td></td>
</tr>
<tr>
<td>标准偏差 (s)</td>
<td>8.3</td>
<td>11.5</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.5 shows that both cycle time average and standard deviation increases for each shovel type as the digging conditions become harder. Giltner and Koski (2010) concluded that in harder digging conditions not only does cycle time increase, but also the variability in the equipment operation. Additionally, this table provides information on how different machine types may affect the cycle time values in the same digging conditions.

In this study shovel operators were also interviewed. According to operators’ comments it was stated that the hardest digging conditions usually occur in the bottom of the muck-pile and it is easier around the areas correspond to the location of blastholes which agrees with the results of Onederra et al. (2004).

Finally, it was concluded that through improved digging conditions and reduced oversize fragments in the muck-pile, achieved by blast design changes, a lower cost and higher productivity could be achieved. Also, the crusher operation could be improved and therefore cost of re-handling material in the surge pile decreases.

All of the studies that have been presented so far are based on one dimensional analysis of shovel
performance data. However, Halatchev and Knights (2007) used geostatistical techniques to analyze the spatial variance of shovel digging performance in 2D space (bench width and height space). They used shovel payload, dig rate, payload frequency and shovel production as key shovel performance indicators captured by available monitoring systems aboard the shovel. The method used in this study to process the mentioned KPIs was ordinary kriging. Halatchev and Knights (2007) defined dig rate as the ratio of payload to the dig time, payload frequency as the number of payloads made within a cell of x and y (coordinates) locations which was used for meshing the data and implementing an interpolation approach, and shovel production as the amount of rock excavated by the shovel within a given time.

The case study undertaken used data from a P&H4100A shovel operating in a copper mine in North America. Using their proposed method, Halatchev and Knights (2007) produced contour maps of the shovel digging performance. They suggested that the contour maps can be used for assessing shovel operating context, operator proficiency and muck-pile characteristics.

2.1.3. Analytical and Dynamic Modeling of Electric Rope Shovels

All the studies that have been presented so far were either based on the shovel instrumentation or experimental and manual studies. Additionally, there are a few studies reported in the past decade based on analytical and numerical modeling of electric rope shovels. Awuah-Offei and Frimpong (2007) employed electric rope shovel kinematics and dynamics, formation resistance model and dynamic payload to model the excavation process. In this case, hoist and crowd forces depend on the shovel kinematics and formation resistance model depends on the muck-pile properties. They asserted that based on the previously conducted research “the resistance to digging by a shovel dipper can be described completely by six forces and that the cutting
resistance, the empty dipper weight and the payload are the most significant in mining applications’’ [Awuah-Offei and Frimpong, (2007), p.1000].

The case undertaken in this study was P&H 2100BL operating in typical surface mine overburden conditions. It was concluded that a lower dipper handle (crowd) speed and a higher hoist rope speed and therefore lower depth of cut gives better performance. Awuah-Offei and Frimpong (2007) introduced energy per unit loading rate, given by Equation 2.9, as a measure of diggability and shovel performance.

\[
\dot{E} = \frac{\text{Digging Energy (J)}}{\text{Payload (tons)}} \times \text{Digging Time (h)}
\] (2.9)

Similarly, Rasuli (2012) as part of his PhD studies created a dynamic model of a P&H2100-XP cable shovel which could simulate DC motors and various parameters such as inertia, friction and forces. Using the kinematic and simplified dynamic equations, a dynamic payload monitoring system was built. To accomplish this, swing, crowd and hoist motor currents were measured and then actuator torques and forces required by the cable shovel were estimated. In addition to payload, cutting forces and loading time could be estimated which are useful in diggability assessment.

Stavropoulou et al. (2013) modeled the excavation process using a kinematic model, dynamic payload and cutting resistance models. In addition, an analytical estimation of specific energy consumed in the process of excavation was presented.

They introduced dipper trajectory and its capacity, the depth of cut, hoist and crowd speeds, geomaterials physical and mechanical properties and the repose angle of the bank as main parameters affecting the digging performance and energy consumed by the cable shovel. To
calculate cutting forces, a theoretical model was considered. They also developed an analytical algorithm to estimate material weight in the dipper.

Finally, using the material weight algorithm and kinematic shovel model, crowd and hoist forces, the specific energy consumed by the crowd and hoist components were calculated. This specific energy was defined as the energy per unit volume of materials in the dipper which depends on the kinematics and material properties.

2.2. Effect of Operator

Shovel productivity and performance are strongly influenced by operator proficiency. A well-trained operator is essential to achieve maximum productivity (Vukotic, 2013). Especially, with the current cost pressure on the mining industry, it is important to have high productivity. The influence of operator practice and skill should be a significant factor in any diggability assessment study. Some research studies have reported the effect of operators on shovel performance.

Hendricks (1990) monitored the performance of four electric rope shovel operators. He concluded that operators adjust their digging tactic to compensate for variations in muck-pile digging conditions; however, each operator operates within a particular range of dipper trajectories.

Jesset (2001), as part of his research, established a framework that might help to set the best operator practice to improve shovel productivity and reduce loading duty. By statistically comparing measured data for different operators, Jessett (2001) concluded that operator’s style affects shovel productivity and duty loading.
In contrast to blasted muckpile digging, Patnayak et al. (2008) reported the influence of operating practice on the shovel performance in oil sand digging. For the purpose of this study, performance parameters, recorded from the shovel, were compared for four teams of operators. They believed that “the operating characteristics of each team of operators will overshadow the influence of material diggability at a given shovel location” [Patnayak et al, 2008, p. 133]. Comparing average shift hoist and crowd motor power during different shifts and for different teams, Patnayak et al. (2008) concluded that the consumed hoist power depends on the way that a team operates the shovel while the crowd power is independent of an operators’ team digging tactic. They also showed that the hoist energy per unit volume of payload can be a measure of the operators team performance. 

As reported by Hendricks (1990) and Patnayak et al. (2008), energy consumption and digging effort of shovels are significantly influenced by operating characteristics. Similarly, other attempts have been made in the past to address the effect of operator practice and skill on equipment energy consumption and its performance. Widzyk-Capehart and Lever (2004) similar to Jessett (2001) stated that operator style has a significant effect on shovel productivity. Similarly, Onederra et al. (2004), based on the result of their case study, showed that operator proficiency is critical in shovel performance which was indicated through production rate variability. Vukotic (2013) established a methodology to evaluate rope shovel operators and then to minimize energy consumption and maximize production rate. He developed a model to analyze operator’s performance in different parts of the shovel loading cycle based on the energy consumption and production rate. Bernold (2007) compared operator’s digging performance by analyzing digging forces through a backhoe simulator. He estimated operator’s performance on the basis of total energy per digging cycle, total path distance per digging cycle and bucket
average velocity. Komljenovic et al. (2010) developed a performance indicator for dragline operators. This indicator was defined as the ratio of dragline hourly production rate and hourly energy consumption. Awuah-Offei and Frimpong (2007) introduced hoist rope and crowd arm speeds as critical parameters in evaluating operator’s performance. In this study, a simulation of a rope shovel was conducted.

2.3. Summary

A literature review highlighted that some studies have been reported in the past to assess diggability. Table 2.6 summarizes the most relevant studies. As this table confirms, the results of most of past studies agree that a properly measured specific energy of digging could be an indicator of digging conditions, but other factors such as operator proficiency and skill as well as machine type and conditions should be taken into consideration.

Based on the literature crowd motor responses are less sensitive to different digging conditions and the dipper is mainly filled through the hoist action, and the crowd action only helps to maintain a proper dipper depth of penetration into the muck-pile. Therefore, a diggability index could be developed based on the hoist motor responses. All the past studies were focusing on the electrical power/energy calculations. Also, most past studies did not have access to accurate enough payload values per pass as well as robust algorithms for machine state identification.

In addition to energy based diggability indices, fill factor, digging rate, excavator efficiency and dig time have been used to assess digging conditions. But some of these indicators like fill factor and dig time could be misleading if they are being used alone. For example, in hard digging conditions, the operator may take shallower paths to fill the bucket, so the dig time could be reduced.
In addition to the aforementioned indices, few researchers have reported using vibrations for diggability assessment, despite the fact that most shovel operators classify digging conditions based on the amount of shaking (vibration) that they feel while filling the dipper.
Table 2.6. Diggability assessment studies

<table>
<thead>
<tr>
<th>Researcher(s)</th>
<th>Diggability Index/Indicator</th>
<th>Loader Type</th>
<th>Operation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Williamson et al. (1983)</td>
<td>( \text{Diggability Index} = \frac{\sum</td>
<td>\delta V</td>
<td>}{\int_{t_1}^{t_2} V , dt} )</td>
</tr>
<tr>
<td></td>
<td>Where ( V ) is crowd motor voltage and ( \delta V ) is change in voltage values.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mol et al. (1987)</td>
<td>( \text{Diggability Index} = f(\text{Crowd Current}, \text{Crowd Current}, \text{Dig time}) )</td>
<td>Electric Shovels (P&amp;H2300)</td>
<td>Open cut coal mine</td>
</tr>
<tr>
<td></td>
<td>( \text{Hoist DI} = \frac{\sum_{i=1}^{n}</td>
<td>HV_{i+1} - HV_i</td>
<td>}{\sum_{i=1}^{n}</td>
</tr>
<tr>
<td></td>
<td>Where: ( n ) = number of readings taken during the dig cycle</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \text{DI} = \text{Diggability Index} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \text{HV} = \text{hoist armature voltage} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \text{HI} = \text{hoist armature current} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \text{SR} = \text{sampling rate} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hendricks (1990)</td>
<td>Williamson et al. (1983)’s diggability index, Boom vibration index</td>
<td>Electric Shovel (P&amp;H 2800XP)</td>
<td>Coal mine</td>
</tr>
<tr>
<td>Hunter et al. (1990)</td>
<td>Williamson et al. (1983)’s diggability index, Boom vibration index</td>
<td>Electric Shovel (P&amp;H2100)</td>
<td>Uranium mine</td>
</tr>
<tr>
<td>Karpuz et al. (1992, 2001)</td>
<td>Specific Digging Energy</td>
<td>Electric Shovels (P&amp;H2100)</td>
<td>Coal mine</td>
</tr>
<tr>
<td>P&amp;H MinePro Services (2003)</td>
<td>( \text{Fill Factor} = \frac{\text{Loose Volume per Load}}{\text{Dipper Rated Volume}} )</td>
<td>Electric and Hydraulic Shovels</td>
<td>Open pit mines</td>
</tr>
<tr>
<td>Onederra et al. (2004)</td>
<td>Digging Rate</td>
<td>Hydraulic Shovels</td>
<td>Gold mine</td>
</tr>
<tr>
<td>Clark et al. (2004)</td>
<td>Dig energy, dig time and dipper payload</td>
<td>Electric Shove (Scaled model of P&amp;H4100XPB)</td>
<td>Laboratory</td>
</tr>
<tr>
<td>Researcher(s)</td>
<td>Diggability Index/Indicator</td>
<td>Loader Type</td>
<td>Operation</td>
</tr>
<tr>
<td>---------------</td>
<td>-----------------------------</td>
<td>-------------</td>
<td>-----------</td>
</tr>
<tr>
<td>Patnayak (2006)</td>
<td>Average Hoist Power</td>
<td>Electric Shovels</td>
<td>Oil sand</td>
</tr>
<tr>
<td></td>
<td>$\text{Hoist Power} = \frac{0.5 \sum_{i=1}^{n}</td>
<td>HV_{i+1} \times HI_{i+1} + HV_{i} \times HI_{i}</td>
<td>}{\text{Dig Time}}$</td>
</tr>
<tr>
<td></td>
<td>Where:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$HV_{i}$ = hoist armature voltage</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$HI_{i}$ = hoist armature current</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Segarra et al. (2007, 2010)</td>
<td>Excavator Efficiency</td>
<td>Front Loaders and Rope Shovels</td>
<td>Iron and Copper ore mines</td>
</tr>
<tr>
<td>Sanchidrian et al. (2011)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Koski and Giltner (2007)</td>
<td>Dig rate, average dig time, crusher delay and incident reports</td>
<td>Electric shovels</td>
<td>Iron ore mine</td>
</tr>
<tr>
<td>Giltner and Koski (2010)</td>
<td></td>
<td>(P&amp;H 2100 and 2800)</td>
<td></td>
</tr>
<tr>
<td>Halatchev and Knights (2007)</td>
<td>Shovel payload, dig rate and shovel production</td>
<td>Electric shovel</td>
<td>Copper ore mine</td>
</tr>
<tr>
<td>Awuah-Offei and Frimpong (2007)</td>
<td>Energy per unit loading rate</td>
<td>Electric shovel</td>
<td>Typical surface mine operation (simulation)</td>
</tr>
<tr>
<td>Stavropoulou et al. (2013)</td>
<td>Specific Energy (Energy per unit volume of materials in the dipper)</td>
<td>Medium sized cable shovel</td>
<td>Simulation</td>
</tr>
</tbody>
</table>
Many researchers have reported the effect of operator practice on diggability assessment and shovel performance. However, there is a lack of a diggability index for the purpose of post-blast evaluation which considers the effect of the operator on the determined index. To achieve this goal, shovel performance data (motors response, payload, dig time, dipper position, etc.) should be gathered and then analyzed for different operators under different digging conditions and different operating shifts (day and night) to establish an index which could reflect changes in muck-pile digging conditions independent of variations induced by operators. However, even a single operator could use varying approaches from cycle to cycle such as different digging height, depth of penetration and digging trajectory. To minimize the effect of equipment operating variability, a proposed index could be averaged over a number of cycles (eg. 50 cycles) as adopted by a few researchers in the past.

Researchers in the past mainly analyzed crowd and hoist motor responses to derive a diggability index, but there are other data such as joysticks reference signals which might be collected and analyzed. For example joystick reference signals provide information on how operators act during different shovel activities.

A successful diggability index should be easily understandable and provide repeatable and reliable results on the muck-pile digging conditions. This research will build upon past work by using energy analysis and considering the effect of operators to develop a universal methodology to determine a diggability index which incorporates muck-pile digging conditions, operator practice and machine type. Advances in data acquisition systems, analysis approaches and new monitoring technologies will enable the development of a more reliable method which can provide feedback on actual muck-pile conditions.
3. Methodology

As discussed in Chapters 1 and 2 the context of this research is based on the instrumentation and performance monitoring of electric rope shovels at Teck Coal Limited Elkview operations. The research consists of two phases: development (Phase I), and deployment, verification and validation (Phase II). The machine chosen for the development phase (Phase I) is a P&H4100XPB shovel, DC drives with a nominal dipper capacity of approximately 90 metric tonnes or approximately 48.4 cubic meters of material volume. The specifications of this machine and its terminology are presented in Appendix II.

The general methodology adopted in this research is shown in Figure 3.1. This methodology is described in following sections.
3.1. Machine Instrumentation

3.1.1. Vibration Sensor and USB Camera

In the phase I of this research, the vibrations experienced by the shovel’s boom during different loading cycles were measured using a tri-axial accelerometer mounted inside an enclosure on the side of the shovel’s boom. The accelerometer is manufactured by Spectrum Sensors and has a
vibration measurement range of ±15 g. Figure 3.2 shows a graphical illustration of the different axes of acceleration measured by the sensor. In this figure, A3 is in the direction of gravity.

![Image of sensor](image.png)

Figure 3.2. Sensor axes orientation

In order to introduce the vibration data acquisition system, Figure 3.3 shows the schematic of the accelerometer enclosure which connects to a smaller junction box also located on the side of the shovel boom. A water proof conduit encases the required cabling; the cabling traverses 30 meters of the shovel boom and ends in the shovel house where it is connected to a laptop mounted in a programmable logic control (PLC) cabinet. Finally, the laptop in the PLC cabinet is connected to a laptop in operator cab through a cross-over cable to be able to record the data while sitting in the operator cab.
Figure 3.3. Overview of vibration data acquisition system

Vibration data were measured at 1012 Hz in three directions (A1-axis, A2-axis, A3-axis). The selection of this sampling rate is to ensure aliasing is avoided which can be a possibility at lower sampling rates. Furthermore, the sensor has a built-in anti-aliasing filter. For the purpose of vibration monitoring, five signals are collected from the sensor and these are listed in Table 3.1.

### Table 3.1. Vibration data recording signals

<table>
<thead>
<tr>
<th>Signal</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1(g)</td>
<td>Channel 1: Accelerometer A1-axis Signal</td>
</tr>
<tr>
<td>A2(g)</td>
<td>Channel 2: Accelerometer A2-axis Signal</td>
</tr>
<tr>
<td>A3(g)</td>
<td>Channel 3: Accelerometer A3-axis Signal</td>
</tr>
<tr>
<td>T1(C)</td>
<td>Channel 4: Temperature</td>
</tr>
<tr>
<td>Time</td>
<td>Day, Hour, Second</td>
</tr>
</tbody>
</table>
In addition to vibration sensors, a USB camera was installed in the operator cab as shown in Figure 3.4 to record the entire shift in parallel to other data. These video recordings help to provide a better interpretation of data and also can be used for a manual time study.

Figure 3.4. USB Camera in the operator cab

3.1.2. Octagon Computer

In order to capture on-board shovel signals such as electrical motor responses and joystick reference signals an embedded computer system, Octagon (Octagon Systems, Westminster, CO, US) (Figure 3.5), has been installed with the assistance of Teck’s electricians in the shovel house. The datalogger software installed on the Octagon computer records the data using an OPC (OLE for Process Control) interface. There are OPC bridges installed on the two computers on the shovel. The datalogger makes a connection to these bridges to collect the signals from digital side of the programmable logic controller (PLC). The signals pertaining to this research are presented in Table 3.2. The sampling rate for these signals has been set at 20 Hz. Higher sampling rates were tested during the instrumentation process; however, because of the interface capabilities on the datalogger side it was unsuccessful.
Figure 3.5. Octagon computer installed in the shovel house

Table 3.2. On-board shovel signals

<table>
<thead>
<tr>
<th>Signal</th>
<th>Unit</th>
<th>Signal</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hoist Count</td>
<td>Count</td>
<td>Crowd Motor Speed</td>
<td>rpm</td>
</tr>
<tr>
<td>Crowd Count</td>
<td>Count</td>
<td>Hoist Armature Voltage</td>
<td>Vdc</td>
</tr>
<tr>
<td>Swing Angle</td>
<td>Count</td>
<td>Hoist Converted Current</td>
<td>amp</td>
</tr>
<tr>
<td>Joystick Dipper Trip</td>
<td>mV</td>
<td>Hoist Field Current</td>
<td>amp</td>
</tr>
<tr>
<td>Joystick Hoist &amp; Lower</td>
<td>mV</td>
<td>Hoist Motor Speed</td>
<td>rpm</td>
</tr>
<tr>
<td>Joystick Retract &amp; Crowd</td>
<td>mV</td>
<td>Swing Armature Voltage</td>
<td>Vdc</td>
</tr>
<tr>
<td>Joystick Swing Left &amp; Right</td>
<td>mV</td>
<td>Swing Converted Current</td>
<td>amp</td>
</tr>
<tr>
<td>Crowd Armature Voltage</td>
<td>Vdc</td>
<td>Swing Field Current</td>
<td>amp</td>
</tr>
<tr>
<td>Crowd Converted Current</td>
<td>amp</td>
<td>Swing Motor Speed</td>
<td>rpm</td>
</tr>
<tr>
<td>Crowd Field Current</td>
<td>amp</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.1.3. Payload Monitoring System

The P&H4100XPB shovel used in this study was equipped with a commercially available payload monitoring system called PulseTerraMetrix\textsuperscript{RS} (PTM) manufactured and supported by BMT WBM Canada. This monitoring system records data from a suite of sensors (load cells, accelerometers, strain gauges, inclinometer, gyro sensors) mounted on the shovel and processes them to estimate a comprehensive set of key shovel performance indicators (KPIs) per pass. These KPIs include dig time, swing time, return time, swing angle, return angle, payload, and equivalent digging energy. Additionally, GPS positions as well as operator ID are available. This data is stored in a SQL database and can be queried. Figure 3.6 illustrates the location of the PTM box on the bail and the associated operator interface.

![Figure 3.6. PTM payload monitoring system](image)

The sensors installed on-board the machine as well as the database were available to this research. The signals from sensors pertaining to this study are listed in Table 3.3. The sampling rate has been set at 50 Hz. The raw sensor data can be collected on a real-time basis and remotely.
Table 3.3. Sensor data

<table>
<thead>
<tr>
<th>Signal</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bail Force</td>
<td>tons</td>
</tr>
<tr>
<td>Bail Acceleration</td>
<td>g</td>
</tr>
<tr>
<td>Crowd angle</td>
<td>deg</td>
</tr>
<tr>
<td>Yaw rate</td>
<td>deg/sec</td>
</tr>
<tr>
<td>Bail angle</td>
<td>deg</td>
</tr>
<tr>
<td>Time channel</td>
<td>sec</td>
</tr>
</tbody>
</table>

To introduce the terminology used in Table 3.3, Figure 3.7 shows a schematic of an electric rope shovel.

Figure 3.7. Shovel Schematic (modified from P&H operator manual, 2005)
According to the P&H4100XPB maintenance manual, bail is “a yoke or spreader hinged to sides of shovel dipper, on which a hoist rope equalizer is mounted”. Bail angle and crowd angle have been shown in Figure 3.7. Yaw rate is also defined as the swing rate and bail force and bail acceleration are measured force and acceleration on the bail using a load-cell based technology as well as accelerometers respectively.

It should be noted that all the shovels used in this research were equipped with the PTM payload monitoring system. The results presented in this thesis are based on the fact that the payload monitoring system provides a real-time feedback for operators, so operators adjust their digging technique to achieve a desired payload per pass.

3.1.4. Technical Challenges

Similar to most field studies, there were technical challenges related to the instrumentation and data collection in this research. Some of the technical challenges encountered are:

- As different sources (Octagon system, PTM, USB camera and accelerometer) were used for data collection, synchronization of data was an important issue. However, it was not always possible due to different time servers used by different sources. It was mainly done manually at the field by two people adjusting times at the same moment.
- In some cases during field trials, the machine was down due to unscheduled maintenance
- On-board shovel signals and sensors data were transferred through a wireless connection. There were missing data sets due to network related problems.
- Due to the storage and processing limitations, sensor data and video recordings could not be recorded continuously to be able to perform the analysis. As a result, every half to one hour the data recording was stopped and started again.
- Payload values measured by PTM were prone to error. Occasionally the system needed to be recalibrated to have accurate enough values. Some of the values collected during field trials were not reliable.

- Shovel operational condition was extremely harsh and sensor enclosure and wiring system could be damaged. Also access to the top of the boom needed extensive resources which made it very challenging.

- The quality of data from some of the sensors was very low and it needed extensive filtering or using different sources.

- Some of the on-board shovel signals were measured in “counts” which needed to be converted to a physical unit.

In spite to all of aforementioned challenges, a large data set was collected during different field trials which will be discussed next.

### 3.2. Field Trials

During the first phase of the research (2013-2015) three field trials were conducted. Additionally, some of the data sets were collected remotely as needed. Table 3.4 summarizes these field trials. During the first field trial a set of controlled studies were also performed. The shovel operator was asked to perform swinging, crowding, hoisting and air digging with an empty bucket in-addition to the regular loading of trucks. Figures 3.8 and 3.9 also show the digging sequence of the shovel with different colours representing different dates during the second and the third field trials respectively.
Table 3.4. Summary of field trials during Phase I

<table>
<thead>
<tr>
<th>Field Trial #</th>
<th>Period</th>
<th>Day(s)</th>
<th>Operator(s)</th>
<th>Blast</th>
<th>Collected Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>April 13-18, 2014</td>
<td>16&lt;sup&gt;th&lt;/sup&gt;</td>
<td>A', B'</td>
<td>N1-1500-14&lt;sup&gt;5&lt;/sup&gt;</td>
<td>Vibration data,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>17&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N1-1500-15</td>
<td>Digital videos</td>
</tr>
<tr>
<td>2</td>
<td>July 12-17, 2015</td>
<td>13&lt;sup&gt;th&lt;/sup&gt;</td>
<td>A,B,C,D</td>
<td>N2-1905-04</td>
<td>Digital videos,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>14&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1905-04/06</td>
<td>On-board shovel signals, Sensors data,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>15&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1905-04/05/06</td>
<td>Production data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>16&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1905-06</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>17&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1905-06</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Nov 22-27, 2015</td>
<td>25&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1875-04</td>
<td>Digital videos,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>26&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1875-05/06</td>
<td>On-board shovel signals, Sensors data, Production data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>27&lt;sup&gt;th&lt;/sup&gt;</td>
<td></td>
<td>N2-1875-05/06</td>
<td></td>
</tr>
</tbody>
</table>

<sup>5</sup> Pit-Bench-Blast
Figure 3.8. Shovel dig sequence during field trial #2 (provided by Elkview Operations)

Figure 3.9. Shovel dig sequence during field trial #3 (provided by Elkview Operations)
In addition to aforementioned field trials, in the phase II of the research, a diggibaility trial a long
strike where rock characteristics where consistent was conducted in March 2016 to validate the
developed diggability index. P&H4100XPC shovels were considered for the phase II with
different operators digging three blast patterns (BR2-1800-03, BR2-1800-07,BR2-1800-10) including a fill area in the east side of the pit during the period of March 16th -28th. Moreover, three more case studies were conducted from April to September 2016 for validation and classification purposes. Surveying the face was employed during this period to be able to compare field observations with recorded diggability data for corresponding coordinates. The results will be presented in Chapter 6.

3.3. Post-Blast Evaluation

In order to fulfill the research objectives, in addition to collecting shovel performance data, the
digging condition and quality of blast should be assessed. Such assessment helps development,
evaluation and calibration of a shovel based diggability assessment technique. To accomplish
this the following approaches were used:

- Operators were interviewed and their comments on digging conditions were recorded;
- Digging conditions were evaluated by the researchers while observing the operation from
  the operator cab during the entire shift;
- The blast engineer and senior short range planner’s comments on digging conditions were
  recorded;
- Controlled digging was done in a set of cases with relatively known digging conditions:
  coal, re-handle materials, blasted waste and fill.
Table 3.5 summarizes blasting parameters for the encountered blast patterns during the field studies (phase I & II). Drill and blast parameters presented in this table were obtained from the drill and blast database at EVO. Table 3.6 also summarizes examples of digging conditions encountered during field trials (phase I) which were used for the analysis. The digging conditions for phase II will be discussed in Chapter 6.

Table 3.5. Blast parameters

<table>
<thead>
<tr>
<th>Blast ID</th>
<th>Blastability Index</th>
<th>Drill Productivity (m/hr)</th>
<th>Bit Size (in)</th>
<th>Burden (m)</th>
<th>Spacing (m)</th>
<th>Sub-drilling (m)</th>
<th>Bench Height (m)</th>
<th>PF (kg/m$^3$)</th>
<th>BCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1-1500-14</td>
<td>30.8</td>
<td>32</td>
<td>13 ¾”</td>
<td>9</td>
<td>10.4</td>
<td>2</td>
<td>15</td>
<td>0.64</td>
<td>120579</td>
</tr>
<tr>
<td>N1-1500-15</td>
<td>25.4</td>
<td>37.9</td>
<td>13 ¾”</td>
<td>9</td>
<td>10.4</td>
<td>2</td>
<td>15</td>
<td>0.57</td>
<td>239299</td>
</tr>
<tr>
<td>N2-1905-04</td>
<td>32.8</td>
<td>42</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.61</td>
<td>493763</td>
</tr>
<tr>
<td>N2-1905-05</td>
<td>31.5</td>
<td>45</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.60</td>
<td>540952</td>
</tr>
<tr>
<td>N2-1905-06</td>
<td>25.2</td>
<td>43</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.47</td>
<td>569133</td>
</tr>
<tr>
<td>N2-1875-04</td>
<td>30.4</td>
<td>47</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.58</td>
<td>482631</td>
</tr>
<tr>
<td>N2-1875-05</td>
<td>27.7</td>
<td>44</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.51</td>
<td>550294</td>
</tr>
<tr>
<td>N2-1875-06</td>
<td>31.3</td>
<td>46</td>
<td>13 ¾”</td>
<td>9.5</td>
<td>11</td>
<td>2</td>
<td>15</td>
<td>0.57</td>
<td>619328</td>
</tr>
<tr>
<td>BR2-1800-03</td>
<td>40.2</td>
<td>38.9</td>
<td>13 ¾”</td>
<td>9.9</td>
<td>8.57</td>
<td>2</td>
<td>15</td>
<td>0.77</td>
<td>164017</td>
</tr>
<tr>
<td>BR2-1800-07</td>
<td>39.8</td>
<td>30.3</td>
<td>12 ¼”</td>
<td>9.3</td>
<td>8.05</td>
<td>2</td>
<td>15</td>
<td>0.79</td>
<td>368336</td>
</tr>
<tr>
<td>BR2-1800-10</td>
<td>41.0</td>
<td>35.4</td>
<td>13 ¾”</td>
<td>9.9</td>
<td>8.57</td>
<td>2</td>
<td>15</td>
<td>0.81</td>
<td>268059</td>
</tr>
</tbody>
</table>
Table 3.6. Digging conditions assessment

<table>
<thead>
<tr>
<th>Blast ID</th>
<th>Date</th>
<th>Operator</th>
<th>Digging Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>N1-1500-14</td>
<td>April 16th, 2014</td>
<td>A'</td>
<td>Shovel was mainly digging sandstone, well fragmented and loose material</td>
</tr>
<tr>
<td>N1-1500-14</td>
<td>April 17th, 2014</td>
<td>A'</td>
<td>Shovel was mainly digging mudstone, high moisture contents and stickiness, tight</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>materials</td>
</tr>
<tr>
<td>N2-1905-04/05/06</td>
<td>July 15th, 2015</td>
<td>B</td>
<td>Towards the edges of patterns digging conditions was harder, hard toe, tight material, average fragmentation</td>
</tr>
<tr>
<td>N2-1905-06</td>
<td>July 17th, 2015</td>
<td>A</td>
<td>Hard toe but well fragmented and loose materials, Occasional big boulders</td>
</tr>
<tr>
<td>N2-1875-04</td>
<td>Nov 25th, 2015</td>
<td>E</td>
<td>Shovel was mainly digging re-handled materials, fine materials.</td>
</tr>
<tr>
<td>N2-1875-05/06</td>
<td>Nov 27th, 2015</td>
<td>F</td>
<td>Loose materials but blocky. No boulders</td>
</tr>
</tbody>
</table>

Table 3.6 shows that the muck-pile encountered during field trials in the phase I of the research were varying in characteristics, but it should be considered that these observations may be subjective and the observed range of digging conditions was narrow.

3.4. Data Pre-Processing

As different data sets are collected from different sources with different qualities and timestamps, the collected data files needed to be processed. This processing included format conversion, data partitioning, time aligning, signal conditioning, and filtering (de-noising). All the analysis and development conducted in this research was done in MATLAB R2015b.

PTM’s sensors data are recorded as different channels and are stored as .dat files. To convert the data files to a readable format for MATLAB (.mat) a previously developed LabView VI by BMT WBM Canada was used. The captured signals were scaled to represent the actual physical units.
To be able to scale the signals, a heading file provided and updated by the PTM system was used to create a scaling matrix to convert voltages to physical units. The physical units are presented in Table 3.3. Finally, to de-noise the signals a 2nd order zero-phase digital filter was used. This filter was used because it is easy to implement, significantly filters out noise and preserves features in a filtered time waveform exactly where they occurred on the unfiltered signal. In addition to captured signals from sensors, the payload values are retrieved from the SQL database based on the date. However, in some cases it was impossible to find corresponding payload values as the data were time-stamped with different formats and occasionally were not synchronized. Figure 3.10 illustrates an example of retrieved tables from the SQL database.

![Table 3.3](image)

Figure 3.10. A sample of data retrieved from SQL database

In contrast to sensors data, on-board shovel signals are stored as .csv files and they do not need format conversion. However, the recorded files do not have a relational structure and different signals are recorded based on a tag list which includes the name of the signals. To be able to parse the data to different signals, a search algorithm was developed. The algorithm searches for
different tags and saves them in a matrix for further analysis. Figure 3.11 shows an example of
data retrieved from the Octagon computer.

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>CwdArmVolt</td>
<td>629.5898</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>CwdConvCur</td>
<td>110.0355</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>HstMtrSpd</td>
<td>0.049695</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>HstArmVolt</td>
<td>629.8828</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>HstConvCur</td>
<td>3.076172</td>
<td>192</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>HstFldCur</td>
<td>124.9073</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>SwgMtrSpd</td>
<td>0.269975</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>SwgArmVolt</td>
<td>625.1953</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>SwgConvCur</td>
<td>-3.076171</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>SwgFldCur</td>
<td>70.0058</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>CwdMtrSpd</td>
<td>0</td>
<td>0</td>
<td>15-07-2015 08:23:44.263</td>
</tr>
<tr>
<td>SwgAngle</td>
<td>13549</td>
<td>0</td>
<td>15-07-2015 08:23:44.353</td>
</tr>
</tbody>
</table>

Figure 3.11. A sample of files retrieved from Octagon system

3.5. Dig Cycle Identification

After processing the collected data, the first step is to develop an approach to identify the dig
cycle or digging portion of the loading cycle. Inconsistencies and errors in the dig cycle
identification will result in highly variable and unreliable diggability index values. Therefore, it
is essential to have an automated approach that accurately and consistently identifies the dig
cycle. Then diggability index values can be calculated per dig cycle. A complete dig phase
involves cleaning of the floor, positioning of the dipper teeth and lip into the bank, engaging the
bank, raising the dipper through the bank until the dipper is full, disengaging the dipper from the
bank and clearing the bank (P&H operators manual, 2005). Figure 3.12 illustrates a complete dig
phase. In addition to a normal dig phase activities, there might be other complex activities such
as swinging during digging, cleaning the face or material loosening.
For the purpose of diggability assessment it is required to identify the moment of engagement and disengagement of the dipper from the bank and perform the analysis during that interval. Also, discarded passes by the operator that will not be loaded into the truck box should be identified as a part of the process. As a result, in this research two approaches for the dig cycle identification were developed which will be discussed next.

3.5.1. Mechanical Approach

According to Hendricks (1990), maximum retraction of the crowd arm or maximum extension of the hoist rope represents the onset of the dig cycle. However, at this moment the dipper is actually a few feet in front of the bank and is not engaged in the bank. As mentioned, for the purpose of calculating the diggability index, the moment of engagement of the dipper in the bank should be defined. Similarly, Hendricks (1990) considered the point of maximum crowd arm
extension as the end of the dig cycle. However, the operators may start swinging (swing-during-dig) before reaching maximum crowd extension\textsuperscript{6}. In the mechanical approach, to overcome these limitations, crowd angle, yaw rate (swing rate) and bail force have been used to develop an automated data processing algorithm to identify the dig cycle. Figure 3.13 shows these signals for 22 passes (~1800 sec) as an example.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure313.png}
\caption{A sample of data from PTM sensors for 22 passes}
\end{figure}

In Figure 3.13 the valleys (local minima) in the crowd angle signal mark the beginning of each cycle which corresponds to the maximum crowd arm retraction. Additionally, the valleys of the crowd angle signal match with the valley in the bail force signal which corresponds to the minimum bail force. However, at this point the yaw rate may not be equal to zero and the dipper

\textsuperscript{6} According to Jesset (2001), 30\% of cycles include swing-during-dig.
may be in motion and a few feet in front of the bank. Once the operator starts the hoisting motion the bail pull builds up towards the weight of the empty dipper and the crowd arm. Once the dipper is engaged in the bank and the material starts flowing into the dipper, the bail force will be higher than the weight of the empty dipper and the crowd arm which is called dead weight. To identify the moment of engagement of the dipper a threshold value (100 tons) has been set for the bail force. At such a point the yaw rate is close to zero.

As the dipper is being filled through hoisting in the bank, the bail force increases to overcome the weight of materials and the resistance of materials to digging. Once the dipper is full and the operator pulls the dipper out of the bank, the dipper loses its contact with the bank and the bail force starts dropping to a value which is equal to the payload plus the dead weight. This moment should be synonymous with the onset of swinging to a haul-truck. During the swinging portion, hoisting continues to a level sufficient for dumping of the load in the truck box. Once the operator dumps the load, the bail force drops to a value equal to the dead weight and then during the lowering portion it drops to a minimum value which is identified as the beginning of the loading cycle. These observations resulted in development of an automated data processing algorithm to identify “start of cycle”, “start of digging” and “end of digging” for each pass. Figure 3.14 shows identified dig phases for 22 passes in Figure 3.13.

In addition to identifying the dig cycle, discarded passes should be identified. During waiting times for trucks operators may clean the face and loosen the material to make it easier to dig. These passes are known as discarded passes and the number of discarded passes can be a representative of digging condition. To identify discarded passes a set of criteria was defined:

---

7 This threshold will vary based on the bucket size and machine type.
8 Because of severe vibrations experienced by the sensors during digging it may not be exactly zero.
• Maximum bail force <200⁹
• Maximum crowd angle < 0

These criteria have been chosen based on the facts that operators do not fill the dipper to its capacity and the maximum bail force is lower than 200 tons, also as there is no load dumping in the truck box, the maximum crowd angle will be lower than 0°.

---

⁹ This threshold may vary for different bucket sizes
Figure 3.14. Identified dig cycles
3.5.2. Electrical Approach

Similar to Hendricks (1990), in this approach crowd arm extension and hoist rope retraction signals are used. Crowd arm extension is recorded by a resolver (position transducer) on the crowd drive motor, indicating the amount of crowd arm extension. Similarly, hoist rope retraction is recorded by a resolver (position transducer) on the hoist drum, indicating the length of hoist rope retracted from the shovel point sheaves. Additionally, dipper trip joystick button signal, swing angle and hoist power have been used. Figure 3.15 shows these signals for the 22 cycles presented in Figure 3.13. The instantaneous power is given by:

\[ \text{Power} = I(t) \times V(t) \]  

(3.1)

where \( I \) and \( V \) are motor\(^{10} \) armature current and voltage respectively. It should be noted that there are two hoist motors on-board the shovel that equally share in hoisting activities, but for comparison purposes the power from one motor is used throughout this thesis unless it is explicitly mentioned.

In Figure 3.15, the valleys (local minima) in the hoist rope retraction trace mark the beginning of the cycle which corresponds to the maximum extension or minimum retraction of the hoist rope. This moment also matches with an initial surge in the hoist power signal due a sudden load on the hoist motor at the onset of hoisting. However, as mentioned before at this moment the dipper is suspended under the shovel boom a few feet in front of the dipper. Following this point, the power drops rapidly and then increases to overcome the dead weight. Once the dipper is engaged in the bank, the load on the hoist motor increases and the power builds up gradually towards a maximum value at the end of the cycle. To identify the moment that the dipper is engaged in the

\(^{10} \) The motor can be either hoist, crowd or swing.
bank a threshold value (500 kW)\textsuperscript{11} has been set for the hoist power. At such a point the swing rate is close to zero.

\textsuperscript{11} This threshold values may vary for different machine types and bucket sizes
Figure 3.15. A subset of on-board shovel signals for 22 passes
As the dipper is being filled through hoisting, the load on the hoist motor increases to overcome the resistance of material to digging as well as the weight of materials flowing into the dipper. Once the dipper is full and the operator pulls the dipper out of the bank, the dipper loses its contact with the bank and the load on the hoist motor rapidly drops to a value which is equal to the payload plus the dead weight. This moment should be synonymous with the onset of swinging to a haul-truck or the maximum crowd arm extension as there are cases that the operator first retracts the dipper and then starts swinging to a haul truck or first start swinging while the crowd arm extension is not maximum. Finally, activation of the dipper trip joystick button indicates dumping the load in the truck box. These observations resulted in the development of an automated data processing algorithm to identify “start of digging”, “end of digging” and “end of cycle” for each pass. Figure 3.16 shows identified dig phases for 22 passes in Figure 3.13.

Similar to the approach discussed in Section 3.5.1 discarded passes and cleaning activities should be identified. As a result, a set of criteria has been defined:

- No dipper trip joystick button activation
- \((\text{end of cycle - start of digging}) < 15 \text{ sec}\)
- Maximum hoist rope retraction < 6000 counts

These criteria have been chosen based on the fact that as there is no dumping of the load in the truck box, the maximum hoist rope retraction will be lower than 6000 counts. Also, usually for face cleaning purposes operators do not close the dipper door during digging so there will be no dipper trip joystick button activation if there is an activation of the dipper trip joystick button the difference between end of the cycle and start of digging will be less than 15 seconds.
Figure 3.16. Identified dig cycles
3.6. Operator Influence on Shovel Digging Productivity

After developing a robust technique for isolating the digging portion of the cycle, the next step of the study is to understand the effect of operators on the digging performance of the shovel. As mentioned in Chapter 2, the performance of electrical rope shovels may vary with the muck-pile characteristics, operator practice and skills, and machine type and conditions. Previous research attempts show that shovel performance is directly influenced by muck-pile characteristics (Osanloo and Hekmat, 2005; Singh and Narendrula, 2007). However, in addition to muck-pile characteristics, operator proficiency and skill play a significant role in the productivity of loading equipment (Hendricks, 1990; Jessett, 2001; Onederra et al, 2004; Patnayak et al, 2008; Oskouei and Awuah-Offei, 2015). In this research, to study the effect of operators, KPIs are compared for different operators, a clustering analysis is performed and operators digging techniques are compared for different operators under different digging conditions. The methodology adopted will be discussed next.

3.6.1. Key Shovel Performance Indicators (KPIs)

In the current research, as the first step in understanding the influence of operators and to compare their performance, different KPIs are identified. The KPIs include payload, cycle time components (dig time, swing time, return time), swing and return angles, equivalent digging energy, loading rate and mucking rate. Most of these KPIs are retrieved from the PTM’ SQL database. In this thesis, productive cycle time is defined as the interval between two consecutive dumps excluding waiting times. Dump time and the positioning of the bucket before digging have been included in return time (PTM system has been coded in this way). Equivalent digging
energy, loading rate and mucking rate are also determined using Equations 3.2 to 3.4 respectively:

\[
\text{Equivalent Digging Energy} = \int_{t_0}^{t_1} F_b \times \text{Crowd Rate} \, dt \tag{3.2}
\]

\[
\text{Loading Rate} = \frac{\text{Payload}}{\text{Dig time}} \tag{3.3}
\]

\[
\text{Mucking Rate} = \frac{\text{Payload}}{\text{Productive Cycle Time}} \tag{3.4}
\]

where \(t_0\) and \(t_1\) are the start and the end of digging respectively, \(F_b\) is the bail force (bail pull) and crowd rate is the rate of change of crowd arm angle with respect to horizon. It should be noted that these KPIs are being estimated by the PTM using a suit of sensors such as load cells and gyro sensors. Equation 3.2 shows the equivalent digging energy estimated by the monitoring system on-board the shovel and is an equivalent mechanical energy (tons \(\times\) deg) during the digging part of the cycle. The equivalent digging energy is measured at the bail and is a measure of mechanical energy transferred to the bucket teeth.

As the first step in the analysis of the data collected during field trials, the estimated KPIs are statistically compared. Especially, their coefficient of variation (COV) are compared to assess the variability in productivity of the machine from cycle to cycle and for different operators. This is done to understand the effect of the operator on shovel performance. Additionally, the analysis of COVs in conjunction with other data analysis can show if the new monitoring technologies are successful in increasing production and reducing variability of machine productivity across different operators.
3.6.2. Clustering Analysis

In order to further investigate the effect of different operators on the shovel performance, a clustering analysis is performed based on equivalent digging energy, dig time and payload per pass. These three parameters or a combination of them have been widely used as a measure of digging efficiency or shovel performance (Hendricks, 1990; Singh and Narendrula, 2007; Awuah-Offei and Frimpong, 2007; Patnayak et al. 2008). The goal of this clustering is to classify shovel digging behavior and effort which depend on operator practice and skills, digging condition and machine type and conditions. In this research, to solve the clustering problem, K-means clustering technique is used because of its simplicity and speed in dealing with large datasets.

K-means (Lloyd, 1982) is an unsupervised learning algorithm that partitions a set of n data points in \( \mathbb{R}^d \) (\( \mathbb{R}^d \) is the data space of d dimensions) into k clusters. Given an integer k and a set of n data points \( X \subset \mathbb{R}^d \), K-means algorithm aims at minimizing an objective function (J), in this case the sum of the square of the distance from data points to the clusters centers (centroid), so that k cluster centers \( C = [c_1, c_2, \ldots, c_k] \in \mathbb{R}^d \) are defined.

\[
J = \sum_{x \in X} d(x,c)^2
\]  

(3.5)

where \( c \in C \) and \( d(x,c) \) denotes the Euclidean distance between data points and each center.

The details of the K-means algorithm have been presented in a paper by Lloyd (1982).

In this research, the number of clusters has been set as \( k = 4 \) based on the understanding of the data. Additionally, Euclidian distance, the most common metric used for clustering, has been chosen to assign data points to each cluster.
Finally, K-means++ algorithm (Arthur and Vassilvitskii, 2007) has been used to initialize cluster centers. According to Arthur and Vassilvitskii (2007), this algorithm improves the speed and quality of clustering of K-means.

In this research to ensure that the K-means algorithm will result in a solution that is a global minimum, 10 replicates with different starting points (according to K-means++ algorithm) have been used.

3.6.3. Operator Digging Practice

3.6.3.1. Joysticks

As mentioned in Chapter 2, digging is mainly a combination of hoist and crowd actions. There are two joysticks in the operator’s cab that allow operators to control the machine. To study the effect of operator practice on digging efficiency, a visual evaluation of their hoist and crowd practices based on joystick signals is done. Figure 3.17 shows joysticks signals for a few loading cycles.

Figure 3.17. A sample of joystick signals
3.6.3.2. Digging Trajectory

According to Awuah-Offei (2016) digging trajectory of the dipper used by the operator is one of the most important factors affecting the digging performance of electric rope shovels. The trajectory variability is a result of different crowd arm extension and/or hoist rope retraction rates. According to past studies (Awuah-Offeik and Frimpong, 2004 & 2007) the best operator digging practice is achieved by lower crowd extension speed and higher hoist rope retraction speed, which result in a decrease in the depth of cut. In the current research crowd arm and hoist rope speeds are estimated using hoist rope retraction and crowd arm extension signals (Figure 3.15). However, they are recorded in “count” and thus need to be converted to “meter” to be able to have the speed values in physical units (m/s)\(^{12}\). As the OEM did not provide a conversion factor for the resolvers to convert “count” to “meter”, an experiment was conducted in the field to estimate conversion factors. As for the hoist counts, two points, 30 inches apart, were marked with red tape on the hoist rope (Figure 3.18) and a reference point was considered. The operator was asked to retract the hoist smoothly and stop once the first point is in the same level as the reference point. The hoist count was recorded at this point. Then the operator again was asked to smoothly retract the hoist rope until the second marked point reaches the reference point. Then the hoist count was recorded again. This practice was repeated three times with two different operators and an average value (1 hoist count= 0.002668 m) was determined.

\(^{12}\) It is also essential for estimating the digging trajectory of the dipper in the bank.
Similarly, for the crowd count conversion factor as the crowd arm has a rack on its underside, the operator was asked to smoothly retract the crowd arm equal to the length of 5 teeth of the rack (Figure 3.19). The crowd counts were recorded at the beginning and the end and the edge-to-edge length of two teeth was measured. Using these values, the crowd count conversion factor (1 crowd count = 0.001111m) was estimated.
Using the crowd and hoist counts conversion factors, Figure 3.20 shows hoist rope retraction and crowd arm extension during digging for the 22 passes presented in Figure 3.13.

Figure 3.19. Crowd arm retraction experiment
In Figure 3.20, the slope of the hoist rope retraction represents hoist speed and the slope of the crowd arm extension represents crowd speed. This figure shows that the slope of the hoist rope retraction is almost constant for each cycle and a straight line can be fitted on the data for each cycle to estimate the hoist speed. The average hoist speed and associated R-squared value for cycles in Figure 3.20 are presented in Table 3.7. In contrast to the hoist rope retraction, Figure 3.20 shows that the crowd arm extension exhibits two different trends:

1. Constant crowd speed until the desired dipper depth of penetration is achieved (the first part of the digging);
2. Once the dipper penetrates into the bank, digging is mainly accomplished by hoist action, and the crowd speed is approximately zero.

This observation confirms that the dipper is mainly filled through the hoist action and the crowd action only helps to maintain a proper dipper depth of penetration into the bank. However, depth of penetration and crowd speed (in the first part of the digging) have effects on digging energy and shovel performance. The crowd speed values are estimated based on the slope of a straight line fitted to the crowd arm extension values in the first part of the digging. The average crowd speed and the associated R-squared value are presented in Table 3.7.

Table 3.7. Crowd and hoist speed values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hoist speed (m/s)</td>
<td>0.74</td>
<td>0.1</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.99</td>
<td>0.01</td>
</tr>
<tr>
<td>Crows speed(m/s)</td>
<td>0.56</td>
<td>0.1</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.98</td>
<td>0.02</td>
</tr>
</tbody>
</table>

The R-squared values in Table 3.7 indicate that a straight line is the best fit to describe the data. A combination of crowd and hoist speeds generates different digging trajectories. To be able to determine the position of the dipper during digging and to reconstruct the digging trajectory, two approaches have been used:

1. **Approach I:** The hoist rope retraction and the crowd arm extension along with the geometry of the shovel are used to determine the actual dipper trajectory during each dig cycle in a
Cartesian co-ordinate system (X,Y). Figure 3.21 shows a schematic representation of the shovel and operating parameters. In this approach the point sheaves and the dipper are treated as a point and the saddle block is considered the origin.

Figure 3.21. Schematic representation of a cable shovel

In Figure 3.21, \(l_b\), \(l_c\), \(l_r\) are shovel boom length, crowd arm extension and hoist rope extension respectively. \(\beta\) is also the crowd angle. Having \(l_b\), \(l_c\), and \(l_r\) at each moment the position of the dipper is given by:

\[
x = l_r \cos(\beta) \tag{3.6}
\]

\[
y = l_r \sin(\beta) \tag{3.7}
\]
where:

\[
\cos \left( \beta + \frac{\pi}{4} \right) = \frac{l_b^2 + l_c^2 - l_r^2}{2l_b l_c}
\]  

(3.8)

Given \(l_b\), \(l_c\), and \(l_r\) at each moment during the dig cycle, the position of the dipper in the Cartesian co-ordinate system \((X,Y)\) can be estimated using the above equations. It should be considered that \(l_b\) is constant and is taken from the shovel geometry (for P&H4100XP, \(l_b=14.95\) m); \(l_c\) is provided by the converted crowd arm extension signal, and considering the range of hoist counts\(^{13}\), \(l_r\) is given by:

\[
l_r = (8000 - \text{hoist count}) \times 0.002668
\]

(3.9)

Using this approach, Figure 3.22 shows an example of a digging trajectory for a dig cycle.

![Figure 3.22. An example of digging trajectory](image)

\(^{13}\) According to P&H operators manual (2005), the maximum hoist count is 8000.
2. **Approach II**: Crowd and bail angles along with the geometry of the shovel are used to determine the actual dipper trajectory during each dig cycle in a Cartesian co-ordinate system (X,Y). Figure 3.23 shows a schematic representation of the shovel and operating parameters. Similarly, in this approach the point sheaves and the dipper are treated as a point.

![Schematic representation of a cable shovel](image)

**Figure 3.23. Schematic representation of a cable shovel**

In Figure 3.23, \(l_b\) and \(l_c\), are shovel boom and crowd arm extension respectively. \(\beta\) and \(\theta\) are also the crowd and bail angles respectively. Having \(l_b\), \(\beta\), and \(\theta\) at each moment the position of dipper is given by Equations 3.6 and 3.7 in the Cartesian co-ordinate system (X,Y) where:

\[
l_c = l_b \frac{\sin \left( \frac{\pi}{4} - \theta \right)}{\sin \left( \frac{\pi}{2} - \beta + \theta \right)}
\]

The accuracy of this approach highly depends on the quality of angles provided by the sensors on-board the machine. During phase I of the research, crowd angle was measured on the saddle block using an inclinometer while bail angle was measured on the bail using an accelerometer.
Figure 3.24 shows examples of recorded crowd and bail angle signals during a dig cycle. As Figure 3.24 shows, the crowd angle signal is not noisy while the bail angle is very noisy. The bail angle is measured on the bail using an accelerometer which experiences lots of vibrations during digging (especially at the beginning). This causes severe fluctuations in the signal especially at the beginning of the cycle where the shovel is digging the toe. To overcome this issue, the data are smoothed out using a local regression technique (Schimek, 2000). Local regression technique is a non-parametric regression method that combines multiple regression models. Figure 3.25 shows the smoothed bail angle signal presented in Figure 3.24.

Figure 3.24. Crowd and bail angles during a dig cycle
In addition to smoothing the signal, in phase II of the research, instead of an accelerometer, a gyro sensor was used to measure the bail angle. It was expected to have less fluctuations in the bail angle signal. Figure 3.26 shows an example of the recorded bail angle signal using the gyro sensor.
Figure 3.26 shows that the bail angle values still fluctuate and the data needs to be smoothed before using the bail angle values for generating the digging trajectory. Using approach II, Figure 3.27 shows an example of a digging trajectory for a dig cycle.

![Figure 3.27. An example of digging trajectory](image)

Finally, it should be noted that the first approach (electrical) is only used for assessing diggability based on on-board shovel signals while the second approach (mechanical) is based on the PTM sensors data. The results from two approaches may not be identical as there are different sources of data with different qualities and also different algorithms for isolating the dig cycle.

### 3.7. Diggability Assessment

To develop a robust approach to assessing diggability, first a few potential indicators based on sensors data are compared and then an energy analysis is performed in three ways. The three
ways include vibration energy analysis, mechanical energy analysis and electrical energy analysis using the methods described next.

3.7.1. Sensor Data Analysis

To better understand the effect of digging conditions on the shovel performance, four KPIs are defined and compared for easier and harder digging conditions. Bail force raggedness, average crowd rate, average equivalent power and instantaneous equivalent power are the four KPIs given by:

\[
\text{Bail Force Raggedness} = \frac{\sum_{i=1}^{n} |F_{bi+1} - F_{bi}|}{\sum_{i=1}^{n} (t_{i+1} - t_i) \times F_{bi}} \quad (3.11)
\]

\[
\text{Average Crowd Rate} = \frac{\sum_{i=1}^{n} \text{Crowd Rate}_i}{n} \quad (3.12)
\]

\[
\text{Average Equivalent Power} = \frac{\sum_{i=1}^{n} \text{Crowd Rate}_i \times F_{bi}}{n} \quad (3.13)
\]

\[
\text{Instantaneous Equivalent Power} (i) = \text{Crowd Rate}_i \times F_{bi} \quad (3.14)
\]

where \( F_b \) is bail force in tons, \( t \) is time in second, \( n \) is sample size, crowd rate is in \text{deg/s} and average equivalent power is in \text{tons×deg/s}.

3.7.2. Vibration Analysis

As mentioned in Section 3.1.1, in this research the vibrations experienced by an electric rope shovel’s boom during different passes are measured using a tri-axial accelerometer mounted
inside an enclosure on the side of the shovel’s boom. It should be noted that the shovel boom’s vibrations data were only collected during the first field trial (April 2014) due to the cable failure and being unable to get it repaired because of mine schedule.

As the first step, it is essential to isolate different shovel cycle activities and then analyze vibration signals specific to each part of the cycle (digging, swinging, waiting, dumping and swinging back to the face) to gain a better understanding of shovel behavior and effort over different activities. During the first field trial (April 2014) sensors data and on-board shovel signals were not available, so digital video recordings captured in parallel to vibration data during the field trial are used to identify different shovel activities.

3.7.2.1. **Time Domain Analysis of Measured Vibrations**

In order to compare vibration signals over different parts of the shovel cycle, the combined acceleration of all the three axes is calculated in the time domain as follows:

\[
Combined \text{ Acceleration Amplitude } A(t) = \sqrt{a_1(t)^2 + a_2(t)^2 + a_3(t)^2}
\]  

(3.15)

where \(a_1\), \(a_2\) and \(a_3\) are the individual A1, A2, A3 vibration axis components respectively and \(t\) is time.

3.7.2.2. **Frequency Domain Analysis of Measured Vibrations**

In order to analyze the various frequencies present in a vibration signal, Fast Fourier transform (FFT) is used. The FFT decomposes a digital signal into components of different frequencies (Stearns, 1953). The resulting frequency domain information highlights the periodic nature of activities present by generating a spike at a location in the frequency axis where the periodic
vibration activity occurs. In this study, MATLAB FFT code which employs the Cooley-Tukey FFT algorithm is used to perform FFT analysis.

The Fourier Transform plots frequency along the x-axis from zero hertz to the Nyquist frequency. The Nyquist frequency of a band limited signal is defined as one half of the recording frequency (Stearns, 1953). Although the Nyquist frequency in this study is 506 Hz, frequency domains are plotted in the range of 0 to 200 Hz since the dipper and face interaction as well as other mechanical sources (motor shaft, etc.) were observed to be band-limited within this frequency range.

### 3.7.2.3. Vibration Energy

In order to further investigate the effect of digging conditions on vibrations, in addition to time domain and frequency domain analysis, based on the collected vibration data from the installed accelerometer on the bail as a part of the PTM system, vibration energy given by Equation 3.16 is compared for different cycles and digging conditions.

\[
VE = \frac{\sum_{i=1}^{n} (x_i)^2}{n}
\]

(3.16)

where \( n \) is the sample size and \( x \) is the amplitude.

### 3.7.3. Mechanical Approach

In this approach, a mechanical energy balance for shovels is done to assess the diggability which is defined as the amount of resistance a particular material creates to being extracted from a muck-pile. As the first step in performing an energy balance, it is essential to understand digging forces generated by the shovel.
3.7.3.1. Dig Forces

The electric rope shovels generate digging forces through hoist and crowd. These forces include the “hoist force” and the “crowd force” as shown in Figure 3.28. These two forces are combined to create the net digging force. However, it should be noted that the crowd force is a thrust for engagement of the dipper teeth into the bank while hoist force is the bail pull for filling the dipper.

Figure 3.28. Digging Forces: Hoist and Crowd Force (after P&H operator manual, 2005)

According to Jessett (2001), crowd machinery imposes a force (crowd force) normal to the digging trajectory. Therefore, the work done by the crowd force along the digging trajectory will be equal to zero:

\[ F_c \perp S \Rightarrow W_c = \int F_c \, ds = 0 \]  \hspace{1cm} (3.17)

where \( F_c \) is the crowd force and \( S \) is the displacement vector along the digging trajectory.
As a result of the above equation and considering the fact that the hoist electrical power is much higher than the crowd electrical power and the hoist motion has a critical role in filling the dipper (Hendricks, 1990; Patnayak 2006), in the current study hoist force (bail pull/force) is used to estimate a diggability index.

### 3.7.3.2. Diggability Index-Mechanical

Considering the definition of diggability presented in Section 3.7.3, to be able to estimate a diggability index, in the current approach digging energy which is equal to the energy loss in the bank due to the resistance of material to digging is calculated. Such energy depends on the hardness of material, moisture content, looseness, interlocking forces between rock fragments, fragmentation size distribution, shape of fragments, etc. As a result, to estimate digging energy an energy balance is done:

\[
E_t = E_d + PE + \Delta K
\]  

(3.18)

where \(E_t\) is the total energy, \(E_d\) is the digging energy; \(PE\) is the potential energy and \(\Delta K\) is the changes in the kinetic energy. Assuming that at the beginning of digging (dipper engagement in the bank) and at the end of digging (dipper disengagement from the bank) the dipper velocity is zero:

\[
\Delta K = k_2 - k_1 = 0
\]  

(3.19)

where \(k_1\) and \(k_2\) are the kinetic energy at the start and at the end of digging respectively.

Therefore:

\[
E_d = E_t - PE
\]  

(3.20)
As mentioned in Section 3.7.3.1 electric rope shovels generate digging forces through the hoist machinery as well as the crowd machinery. Crowd motion helps to maintain a proper penetration of the dipper in the bank while hoist motion helps to fill the dipper. The type and the weight of material being excavated mainly affect the hoist motion during digging. Therefore, in the current approach, the integral of bail force (bail pull) over digging trajectory is used to estimate the total energy consumed by the shovel during the digging phase:

$$E_i = \int_{s_i}^{s_2} F_b \cdot ds$$

(3.21)

where $F_b$ is the bail force (in tons) and $ds$ is the displacement vector of the bail (dipper) in either Polar coordinates or Cartesian. Also, $s_1$ and $s_2$ represent the location of the bail (dipper) at the beginning and at the end of digging phase. As Equation 3.21 illustrates, the accuracy of these calculations highly depends on the way that the start and the end of digging are being determined. As such, the approach presented in Section 3.5.1 should be employed to isolate the digging phase.

To be able to estimate the total energy using Equation 3.21 in a Cartesian system (X,Y), the equation is restated to a discrete form:

$$E_i = \sum_{i=1}^{n} F_{b,i} ds_i \cos(\phi_i)$$

(3.22)

where $n$ is the total number of samples and $\phi$ is the angle between $F_b$ and $ds$ at each moment. $\phi_i$ values at each moment are given by Equation 3.23. Figure 3.29 displays different parameters in Equation 3.23. It should be noted that $x_i$ and $y_i$ values are calculated using Equations 3.6 and 3.7 respectively.
\[ \varphi_i = \frac{\pi}{2} - \theta(i) - \tan^{-1}\left(\frac{y_{i+1} - y_i}{x_{i+1} - x_i}\right) \tag{3.23} \]

Figure 3.29. Dipper incremental movement schematic

In addition to the total energy, potential energy should be estimated per pass. The average potential energy for each pass is given by:
where $M_e$ is the mass of empty bucket in tons, $M_f$ is the mass of full bucket in tons and $\Delta H$ is the digging height in meters. It should be noted that the gravitational acceleration ($g$) has been removed from the definition of potential energy in Equation 3.24 to have the same dimensions as $E_t$. Finally, the digging energy is given by:

$$E_d = \sum_{i=1}^{n} F_{bi} ds_i \cos(\varphi_i) - \left( \frac{M_e + M_f}{2} \right) \times \Delta H$$  \hspace{1cm} (3.25)$$

However, this energy is a function of digging trajectory as the bail force is integrated over the digging trajectory. Digging trajectory is significantly influenced by the operator practice. With different hoist and crowd speeds operators create different trajectories. Therefore, calculated digging energy from Equation 3.25 needs to be normalized for variations in digging trajectory (operator effect):

$$\text{DI} = \frac{\sum_{i=1}^{n} F_{bi} ds_i \cos(\varphi_i) - \left( \frac{M_e + M_f}{2} \right) \times \Delta H}{\int ds}$$  \hspace{1cm} (3.26)$$

where DI is the diggability index in tons-force which is a measure of resistance force to digging. Additionally, the operators may do retractions during digging phase which are detected and removed from the energy calculations. Equation 3.26 considers the bail force, dipper position in space, payload, digging height, dig time and digging trajectory to calculate the diggability index.
3.7.4. Electrical Approach

Similar to the mechanical approach, in the electrical approach, an energy balance is done to assess the diggability. However, in this approach on-board shovel signals listed in Table 3.2 have been used to calculate the diggability index.

In this approach, the similar energy balance as the mechanical approach has been done; however, the total energy is given by:

\[
E_t = \int_{t_1}^{t_2} (2 \times V_h \times I_h + V_c \times I_c) \, dt
\]

(3.27)

where \( V_h \) and \( I_h \) are hoist voltage and current respectively, \( V_c \) and \( I_c \) are crowd voltage and current respectively and \( t_1 \) and \( t_2 \) are the time of the start and the end of digging respectively\(^{14}\).

Using above equation, the definition of DI (Equation 3.26) is restated as:

\[
DI = \frac{\int_{t_1}^{t_2} (2 \times V_h \times I_h + V_c \times I_c) \, dt - \left( \frac{M_e + M_l}{2} \right) \times \Delta H \times g \times 1000}{g \oint ds} \times \frac{1}{1000}
\]

(3.28)

\[
DI = \frac{\int_{t_1}^{t_2} (2 \times V_h \times I_h + V_c \times I_c) \, dt - \left( \frac{M_e + M_l}{2} \right) \times \Delta H \times g \times 1000}{g \oint ds} \times \frac{1}{1000}
\]

(3.29)

where \( ds \) and \( \Delta H \) are given by:

\[
ds_i = \sqrt{(x_{2(i)} - x_{1(i)} )^2 + (y_{2(i)} - y_{1(i)} )^2}
\]

(3.30)

\[
\Delta H = \max(y) - \min(y)
\]

(3.31)

\(^{14}\) The calculated energy includes two hoist motors and one crowd motor. For comparison purposes, one may consider only one hoist motor.
where \( x \) and \( y \) are calculated based on the approach presented in Section 3.6.3.2. The gravitational acceleration \( (g) \) has been included in the denominator of DI definition in Equation 3.29 to have the same unit (tons) as the mechanical DI defined in Equations 3.26.

In all diggability calculations, when the dipper is stuck in the bank or the operator does retraction the energy calculation is stopped as it is not a part of the useful digging energy. The proposed approaches have been coded in MATLAB and LabView and implemented on operating shovels for evaluations. The results will be presented and discussed in next chapters.
4. Effect of Operator on Shovel Performance

Based on the methodology presented in Section 3.6 the data collected during the second field trial (July 13-17th, 2015) has been analyzed to assess the digging productivity of the shovel for different operators. The second field trial was chosen for this analysis as all of the required data were collected during that trial for the first time during the research and two distinct digging conditions were identified during the trial. According to Table 3.4 during the monitoring trial, four different operators worked the shovel (Operators A, B, C and D). Two zones have been identified in Figure 4.1 as easier (coarse but loose material) and harder digging (hard toe and coarse and tight material) conditions. Operator A was working on the easier condition and Operator B was working on the harder one. It should be noted that Operators C and D were working during the night which prevented using that data due to no knowledge about the digging conditions.
4.1. Productivity Analysis

A total of 4791 shovel cycles were monitored during the course of the second field trial. The PTM system was used to record different shovel activities such as digging, swinging and returning. Additionally, the PTM system detects and records activities that are not associated with loading the truck such as cleaning up the face. In this section, such activities are not included in the analysis. As the current study mainly focuses on the digging part of each loading cycle, Figure 4.2 illustrates a histogram and a box plot of dig time values. The histogram indicates that dig times are positively skewed and they range from 2 to 48 s. The box plot also describes the spread of data and highlights outliers. In this study an outlier is defined as a value that is more than 1.5 times the interquartile range away from the top or bottom of the box in the boxplot.
Outliers were removed from the data and statistics for different KPIs defined in Section 3.6.1 were calculated. The KPIs include payload, cycle time components, swing and return angles, equivalent digging energy, loading rate and mucking rate. A summary of the aforementioned KPIs for all of the operators is presented in Table 4.1.
### Table 4.1. Key Shovel Performance Indicators

<table>
<thead>
<tr>
<th>Operator</th>
<th>Statistics</th>
<th>Payload (tons)</th>
<th>Dig Time (s)</th>
<th>Swing Time (s)</th>
<th>Swing Angle (°)</th>
<th>Return Time (s)</th>
<th>Return Angle (°)</th>
<th>Productive Cycle Time (s)</th>
<th>Waiting Time (s)</th>
<th>Equivalent Digging Energy (tons × deg) ($\times 10^5$)</th>
<th>Loading Rate (tons/s)</th>
<th>Mucking Rate (tons/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operator A</td>
<td>Mean</td>
<td>98.3</td>
<td>16.4</td>
<td>8.2</td>
<td>68.8</td>
<td>8.6</td>
<td>62.3</td>
<td>33.3</td>
<td>18.9</td>
<td>2.66</td>
<td>6.2</td>
<td>3.0</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>0.17</td>
<td>0.20</td>
<td>0.31</td>
<td>0.36</td>
<td>0.24</td>
<td>0.36</td>
<td>0.15</td>
<td>1.94</td>
<td>0.36</td>
<td>0.26</td>
<td>0.19</td>
</tr>
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<td></td>
<td>589 Cycles</td>
<td>Min</td>
<td>13</td>
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<td>9</td>
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<td>0</td>
<td>21</td>
<td>0.36</td>
<td>1</td>
<td>0</td>
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<tr>
<td></td>
<td>Max</td>
<td>133</td>
<td>24</td>
<td>18</td>
<td>180</td>
<td>27</td>
<td>173</td>
<td>53</td>
<td>373</td>
<td>5.88</td>
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<td>6</td>
</tr>
<tr>
<td>Operator B</td>
<td>Mean</td>
<td>104.1</td>
<td>16.5</td>
<td>8.5</td>
<td>66.8</td>
<td>8.1</td>
<td>61.8</td>
<td>33.1</td>
<td>18.9</td>
<td>2.32</td>
<td>6.5</td>
<td>3.2</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>0.14</td>
<td>0.18</td>
<td>0.33</td>
<td>0.32</td>
<td>0.33</td>
<td>0.43</td>
<td>0.16</td>
<td>2.18</td>
<td>0.32</td>
<td>0.20</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>1629 Cycles</td>
<td>Min</td>
<td>11</td>
<td>8</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>18</td>
<td>0.067</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>139</td>
<td>24</td>
<td>30</td>
<td>166</td>
<td>36</td>
<td>175</td>
<td>67</td>
<td>411</td>
<td>6.17</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>Operator C</td>
<td>Mean</td>
<td>98.6</td>
<td>15.7</td>
<td>8.5</td>
<td>70.8</td>
<td>8.5</td>
<td>64.6</td>
<td>32.7</td>
<td>17.0</td>
<td>2.05</td>
<td>6.5</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>0.16</td>
<td>0.20</td>
<td>0.32</td>
<td>0.32</td>
<td>0.30</td>
<td>0.38</td>
<td>0.15</td>
<td>2.03</td>
<td>0.34</td>
<td>0.22</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>1633 Cycles</td>
<td>Min</td>
<td>17</td>
<td>8</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0</td>
<td>16</td>
<td>0.19</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>137</td>
<td>24</td>
<td>23</td>
<td>172</td>
<td>46</td>
<td>161</td>
<td>70</td>
<td>540</td>
<td>4.91</td>
<td>15</td>
<td>6</td>
</tr>
<tr>
<td>Operator D</td>
<td>Mean</td>
<td>97.0</td>
<td>15.3</td>
<td>7.6</td>
<td>66.8</td>
<td>8.5</td>
<td>58.8</td>
<td>31.4</td>
<td>12.8</td>
<td>2.53</td>
<td>6.4</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>0.21</td>
<td>0.21</td>
<td>0.31</td>
<td>0.37</td>
<td>0.31</td>
<td>0.37</td>
<td>0.16</td>
<td>2.46</td>
<td>0.37</td>
<td>0.22</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>671 Cycles</td>
<td>Min</td>
<td>11</td>
<td>8</td>
<td>2</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>19</td>
<td>0.23</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>139</td>
<td>24</td>
<td>23</td>
<td>165</td>
<td>32</td>
<td>131</td>
<td>59</td>
<td>476</td>
<td>5.57</td>
<td>17</td>
<td>5</td>
</tr>
<tr>
<td>All Data</td>
<td>Mean</td>
<td>100.3</td>
<td>16.0</td>
<td>8.3</td>
<td>68.5</td>
<td>8.4</td>
<td>62.5</td>
<td>32.7</td>
<td>17.4</td>
<td>2.30</td>
<td>6.4</td>
<td>3.1</td>
</tr>
<tr>
<td></td>
<td>COV</td>
<td>0.16</td>
<td>0.20</td>
<td>0.32</td>
<td>0.34</td>
<td>0.31</td>
<td>0.40</td>
<td>0.16</td>
<td>2.14</td>
<td>0.36</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>4522 Cycles</td>
<td>Min</td>
<td>11</td>
<td>8</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>16</td>
<td>0.067</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>139</td>
<td>24</td>
<td>30</td>
<td>180</td>
<td>46</td>
<td>175</td>
<td>70</td>
<td>540</td>
<td>6.17</td>
<td>17</td>
<td>6</td>
</tr>
</tbody>
</table>
Table 4.1 shows that the largest component of the cycle is the dig phase which on average accounts for about 50% of the cycle time. Swing time and return time each accounts for 25% of the cycle time which is lower than dig time portion. This could be due to low swing and return angles (<90°).

Among the parameters presented in Table 4.1, waiting time has the highest variation (highest COV) which is independent of machine performance. Furthermore, the largest variations within each cycle occur in the swing and return phases which are mainly controlled by the operator. Payload also has the lowest variation which demonstrates that operators try to adapt their digging technique to current digging conditions to achieve the desired payload which is the highest target load per pass without exceeding the truck capacity; therefore, it is mainly consistent from cycle to cycle. It should be noted that current loading practice is not an automated process and machine monitoring systems only help the operators to more consistently fill the bucket. The variations in payload can also be a representation of variations in productivity of the machine. Generally, operations are interested in lower variations in their shovel productivity which should be reflected in a narrow distribution of truck loads.

Table 4.1 also shows that although different operators have different average equivalent digging energy per cycle, they have similar average loading rates as well as mucking rates. Among the four operators, Operator A has the lowest loading rate and mucking rate while he has the highest average equivalent digging energy per cycle. It should be noted that Operator A encountered one of the easier digging conditions during the field trial. Operator B has the highest loading and mucking rates while he was digging one of the harder digging conditions during the field trial. The digging practice of these two operators will be compared in Section 4.3 using recorded
signals from PLC to better understand the effect of different operational parameters on the shovel performance. Operators C and D have not been chosen for comparison due to technical issues that caused the on-board shovel signals not to be recorded while they operated the shovel.

In order to further investigate the effect of operator on the machine productivity, especially digging, as described in section 3.6.2 a clustering analysis is performed and operators’ techniques during digging are compared. The results are presented next.

**4.2. Clustering of Shovel Cycles**

To classify shovel digging behavior and effort for the purpose of understanding the influence of operators on digging, first a 3D space of equivalent digging energy, dig time and payload for a total of 4522 cycles is built. Then, using the K-means method (Lloyd, 1982), this space is divided into four clusters. Figure 4.3 shows different clusters in the 3D space.
As the results of clustering show (Figure 4.3), clusters have been generated based on the equivalent digging energy which means that equivalent digging energy explains the majority of variability in the data. Therefore, a classification for equivalent digging energy based on the results of clustering analysis is presented in Table 4.2. This table illustrates that most cycles (70%) are within the range of average to high equivalent digging energy. Among all operators, Operator C has the highest percentage of cycles in the low energy class and the lowest percentage of cycles in the extremely high energy class while Operator A has the lowest
percentage of cycles in the low energy class and the highest percentage of cycles in the extremely high energy class.

Table 4.2. Equivalent digging energy classification

<table>
<thead>
<tr>
<th>Equivalent Digging Energy Class</th>
<th>Energy Range (tons x deg)</th>
<th>Percentage of Cycles (All Data)</th>
<th>Percentage of Cycles (Operator A)</th>
<th>Percentage of Cycles (Operator B)</th>
<th>Percentage of Cycles (Operator C)</th>
<th>Percentage of Cycles (Operator D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Energy</td>
<td>&lt;1.57</td>
<td>18</td>
<td>14.2</td>
<td>14.4</td>
<td>24</td>
<td>15.2</td>
</tr>
<tr>
<td>Average Energy</td>
<td>1.57–2.36</td>
<td>37</td>
<td>22.6</td>
<td>39.1</td>
<td>44</td>
<td>25.4</td>
</tr>
<tr>
<td>High Energy</td>
<td>2.36–3.23</td>
<td>33</td>
<td>34.2</td>
<td>36.2</td>
<td>27</td>
<td>37.5</td>
</tr>
<tr>
<td>Extremely High Energy</td>
<td>&gt;3.23</td>
<td>12</td>
<td>29</td>
<td>10.3</td>
<td>5</td>
<td>21.9</td>
</tr>
</tbody>
</table>

In order to further investigate the relationship between equivalent digging energy, payload and dig time, Figures 4.4 and 4.5 compare dig time and payload for the different classes of equivalent digging energy from Table 4.2.
Figure 4.4. Result of clustering analysis for comparison of payload and equivalent digging energy

Figure 4.5. Result of clustering analysis for comparison of dig time and equivalent digging energy
As the above figures show, dig time and payload vary widely across all the clusters, but Figure 4.4 indicates that the average payload increases with increasing equivalent digging energy. Similarly, Figure 4.5 shows that the higher energy clusters have higher average dig time. To combine the effect of dig time and payload, loading rate given by Equation 3.3 is analyzed.

Figure 4.6 shows how loading rate changes as equivalent digging energy increases. This figure indicates that there is no relationship between loading rate and equivalent digging energy (correlation coefficient = 0.0302). In addition, average loading rate is almost the same for all of the clusters (all energy classes). Therefore, one would conclude that variations in equivalent digging energy are caused by variations in muck-pile digging conditions or operators. However, even for one operator working in the same location (nearly same digging condition), equivalent digging energy will vary from cycle to cycle while average loading rate is almost constant. This can be explained by the effect of operator digging practice and its variability. Figure 4.7 compares loading rate values for different energy classes for Operator A. These results indicate that for this case the loading rate is independent of operator or digging condition.
Figure 4.6. Loading rate vs. digging energy for all operators

Figure 4.7. Loading rate vs. digging energy for Operator A

107
In order to further understand the effect of operator digging practice on the shovel performance, the digging practice of two operators (A and B) are compared in the next section. In addition to the data presented in Section 4.2 (from the PTM), the joysticks reference signals, as well as hoist rope retraction and crowd arm extension (from the Octagon computer), are analyzed for Operators A and B.

4.3. Operator Digging Practice

To study the effect of operator practice on digging efficiency, an evaluation of their hoist and crowd practices based on joystick signals was done. Figure 4.8 shows the hoist joystick reference signal for Operators A and B during a period of 250 s (5 cycles). The signals for Operators A and B have been annotated to show the start of digging (red circles), the end of digging (blue circles) and the end of the cycle (green circles). Similarly, Figure 4.9 shows the crowd joystick reference signals for Operators A and B for the same period of time.

---

15 Based on the algorithm presented in Section 3.5.2
Figure 4.8. Hoist joystick reference

Figure 4.9. Crowd joystick reference
The above figures show that each operator has a unique style in filling the dipper. Operator B has a smoother hoist action during digging while he frequently pulls the crowd joystick towards himself (retraction) which is shown as valleys in the crowd joystick reference signal. Although, the above signals exhibit some similar trends, it is clear that each operator has different digging habits/techniques. To better understand the effect of operator digging techniques on shovel performance, Figures 4.10 and 4.11 compare the average dig time and payload respectively for the different equivalent digging energy classes presented in Table 4.2. These figures show that average dig time and payload increase with higher equivalent digging energy classes. Figure 4.10 shows that Operators A and B have similar average dig time values except for the low energy class where Operator A has slightly lower (~1 s) average dig time.

Figure 4.10. Average dig time for different digging energy classes
In contrast to dig time, Figure 4.11 shows that for average to extremely high equivalent digging energy classes, Operator B has a higher average payload. In other words, to fill the bucket to the same payload, the shovel consumed more energy when Operator A worked. One might conclude that Operator A worked in harder digging conditions since the shovel consumed more energy during digging for the same payload as Operator B (Figures 4.11); however, based on the field observations, the blast engineer’s comments and operator’s comments, as mentioned before, muck-pile digging conditions were easier for Operator A. Therefore, to understand the differences in equivalent digging energy, as an example Figure 4.12 compares the digging trajectories of 5 consecutive cycles for each of the operators. This figure indicates that Operator A takes deeper cuts compared to Operator B which causes higher energy consumption.
According to past studies (Awuah-Offei and Frimpong, 2004 & 2007) the best operator digging practice is achieved by lower crowd extension speed and higher hoist rope retraction speed, which result in a decrease in the depth of cut. Such a practice should result in lower digging energy consumption per unit of loading rate known as specific digging energy. However, a limit of using specific digging energy as a measure of shovel performance is the inability to determine causes for its variations. In Section 4.2 it was shown that there is no relationship between equivalent digging energy and loading rate; therefore, based on the definition of specific digging energy, digging energy is not normalized for the effect of loading rate\(^\text{16}\). Additionally, digging energy can be affected by other factors, such as muck-pile digging conditions and machine type.

\[^{16}\text{This is based on the fact that shovels used in this study were equipped with a payload monitoring system.}\]
To demonstrate how operators control the machine during digging, hoist and crowd speeds are calculated for cycles presented in Figure 4.12 based on the approach described in Section 3.6.3.2. The results are presented in Table 4.3.

Table 4.3. Crowd and hoist speed values

<table>
<thead>
<tr>
<th>Operator</th>
<th>Cycle #</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Crowd Speed (m/s)</td>
<td>0.460</td>
<td>0.523</td>
<td>0.567</td>
<td>0.599</td>
<td>0.402</td>
<td>0.510</td>
<td>0.080</td>
</tr>
<tr>
<td></td>
<td>Hoist Speed (m/s)</td>
<td>0.692</td>
<td>0.816</td>
<td>0.518</td>
<td>0.528</td>
<td>0.571</td>
<td>0.625</td>
<td>0.127</td>
</tr>
<tr>
<td>B</td>
<td>Crowd Speed (m/s)</td>
<td>0.379</td>
<td>0.654</td>
<td>0.553</td>
<td>0.462</td>
<td>0.493</td>
<td>0.508</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>Hoist Speed (m/s)</td>
<td>0.782</td>
<td>0.617</td>
<td>0.766</td>
<td>0.591</td>
<td>0.792</td>
<td>0.709</td>
<td>0.097</td>
</tr>
</tbody>
</table>

Table 4.3 shows that the average hoist speed is higher for operator B while the average crowd speeds are almost the same for both operators. A combination of crowd and hoist speeds generates different digging trajectories, as shown in Figure 4.12, which directly affects the energy consumption and consequently shovel performance.

Therefore, to compare the digging performance of different operators, in contrast to the common approach of using one indicator, such as loading rate or specific digging energy, in this section, a rating system similar to surface excavating classification systems (Kirsten, 1982; Scoble and Muftuoglu, 1984; Hadjigeorgiou and Poulin, 1998) developed in the past is proposed based on the product of digging energy, loading rate, crowd speed and hoist speed:

\[ N = a_1 \times a_2 \times a_3 \times a_4 \] (4.1)
where $a_1$, $a_2$, $a_3$, $a_4$ are the numerical ratings of equivalent digging energy, loading rate, crowd speed and hoist speed, respectively. The product has been used in Equation 4.1 to simplify calculations and to be consistent with the work done by other researchers in the past.

Because of high variability in equivalent digging energy, a weighted average based on the percentage of cycles within each class can be used to calculate the numerical rating of digging energy ($a_1$):

$$a_1 = p_1 \times 5 + p_2 \times 4 + p_3 \times 3 + p_4 \times 2$$

(4.2)

where $p_1$, $p_2$, $p_3$, $p_4$ denote the percentage of cycles in low, average, high and extremely high energy classes, respectively.

Despite the fact that it was shown in Section 4.2 that loading rate is independent of the operator, to have a more generic equation it has been included in this approach. Additionally, equivalent digging energy is influenced by not only operator practices (crowd and hoist speeds) but also digging conditions and machine type. Therefore, to ensure that other factors such as digging conditions do not mislead the assessment, it is essential to include crowd and hoist speeds in addition to digging energy. It should be noted that the proposed formulation has operational purposes and is an experimentally derived approach that can be employed by different operations to assess digging performance of electric rope shovels operators.

The rating of each of the parameters in Equation 4.2 is subjective and their weights can change according to management policies. For example, if the focus of an operation is mainly on the volume produced, loading rate should have the highest weight in the rating system. Table 4.4 suggests an example of the rating system based on the observed data during the second field trial.
The ratings may vary from mine to mine with different types of operations and management strategies, and can be modified by operations as more data is collected. In this study, the classification for equivalent digging energy is based on the clustering analysis performed, and the classes for loading rate, hoist speed and crowd speed have been defined based on the observed distribution of data and the discussion with senior mine engineers. To be able to have a universal classification data needs to be collected from different types of operations and from different machines. The proposed rating/classification in Table 4.4 can only be used as a guideline. In this table, higher loading rates, lower digging energy, higher hoist speed and lower crowd speed should have higher rating numbers. Such a rating will result in higher N values for operators with a better performance. N values can be calculated for each operator per shift. To validate the proposed approach, Table 4.5 compares the N values for Operators A and B. Although Operator B was digging harder conditions, he has a higher N value compared to Operator A which means he has a better digging performance.

Table 4.4. Operator rating system

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rating</td>
</tr>
<tr>
<td>Loading Rate (tons/s)</td>
<td>&lt;5.4 5.4–6.9 6.9–8.8 &gt;8.8</td>
</tr>
<tr>
<td></td>
<td>4 6 8 10</td>
</tr>
<tr>
<td>Equivalent Digging Energy</td>
<td>Low Average High Extremely High</td>
</tr>
<tr>
<td></td>
<td>5 4 3 2</td>
</tr>
<tr>
<td>Hoist Speed (m/s)</td>
<td>&lt;0.6 0.6–0.7 0.7–0.8 &gt;0.8</td>
</tr>
<tr>
<td></td>
<td>1 2 3 4</td>
</tr>
<tr>
<td>Crowd Speed (m/s)</td>
<td>&lt;0.3 0.3–0.4 0.4–0.5 &gt;0.5</td>
</tr>
<tr>
<td></td>
<td>0.5 0.4 0.3 0.2</td>
</tr>
</tbody>
</table>
Table 4.5. N values for Operators A and B

<table>
<thead>
<tr>
<th>Operators</th>
<th>Loading Rate (tons/s)</th>
<th>Equivalent Digging Energy</th>
<th>Hoist Speed (m/s)</th>
<th>Crowd Speed (m/s)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>6.2</td>
<td>266,265.5</td>
<td>0.625</td>
<td>0.510</td>
<td>7.2</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>3</td>
<td>2</td>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>6.5</td>
<td>231,875.7</td>
<td>0.709</td>
<td>0.508</td>
<td>14.4</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>4</td>
<td>3</td>
<td>0.2</td>
<td></td>
</tr>
</tbody>
</table>
5. Effect of Digging Conditions on Shovel Performance

After studying the influence of operators on shovel performance in Chapter 4, in this chapter the effect of digging conditions is discussed. In particular the relationship between digging conditions and cycle time components, vibrations experienced by the shovel’s boom, shovel KPIs, dig forces and electrical power is investigated. The relevant results will be presented in following sections.

5.1. Time Studies

Based on the current literature, the relationship between muck-pile digging conditions and cycle time components is not conclusive. Some researchers agree that variation in dig time or cycle time depend on operator proficiency and digging trajectory and it is slightly related to muck-pile digging conditions (Hendricks 1990; Onederra 2004; Patnayak 2006, Sari and Lever 2000) while several studies reported the relationship between different muck-pile characteristics (such as mean particle size, uniformity index, pile density, looseness, P80) and loading efficiency including dig time (Doktan 2001; Brunton et al. 2003; Clark et al. 2004; Singh and Narendlura 2006 ; Tosun et al. 2013). Therefore, in the first field trial of this study dig time as well as swing and dump times were analyzed for different digging conditions to study the relationship between them and muck-pile digging conditions.

To facilitate the research, digital video records\textsuperscript{17} of the operation of an electric rope shovel during the first field trial (April 13-18, 2014) are analyzed to isolate different shovel activities and then to calculate dig, swing and dump time. The video records of continuous loading of 25 haul trucks (930 E) on the morning of April 16\textsuperscript{th} (case A) and 25 haul trucks (930 E) on the

\textsuperscript{17} A USB camera has been installed in the operator cab to record the entire shifts during the field trial.
morning of April 17th (case B) have been analyzed and dig, swing and dump times have been calculated. In case A, the shovel was mainly digging sandstone (Uniaxial Compressive Strength ~ 163 Mpa) while in case B the shovel was digging mudstone (Uniaxial Compressive Strength ~ 26 Mpa). The operator was the same on both days with over five years of experience, so it minimizes the effect of operator variability. Based on operator’s qualitative ranking, case A was relatively easy digging conditions while case B was classified as medium digging conditions\(^1\). Table 5.1 summarizes the details of two cases.

<table>
<thead>
<tr>
<th></th>
<th>Case A</th>
<th>Case B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rock Type</td>
<td>Sandstone</td>
<td>Mudstone</td>
</tr>
<tr>
<td>UCS</td>
<td>~163 Mpa</td>
<td>~ 26 Mpa</td>
</tr>
<tr>
<td>Shovel Operator</td>
<td>Same operator</td>
<td>Same operator</td>
</tr>
<tr>
<td>Shift</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Operator Diggability Ranking</td>
<td>Easy</td>
<td>Medium</td>
</tr>
<tr>
<td>Haul Truck</td>
<td>930 E</td>
<td>930 E</td>
</tr>
</tbody>
</table>

In order to represent the data, a boxplot and a histogram are used. Since the digging part of the loading cycle is the actual time that the dipper is engaged in the bank, and is directly influenced by muck-pile digging conditions, only the histogram of dig times is presented and the swing and dump times are only presented in the boxplot to describe the spread of them. Figure 5.1 illustrates the histogram of dig time and boxplot of dig, swing and dump times for case A.

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\(^1\) This should be noted that this classification can be subjective.
In Figure 5.1, DIG, SWG and DMP represent digging, swinging to haul truck and dumping actions respectively. The histogram shows that dig times are positively skewed and they range from 7 to 25 seconds. The boxplot also describes the spread of data and highlights outliers for dig, swing and dump times. The boxplot indicates that 25% of dig cycles are less than 11 seconds, 50% percent of them are between 11 and 14 seconds and 25% percent are above 14 seconds. A possible interpretation for these three segments based on analysis of video records is that dig cycles less than 11 seconds are mostly related to the fourth loading cycle and/or when the operator does partial face digging, dig cycles between 11 to 14 seconds are related to normal digging and finally digging cycles above 14 seconds are related to high depth of cut with high height of digging.
Similar to Figure 5.1, histogram and boxplot of data for case B are plotted in Figure 5.2.

Figure 5.2. Histogram and boxplot of case B

The histogram plot in Figure 5.2 shows that dig times range from 6 to 36 seconds. The boxplots also indicates that 25% of dig times are less than 12 seconds, 50% percent of them are between 12 and 16 seconds and 25% percent are above 16 seconds.

To compare cases A and B, Table 5.2 shows simple statistics for each one after removing outliers from the data. This table illustrates that the total number of cycles to fill 25 930E haul trucks (double side) in case A is 75 while in case B is 85. It indicates that in case B, the payload per pass is less than case A\(^ {19}\) and the shovel operator needed more cycles to fill the trucks. Mudstone in case B has a high moisture content and therefore stickiness. As a result, usually a portion of

\(^ {19}\) Assuming the operator fills the truck to its nominal capacity. During this field trial the shovel was not equipped with the payload monitoring system and the payload values were not available.
load sticks to the dipper door and walls, and to fill the truck to its nominal capacity, more loading cycles are required. Moreover, if the operator wants to fully dump each load in case B, more time and more movements of the dipper while dumping are required. Table 5.2 confirms that the average dump time in case B is almost twice the average dump time in case A.

Table 5.2. Time value statistics

<table>
<thead>
<tr>
<th></th>
<th>Case A</th>
<th></th>
<th></th>
<th>Case B</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dig Time</td>
<td>12.36</td>
<td>9</td>
<td>3.54</td>
<td>13.8</td>
<td>9</td>
<td>5.87</td>
</tr>
<tr>
<td>Swing Time</td>
<td>2.54</td>
<td>2.54</td>
<td>0.73</td>
<td>3.18</td>
<td>1.53</td>
<td>1.99</td>
</tr>
<tr>
<td>Dump Time</td>
<td>3.54</td>
<td>3.54</td>
<td>0.73</td>
<td>3.18</td>
<td>1.53</td>
<td>1.99</td>
</tr>
<tr>
<td>Min</td>
<td>7</td>
<td>5</td>
<td>2</td>
<td>6</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Max</td>
<td>18</td>
<td>16</td>
<td>5</td>
<td>21</td>
<td>13</td>
<td>11</td>
</tr>
<tr>
<td>Mode</td>
<td>12</td>
<td>7</td>
<td>3</td>
<td>13</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>Median</td>
<td>12</td>
<td>8</td>
<td>3</td>
<td>14</td>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>Total Number of Cycles</td>
<td>75</td>
<td></td>
<td></td>
<td>85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Number of Trucks</td>
<td>25</td>
<td></td>
<td></td>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rock Type</td>
<td>Sandstone</td>
<td></td>
<td></td>
<td>Mudstone</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Comparing dig time statistics in Table 5.2, average dig time in case B is slightly higher than case A. It also has higher variation in case B as indicated by the high standard deviation. The variation in dig time could be due to inconsistencies in operator digging practice. Even one operator can use different techniques from cycle to cycle. For example, to reduce dig time, the shovel operator could attack the muck-pile without digging the floor. In this case the operator digs the face half way to the crest to fill the bucket. However, in this way a bench with a flat surface and constant grade will not be achieved as desired and more time will be required later.
for preparing the bench. In addition, depth of dipper penetration (depth of cut) can vary and thus manipulate dig time. In hard digging conditions, the operator may take shallower paths to fill the bucket, so the dig time will be reduced. Finally, to reduce digging time even in hard digging conditions, shovel operators usually push rocks from the top portion of the bench to the toe during long waiting times to make it easier to dig. So dig times could be biased by operators and one should be cautious using them for assessing muck-pile digging conditions.

To statistically determine if different muck-pile digging conditions had any effect on dig, swing and dump times, two-sample t-test hypothesis testing with unequal variances is used. The null hypothesis is that the means of dig, swing and dump time for both cases (A & B) are equal. The results are shown in Table 5.3. The null hypothesis was rejected for both dig and dump time while it was accepted for swing time. Therefore, it is concluded that the difference between means of dig time and dump time for both cases (A & B) at 95 % confidence level is statistically significant while it is not significant for swing time, given the available data.

<table>
<thead>
<tr>
<th></th>
<th>Dig Time</th>
<th>Swing Time</th>
<th>Dump Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Case A</td>
<td>Case B</td>
<td>Case A</td>
</tr>
<tr>
<td>Number of Samples</td>
<td>73</td>
<td>84</td>
<td>72</td>
</tr>
<tr>
<td>Mean</td>
<td>12.36</td>
<td>13.8</td>
<td>9</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>2.54</td>
<td>3.18</td>
<td>2.54</td>
</tr>
<tr>
<td>Degree of Freedom</td>
<td>152</td>
<td>116</td>
<td>105</td>
</tr>
<tr>
<td>t-statistics</td>
<td>-3.1967</td>
<td>-0.0644</td>
<td>-9.9014</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0017</td>
<td>0.9488</td>
<td>1.1102e-016</td>
</tr>
<tr>
<td>H₀</td>
<td>μₐ=μₛ₉</td>
<td>μₐ=μ₄₉</td>
<td>μₐ=μ₄₉</td>
</tr>
<tr>
<td>Test Results²⁰</td>
<td>h=1</td>
<td>h=0</td>
<td>h=1</td>
</tr>
</tbody>
</table>

²⁰ If h = 1, this indicates the rejection of the null hypothesis at the α significance level. If h = 0, this indicates the acceptance of the null hypothesis at the α significance level.
Based on the t-test results at 95% confidence level, one would have to conclude that the means of dig times for the two cases are not equal. Then the hypothesis that dig cycles for case B are longer is examined. The null hypothesis ($\mu_B > \mu_A$) is accepted, so digging cycles are longer in case B. Mudstone because of its high moisture content and tight digging conditions, slows down the digging process and increases dig time.

Dig time highly varies based on different digging tactic and operator practices, but it can be combined with other indicators such as payload, hoist energy to assess muck-pile digging conditions. Moreover, based on the results of this time study, average dig time over a long period for one operator and machine type could be used to assess variations in muck-pile digging conditions; however, more cases are required to make a robust conclusion.

Based on the results of this study as well as the literature, it is believed that in addition to fragmentation size distribution, other characteristics of the muck-pile such as moisture content might influence muck-pile digging conditions. Moreover, it is believed that digging conditions could also vary within a muck-pile for different rock types. For example, based on the presented results it was shown that although sandstone (case A) has higher average UCS value compared to mudstone (case B), average dig time was lower in case A and the operator classified it as an easier digging condition which was well fragmented and loosened.

5.2. Vibration Data Analysis

In order to understand the relationship between vibrations and digging conditions, the data collected during the first field trial (April 13-18, 2014) are analyzed. A set of controlled studies has been performed in the field. The shovel operator has been asked to perform swinging, crowding, hoisting and air digging with an empty bucket in addition to the regular loading of
haul trucks. Figure 5.3 compares combined time domains of different activities for the first loading cycle of a 930E haul truck.

Figure 5.3. Time domain of vibration amplitude of first loading cycle

Figure 5.3 shows that the accelerometer experienced the highest vibrations over the digging and swinging back (return) parts of the cycle and experienced the lowest vibrations during dumping and waiting. The digging part of the loading cycle includes different phases. During the interval of 0-2 seconds the shovel was cleaning loose material near the toe of the muck-pile, so the accelerometer sensed less vibration. Then during the interval of 2-6 seconds while the shovel was digging the bench toe with harder digging conditions compared to the rest of the bench face, the accelerometer sensed more activities. Finally, during the interval of 6-18 seconds the dipper
followed a normal digging trajectory while it started clearing the bank (retraction) around the 15th second.

With respect to the waiting part of the loading cycle, as can be seen there is a high amplitude vibration around the 55th second. During the waiting time, the machine is in the steady state condition. Once the truck operator starts positioning to be loaded, the shovel operator usually hoists up the dipper and prepares to dump the load into the truck box. Therefore, at this moment the shovel’s structure experiences a high load around 250 tons (empty dipper + payload) which is overcome by electrical power and is reflected in the vibration time domain plot.

To see the frequency domain of different activities, Figure 5.4 shows the frequency domain content for different parts of the first loading cycle of a 930E haul truck. In order to be able to visualize the frequency data with lower amplitude the constant acceleration due to gravity has been removed in all the frequency plots to better see the frequency contribution of various activities.
Figure 5.4. Frequency domain content of different stages of first loading cycle of a 930 haul truck (A1-axis)

Figure 5.4 shows that there are similar frequency peaks that occur regardless of which part of the cycle the shovel was in; however, their relative amplitudes vary. It can also be seen from Figure 5.3, that the shovel’s boom experienced relatively higher apparent energy over the digging and swinging back parts of the cycle compared to swinging, dumping and waiting. Similar to the time domain in Figure 5.3, Figure 5.4 confirms that during dumping and waiting the accelerometer experienced the lowest level of vibration.

In order to further investigate the effect of digging conditions and vibrations, Figure 5.5 compares FFT plots of an actual digging cycle and air digging.
Figure 5.5. Frequency domain content of air digging and actual digging (A1-axis)
Figure 5.5 shows that the dominant frequency spikes occur at the same frequency for both air digging and actual digging with higher amplitudes observed for the actual digging as expected (~3 times higher). This observation confirms the hypothesis that under different digging conditions dominant frequencies of the digging cycle have different amplitudes which are related to digging conditions.

To further study this, two different operating cases (case A and case B) described in Section 5.1 have been evaluated. As mentioned in section 5.1 in case A, the shovel was mainly digging sandstone (Uniaxial Compressive Strength ~163 Mpa), while in case B, it was digging mudstone (Uniaxial Compressive Strength ~26 Mpa). The operator was the same on both days with over five years of experience, so it minimises the effect of operator variability. However, a single operator could use varying approaches to digging: different depth of penetration, different trajectories and different digging heights over the course of a shift which may affect the observed results. Based on operator’s qualitative ranking, case A is relatively easy digging conditions while case B was classified as medium digging conditions. Figure 5.6 shows an FFT plot of two digging cycles from case A and case B.

Similar to Figure 5.5, Figure 5.6 shows that the dominant frequency spikes are a match for both cases (A and B) though higher amplitudes (~2 times higher) are observed in case B where the shovel was digging mudstone. To understand what is happening, it is needed to consider the effect of payload and other factors such as digging trajectory and face profile\(^\text{21}\). As mentioned in Section 5.1 the mudstone in case B has high moisture content and tight digging condition and usually the operator should spend more time in the bank to fill the dipper. This can be a possible explanation for higher amplitudes in case B though more digging cycles as well as digging

\(^{21}\) This information was not available during the first field trial.
conditions should be analysed to better investigate the effect of different rock types on shovel boom vibrations.

Figure 5.6. Frequency domain content of two digging cycles from case A and case B (A1-axis)

In addition to the variation in digging conditions, operator performance and digging technique have to be taken into account for a more complete analysis. The vibration energy in any shovel activity could be a key operator performance indicator. To analyze the variation from operator to operator as well as variation with the same operator for different cycles requires analysis of vibration data over many cycles. As an example to this approach, vibration signals in the A1-
axis direction\textsuperscript{22} for the third loading cycle\textsuperscript{23} of three haul trucks with two different operators are compared in Figure 5.7.

Figure 5.7 shows that there are frequency spikes that are consistent for the loading cycles but there is variation in the vibration amplitude between different operators and even for the same operator as he/she loads a different truck. Another observation is that there are frequency spikes that only exist when only loading some of the trucks. For instance, there is a dominant frequency around 150 Hz during the swing back (return) period with high amplitude for the first and second haul trucks while there is none for the third haul truck. This shows the variability of operator influence on measured vibration. Furthermore, it can be seen from this figure that the boom experiences less vibration when operator Aʹ was digging compared to operator Bʹ. It should be mentioned that to be more thorough the results need to be normalised for payload and digging conditions. However, based on discussions with mine personnel, operator Aʹ was one of the more efficient operators at the mine and had been a shovel operator for over 30 years. This could explain the lower average vibrations values due to improved skill and experience.

In addition to the time and frequency domain analysis, the energy carried by the vibration signals has been also estimated using Equation 3.16 as a key shovel performance indicator. The related results will be presented next along with the results of other KPIs based on the PTM system.

\textsuperscript{22} Field observations show that the A1-axis of the accelerometer has higher amplitudes than the others during a loading cycle.

\textsuperscript{23} Third cycle was chosen as it had no waiting time and it was easier to isolate different actions using video recordings.
Figure 5.7. Frequency domain of A1-axis vibration during loading of three haul trucks
5.3. Effect of Digging Conditions on Sensor Data

A subset of sensors raw data from the PTM system, collected during the second field trial (July 13-17, 2015) for the easier and harder digging conditions marked in Figure 4.1, has been analyzed to better understand the effect of digging conditions on the shovel performance.

Examples of sensors data from the PTM system in easier and harder digging conditions during a period of 250 seconds are shown in Figures 5.8 and 5.9 respectively. As these figures show, bail force and crowd angle rate become more ragged in harder digging conditions. Additionally, it seems that more activities are recorded by the accelerometer\textsuperscript{24} in harder digging conditions.

\textsuperscript{24} The accelerometer was mounted on the bail as a part of the PTM system
Figure 5.8. A sample set of sensors data for easier digging condition
Figure 5.9. A sample set of sensors data for harder digging condition
To quantify the effect of digging conditions on shovel performance, in addition to the vibration energy (Equation 3.16) and KPIs presented in Section 3.6.1, bail force raggedness, average crowd rate and average equivalent power are estimated per pass based on the equations presented in Section 3.7.1. It is expected to have higher bail force raggedness, lower crowd rate and higher power in harder digging condition.

To be able to compare the easier and harder digging conditions, as an example, a subset of data from the morning of day shift for each case was analyzed. The results are presented in Table 5.4.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Easier Digging</th>
<th>Harder Digging</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>C.o.V</td>
</tr>
<tr>
<td>Vibration Energy</td>
<td>0.87</td>
<td>0.08</td>
</tr>
<tr>
<td>Bail Force raggedness</td>
<td>0.93</td>
<td>0.31</td>
</tr>
<tr>
<td>Average Crowd Rate (deg/s)</td>
<td>4.58</td>
<td>0.14</td>
</tr>
<tr>
<td>Average Equivalent Power</td>
<td>1038.52</td>
<td>0.16</td>
</tr>
<tr>
<td>average Equivalent Power/Payload (tons.deg/s)</td>
<td>10.13</td>
<td>12.11</td>
</tr>
<tr>
<td>Payload (tons)</td>
<td>102.53</td>
<td>0.13</td>
</tr>
<tr>
<td>Dig time (sec)</td>
<td>12.01</td>
<td>0.33</td>
</tr>
<tr>
<td>Average Equivalent Power/Payload</td>
<td>10.13</td>
<td>12.11</td>
</tr>
<tr>
<td>Total Number of Cycles</td>
<td>118</td>
<td></td>
</tr>
<tr>
<td>Operator</td>
<td>A</td>
<td></td>
</tr>
</tbody>
</table>

As shown in Table 5.4, dig time is lower in the harder digging condition which is explained by the better digging practice by operator B (Section 4.3). The vibration energy and bail force
raggedness are almost the same for both cases. The average crowd rate is higher in the harder digging condition which is due to a better digging practice used by operator B. Finally, in spite of the fact that Operator A was taking longer trajectories in easier digging conditions to fill the dipper, average equivalent power as well as average power per unit mass of materials loaded are higher in the harder digging condition.

To further investigate the effect of digging conditions on the power, the instantaneous equivalent power values for the cycles presented in Figures 5.8 and 5.9 are compared in Figure 5.10. The instantaneous equivalent power is given by Equation 3.14.

![Instantaneous equivalent power for easier and harder digging conditions](image)

Figure 5.10. Instantaneous equivalent power for easier and harder digging conditions
This figure shows that the instantaneous equivalent power dramatically increases to a maximum value upon the penetration of the dipper into the muck-pile. This increase reflects characteristics of muck-pile’s toe (toe hardness). The harder the digging conditions of the toe, the higher the instantaneous power value. According to a discussion with a shovel operator trainer at EVO, toe condition is one of the main factors which dominate ease of digging for a cycle. Once the obstruction is overcome (i.e. strong interlocking of fragmented rocks at the toe), the instantaneous equivalent power drops. However, it still may increase depending on impediments to dipper advance (i.e. interlocking of fragmented rocks). This observation confirms that the power and so the energy are sensitive to digging conditions.

5.4. Dig Force Analysis

To study the effect of different digging conditions on the dig forces, Figure 5.11 shows the bail force during the digging phases of different cycles for two digging cases: re-handled materials and blasted (waste) muck-pile.
Figure 5.11. Bail force vs. time for two cases of re-handled materials and blasted muck-pile

As the thick lines in the above figures show, in the re-handled materials case the plot of the bail force signals is close to a straight line while in the blasted muck-pile case the plot is pushed to the left and as the digging conditions get harder, the shape of the signal changes and it gets pushed further to the left. In an easier digging condition similar to the re-handled materials, the bail force gradually increases at an almost constant rate while in a harder digging condition the bail force rapidly increases to a maximum value to overcome the resistance to dig and to have a high efficiency both low and high in the bank.

The area under the $F_b$-$t$ (bail force-time) curve is a representation of the energy consumed during digging; however, it should be noted that the bail force at the beginning of the digging has an initial value of ~100 tons which is due to the weight of the empty dipper and the crowd arm. The
energy consumed by the shovel as a result of the weight of the dipper and the crowd arm should not be included in the diggability calculations as it is independent of the muck-pile conditions and depends on the machine type and bucket size. Figure 5.12 highlights the area under the $F_b$-t curve related to the empty dipper and the crowd arm weight.

Figure 5.12. $F_b$-t curve and the area related to the empty dipper and the crowd arm weight

In addition to the digging conditions, the position of the shovel relative to the face affects the ability of the dipper to achieve a proper depth of cut and so the effectiveness of the dipper’s available digging power. With a well-positioned shovel, the hoist rope should be close to vertical throughout the digging phase (P&H operator manual, 2005). In the current study the bail angle is monitored which can be an indicator of the position of the machine; however, the direct measurement of the distance of the machine from the face is out of the scope of this research.
5.5. Electrical Power Analysis

The digging forces described in section 3.7.3.1 are provided by heavy duty electrical motors (crowd and hoist) on-board the shovel. As shown by different researchers in the past (Hendricks 1990; Patanayak 2006) crowd motor responses are not sensitive to digging conditions; however, they have been included as part of the analysis in this research to be able to calculate the total energy consumed by the shovel during digging. In the crowd system, a band belt drive system couples the crowd motor to the transmission. While the crowd machinery provides the shovel with the crowd motion; this belt drive system helps with shock protection (4100XPB Mechanical Systems Manual, 2002). According to Hendricks (1990) it is believed that this belt is responsible for the relative lack of sensitivity of crowd motors responses to the digging conditions.

The instantaneous hoist and crowd power during the digging phase of two cycles are shown in Figures 5.13 and 5.14 respectively for two digging cases: re-handled materials and blasted muck-pile. The instantaneous power is given by Equation 3.1.
Figure 5.13. Hoist power vs. time for two cases of re-handled materials and blasted muck-pile

Figure 5.14. Crowd power vs. time for two cases of re-handled materials and blasted muck-pile
Similar to Figure 5.11, Figure 5.13 shows that for harder digging condition the $P_h$-t (hoist power-time) curve is pushed to the left and the area under the curve which is equal to the total hoist energy consumed during digging increases. Comparing the $P_h$-t (Figure 5.13) and $F_h$-t (Figure 5.11) curves, one would conclude that the mechanical bail force is more sensitive to the digging condition as it is measured on the bail using the PTM’s mounted load cell technology and is closer to the point of interaction between the bank and the dipper. Also, as expected crowd motor showed less sensitivity to variations in digging conditions.

Based on the results of past studies in the literature and discussion presented in this chapter, it became obvious to the researchers that the energy analysis is the correct approach for developing a robust diggability index. As such, the approaches presented in Sections 3.7.3.2 and 3.7.4 were developed for diggability assessment which will be evaluated in the next chapter.
6. Algorithm Evaluation

6.1. Background

To be able to validate the proposed diggability index in phase II of the research, field testing was done. The proposed index was built into the PTM system and implemented on two shovels (P&H4100XPC) as the first step. As mentioned in Section 3.2 a diggability trial was conducted and three test blasts with similar rock structure and characteristics were dug and the corresponding diggability data were collected. In addition to the test blasts, four cases consisting of re-handle, coal, fill and blasted waste were used to validate the developed diggability index. Once the validity of the developed index was confirmed, the new index was implemented on three more shovels. Currently, the diggability data are being collected on a real-time basis per pass and are stored in a SQL database from five shovels at Elkview mine.

As all the shovels at Elkview mine were equipped with the PTM system, the mine decided to implement only the mechanical approach. However, the data collected from the third field trial (Nov 22-27, 2015) was used to validate the electrical approach as well. This chapter presents the results of algorithm evaluation along with the current practice being used at EVO for visualization and analysis of the diggability data.

6.2. Dig Cycle Isolation Algorithms Evaluation

As the first step, the dig cycle isolation algorithms should be validated. To evaluate the mechanical and electrical algorithms presented in Sections 3.5.1 and 3.5.2 for dig cycle isolation, the video recordings related to 20 cycles during\textsuperscript{25} the third field trial (Nov 22-27, 2015) were analyzed and the dig time values were estimated to compare with the mechanical and electrical

\textsuperscript{25}During these 20 cycles the PTM system, Octagon computer and data collection laptops were synchronous.
approaches. Video recordings confirm that there are 20 passes for the same period of time and both algorithms detect 100% of passes. In addition to video recordings, the number of passes determined by the PTM system is equal to the one determined by video recordings as well as both electrical and mechanical approaches proposed in this thesis. Figures 6.1 and 6.2 compare the dig time estimated by Mechanical and Electrical approaches versus video recordings.

![Figure 6.1. Video recordings vs. mechanical approach](image-url)
Figures 6.1 and 6.2 show that the relationship between the dig time values derived from video recordings and electrical and mechanical approaches can be described by a linear function. Also, there is a strong correlation between dig time values derived from mechanical and electrical approaches (correlation coefficient = 0.83). These observations demonstrate the applicability of proposed approaches for dig cycle isolation.

6.3. Diggability Index Evaluation: Validation & Verification

In this section four case studies are presented. Different approaches such as histogram, normal distribution, contour map, etc. that are currently being used at EVO to present diggability data have been used to evaluate the diggability index. These case studies are as follow:
Case Study 1: During the period of March 3-7th, 2016 diggability data was collected from a P&H4100XPC shovel. The dig sequence has been shown in Figure 6.3.

![Figure 6.3. Dig sequence of P&H4100XPC shovel for the period of March 3-7th (Elkview operations, 2016)](image)

This figure shows that the muck-pile in the east side of the pit should represent easier digging conditions compared to the west side as it is mainly re-handled material. Also, the dig points in the east side of the pit include about 80 loads of free dumped materials. Figure 6.4 compares the histogram of diggability values for the two areas.
As expected and as Figure 6.4 confirms, diggability values in the re-handle area are lower than in the run of mine waste area. Table 6.1 summarizes the diggability values for these two areas.
The mean diggability values in Table 6.1 show that in the waste area the resistance force to dig (diggability) on average is about 20 tons\(^2\) higher per pass compared to the re-handle area. Based on the independent trials done by the mine during a period of several weeks and considering the large size of datasets, it can be considered that the observed difference in mean diggability values is not random.

Standard deviation values show a degree of variability in diggability. This can be caused by the presence of a mixture of different materials in each area as shown in Figure 6.3. For example lower diggability values in the waste area could be due to the free dumped material or loose material rolling down to the toe. To reduce the operational and geological variability and so to reduce the variability of diggability, it is suggested to average diggability values for blocks of “Burden×Spacing” size with a blasthole at the center of each block. In this case the average diggability values can also be compared with other blast related indices such as blastability index. However, this comparison is out of the scopes of this research. As an example for the

\(^{2}\) This is a measure of force
current case, diggability values are averaged over the blocks of 10m×10m (N,E). To present the results, a contour map is shown in Figure 6.5.

As expected, the contour map displays higher values for the waste area. Potentially, the blue and green islands shown on the map in the waste area are related to the free dump material loads. In order to see if other KPIs are capable to distinguish these two areas (waste, re-handle), dig time and loading rate are compared as histograms for the two areas in Figures 6.6 and 6.7 respectively.
Figure 6.6. Histogram of dig time values for re-handle material and run of mine waste

Figure 6.7. Histogram of loading rate values for re-handle material and run of mine waste
Figures 6.6 and 6.7 demonstrate that dig time and loading are not successful in distinguishing the two areas. Table 6.2 compares the mean and standard deviation of dig time and loading rate for the two areas.

Table 6.2. Summary of dig time and loading rate values

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Run of mine waste</th>
<th>Re-handling</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Dig time (sec)</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>Loading Rate (tons/sec)</td>
<td>14</td>
<td>11</td>
</tr>
</tbody>
</table>

Based on the presented values in Tables 6.1 and 6.2, on average diggability index is 19% higher in the waste area while dig time is the same and loading rate is 7% lower. Additionally, a comparison of standard deviation values shows that the diggability index has the lowest variability while loading rate is extremely variable. These results confirm the applicability of the developed index for diggability assessment.

*Case Study II:* During the period of July 15-19th, 2016 diggability data was collected from a P&H4100XPC shovel. Figure 6.8 displays the corresponding face.
Figure 6.8. The muck-pile related to case study II

The shovel operator feedback was that in the west side of the face digging was harder and moving towards east the digging gets easier. As a result, to be able to examine diggability values for the corresponding coordinates, the face was surveyed and different locations were marked in the mine grid coordinates. Figure 6.9 shows the surveyed face.
To examine the responsiveness of the diggability index as well as the dig time and loading rate to digging conditions, these KPIs are plotted against easting in the mine grid in Figures 6.10 to 6.12 respectively. It should be noted that they have been averaged over blocks of 10m×10m (N,E).
Figure 6.10. Averaged diggability index values

Figure 6.11. Averaged dig time values
Figure 6.12. Averaged loading rate values

Figure 6.10 shows that the diggability index decreases towards the east while Figures 6.11 and 6.12 display that dig time and loading rate do not show sensitivity to changes in digging condition. Similar to the case study I, these observations confirm the applicability of the diggability index for assessing digging conditions.

Case Study III: In March 2016, the mine sequence accommodated a diggability trial along strike where shovel heading, set up and rock characteristics (Rock type, Bedding type, Bedding dip, BI) were consistent (Elkview internal report, 2016). During the period of March 16-28 diggability data was collected from a P&H4100XPC shovel while digging the BR2-1800-03, BR2-1800-07 and BR2-1800-10 blasts including a fill area on the east side of the pit. Diggability data points are shown in Figure 6.13 as purple dots.
Diggability data are shown in Figure 6.14 as normal distributions (12510 cycles). As expected diggability values in the fill area were lower than in the blasted rock. Mean diggability was similar for all the three blast patterns ranging from 131-136 (tons) summarized in Table 6.3.
Figure 6.14. Diggability distributions (modified after Elkview Internal Report, 2016)

<table>
<thead>
<tr>
<th>Blast</th>
<th>Mean Diggability Index (tons)</th>
<th>Standard Deviation (tons)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BR2-1800-03</td>
<td>131</td>
<td>20</td>
</tr>
<tr>
<td>BR2-1800-07</td>
<td>134</td>
<td>15</td>
</tr>
<tr>
<td>BR2-1800-10</td>
<td>136</td>
<td>13</td>
</tr>
<tr>
<td>BR2-Fill</td>
<td>112</td>
<td>14</td>
</tr>
</tbody>
</table>

Comparing the mean values in Tables 6.3 and 6.1, it can be concluded that the average diggability index for the re-handled and fill materials are in the same range though the operators
and machines were different. This observation confirms independency of the diggability index from operators and also shows the applicability of the index for digging conditions assessment.

**Case Study IV:** All the cases that have been presented so far were based on the diggability data collected from the PTM system. To be able to evaluate the electrical approach as well, the dataset collected during the third field trial is used. Two cases of re-handled and blasted waste materials have been chosen for comparison. The diggability results have been shown as histograms and normal distributions in Figure 6.15. Mean and standard deviation values are also summarized in Table 6.4.

![Figure 6.15. Histogram of diggability values for re-handle and blasted materials](image-url)
Table 6.4. Summary of diggability values

<table>
<thead>
<tr>
<th>Material</th>
<th>Mean Diggability Index (tons)</th>
<th>Standard Deviation (tons)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Re-handling</td>
<td>109</td>
<td>38</td>
</tr>
<tr>
<td>Blasted muck-pile</td>
<td>125</td>
<td>29</td>
</tr>
</tbody>
</table>

As expected, the average diggability value for re-handled materials was lower which confirms applicability of the electrical approach for diggability assessment. Additionally, comparing the values in Tables 6.1 and 6.4, both mechanical and electrical approaches show almost the same average values for the re-handle case. A two-sample t-test hypothesis testing with unequal variances with the null hypothesis that mechanical and electrical diggability populations for re-handle have equal means was used. Based on the t-test results at 95% confidence level the null hypothesis was not rejected, so one would conclude that both approaches provide the same results for the same digging conditions, given the available data. However, the behavior of both indices should be studied for more cases to be able to make a conclusive conclusion. \(^{27}\)

6.4. Diggability Classification

The case studies presented in Section 6.2 revealed that the proposed index is able to distinguish different digging conditions. The next step is to classify diggability values to a few qualitative classes. This can be a base for a practical approach for diggability assessment. To be able to

\(^{27}\) It should be noted that electrical diggability was not collected for many cases and it hasn’t been implemented on any shovels for continuous data collection and then evaluation and improvement.
classify diggability values, diggability data was collected over a three month period for a P&H4100XPC shovel. The collected database has been filtered for material types: “Waste” (22050 cycles) and “Coal” (1752 cycles). Figures 6.16 and 6.17 show the diggability map for the waste and coal materials respectively.

Figure 6.16. Diggability map for waste
In Figure 6.16 and 6.17 the dots have been colour coded based on their diggability value to be able to define harder zones. Figure 6.16 displays a harder zone in the west side which is compatible with field observations and drill and blast engineer comments. To be able to compare waste and coal materials, their diggability histograms are presented in Figures 6.18 and 6.19 respectively.
Figure 6.18. Diggability histogram for waste

Figure 6.19. Diggability histogram for coal
Figures 6.18 and 6.19 show that as the digging conditions get easier the distribution will be positively skewed.

To be able to classify diggability values, the behavior of the new index should be observed under different digging conditions and materials. Based on the current field observations a classification is presented in Table 6.5. In this classification the digging conditions are divided into five groups of very easy, easy, medium, hard and very hard. It should be noted that the suggested range for DI is subjective and site specific. It requires comprehensive field studies per site to be able to come up with a more accurate range of DI values. The proposed range in Table 3.14 can be used as a guideline by different operations.

Table 6.5. Diggability classification

<table>
<thead>
<tr>
<th>Digging Condition</th>
<th>Description</th>
<th>DI Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Easy</td>
<td>Loose, free running and fine materials, free of boulders. This might include coal, finely crushed rocks and other material that is being re-handled.</td>
<td>&lt;75</td>
</tr>
<tr>
<td>Easy</td>
<td>Well fragmented and loose materials but some forces are required to dig specially at the toe. Occasionally big boulders could be seen. Heavily weathered materials such as weathered sandstone, clay and also coal could be included in this category. This might include re-handled as well as pushed materials.</td>
<td>75-115</td>
</tr>
<tr>
<td>Medium</td>
<td>Well fragmented but tighter materials (less looseness). Some forces are required to dig specially at the toe. The toe condition could be harder compared to the easy digging condition. Boulders could be seen as well. Mudstone is an example of materials in this category which has high moisture content and stickiness and occasionally results in a tight digging condition.</td>
<td>115-175</td>
</tr>
<tr>
<td>Hard</td>
<td>Larger fragments, less uniform and tight materials. Higher vibrations</td>
<td>175-250</td>
</tr>
<tr>
<td>Digging Condition</td>
<td>Description</td>
<td>DI Range</td>
</tr>
<tr>
<td>-------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>----------</td>
</tr>
<tr>
<td>are being sensed by the operators in the cab. Hard toe which requires excessive forces to penetrate into the bank. Some boulders can be seen. The materials in this category have some abrasiveness and are usually of medium density.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very Hard</td>
<td>Very poor fragmentation and looseness. Extra forces are required to dig materials out of the bank. Very hard toe which could cause excessive damages to the machine. Materials in this category usually have high abrasiveness, UCS and density.</td>
<td>250&gt;</td>
</tr>
</tbody>
</table>
7. Conclusion and Future Work

This thesis presented research results examining the performance of electric rope shovels in a steelmaking coal operation in Canada. Machine behaviour and efforts during digging as well as operator practices were closely monitored and studied to be able to establish an approach for post-blast assessment. The main objective of this research was to use shovels as a tool for diggability assessment and so quality of blasts. Diggability was defined as the resistance of materials to digging. To be able to develop an approach for determining diggability, shovels were instrumented. Additionally, pre-existing sensors belonging to a payload monitoring system called PulseTerraMetrix (PTM) were employed. A large dataset during different field trials was collected which included on-board shovel signals, vibration data, PTM’s raw sensors data and digital video recordings. The collected database was sorted based on the operator, shift and date and material types including waste or coal.

Two different algorithms were developed for diggability assessment: one based on the sensors that the PTM system has and the other based on the onboard shovel technology provided by P&H. At the end of the day, the two algorithms are expected to come up with similar results. The reason for two algorithms was to accommodate different shovel configurations at the mines. The algorithm based on the PTM system has already been implemented on five shovels at Elkview mine and the diggability data are being collecting on a real-time basis. In this study an approach was sought for diggability assessment that is independent of the operator. At the same time, it was needed to have an operational perspective and provide information on a real-time or near real-time basis. Also operations are interested in combining the diggability index with other
indicators, like load time and the location of the buckets for every scoop that is taken from the bank. With the developed methods all these features are possible.

The approach adopted in this research to develop a diggability index was based on the energy analysis of electric rope shovels during digging. More than one hundred thousand digging cycles were analyzed for development and testing purposes. Based on the presented results, the proposed index is able to distinguish different digging conditions. Diggability values can be reported per pattern, bench, operator and machine as a histogram, probability density function, colour coded scattered map, contour map, or they can be spatially plotted using GIS tools such as ArcMap.

7.1. Research Conclusions

The conducted research has provided a further understanding of shovels digging effort and behaviour as well as the effect of operators on machine performance. A comprehensive literature review was conducted and highlighted pros and cons of previously developed approaches for diggability assessment. Although a few metrics have been developed to assess diggability, it was found that no universally accepted and established method for digging assessment has been defined.

In order to meet the research objectives an approach was established to collect on-board shovel signals and performance data from the machine. A large database was collected including several key shovel performance indicators. The higher sampling rates used for collecting data in this research compared to the past studies provided an opportunity to better understand shovel behaviour.
Different key shovel performance indicators including dig time, swing time, return time, cycle time, loading rate, mucking rate and equivalent digging energy were determined and compared. It was found these KPIs are not suitable for diggability assessment and are significantly affected by operator performance. It was found that among different key shovel performance indicators for each operator, payload has the lowest variability. The low variability of payload values was found to be influenced by an operator’s response to the payload monitoring system. To further understand the digging practice of operators and to be able to normalize diggability for the effect of operator practice, digging trajectories were defined per pass either using bail and crowd angles or crowd arm extension and hoist rope retraction signals.

It was found that the joystick reference signals can be used to compare operator styles. It was shown that digging energy is not only a function of muck-pile digging conditions but also is a function of operator digging practice. Even for the same loading rate, a good operator operating the shovel in harder digging conditions can achieve lower digging energy by adjusting the hoist and crowd speeds. It was found that the operator with the lower hoist speed and higher crowd speed takes deeper cuts in the bank and the shovel consumes more energy during digging to achieve a targeted payload.

The research revealed that the bail force and hoist power are responsive to digging conditions. This knowledge was a basis to the development of an approach to use shovels as a tool for diggability assessment. It was shown that the proposed diggability index can reflect muck-pile digging conditions. Also, a classification for diggability values based on the field observations was presented. The next section summarizes the significant novel contributions of the research.
7.2. Research Novel Contribution

As mentioned before, the context of this research was focused on the performance monitoring of electric rope shovels in open pit operations for understanding and modeling the influences on digging. The novel contributions of this research include:

1. Two automated algorithms were developed to define the start and the end of the digging. These approaches support different shovel installations and are not site specific. Also, the proposed methods identify the moment of engagement and disengagement of the dipper in the bank. It was found that the accuracy of the diggability algorithm highly depends on how the digging part of the cycle is isolated. In the mechanical approach crowd angle, yaw rate (swing rate) and bail force were used to define the start and the end of digging while in the electrical approach hoist rope retraction, crowd arm extension, swing angle, dipper trip button and hoist power were used. The mechanical approach has been adopted by BTM WBM Canada for dig cycle isolation.

2. The knowledge gained through shovel performance monitoring revealed that diggability can be a more comprehensive post blast assessment measurement than fragmentation. Fragmentation only provides a size distribution, whereas diggability is responsive to all the properties of a muck-pile: the looseness, the fragmentation, the uniformity of the materials, the type of materials, the moisture content, and the hardness of materials.

3. It was shown that under different digging conditions, dominant frequencies of vibrations experienced by an accelerometer mounted on the side of the shovel boom have different
amplitudes which are related to the degree of difficulty of digging or muck-pile diggability. This confirms the applicability of continuous vibration monitoring of electric rope shovels for diggability assessment. Moreover, the effect of operator on shovel boom vibration was studied. It was shown that vibration analysis can be used as part of a system to monitor operator performance. Using recorded vibrations during different shovel activities for different operators, it is possible to set best operator practice and monitor operator performance on a real time basis.

4. A clustering analysis was performed to classify shovel digging effort and behaviour based on equivalent digging energy, dig time and payload. It was found that equivalent digging energy is the principal component which describes the majority of variability in the data. Therefore, based on the result of clustering analysis, a classification for equivalent digging energy was presented. It was shown that most of the cycles during the monitoring trial were in the range of average to high energy. The best operator practice should result in a higher percentage of cycles in the lower energy classes while maintaining consistent loading rate.

5. To compare operator digging performance an experimentally derived rating system based on digging energy, loading rate, hoist speed and crowd speed was proposed. Given the rapid implementation of onboard shovel performance monitoring systems, the proposed rating system should be easy to implement in mining operations.

6. Diggability was defined as the quantified resistance force to dig measured in tons. Two approaches based on mechanical and electrical measurements have been developed to estimate this index based on an energy balance and analysis of shovels during digging. The electrical approach was built upon the work done by previous researchers. However, this research is the first attempt to do the energy balance for diggability analysis. This study had
access to a variety of information such as payload, and the sampling rate was higher than previous work in literature. Also, the results were normalized for the effect of operator. Electrical calculations consider hoist and crowd motors current and voltage, dipper position, payload, dig height, dig time and digging trajectory.

7. This is the first work that used strain gauges, accelerometers, gyros and inclinometers for mechanical diggability assessment. As part of the energy balance, the potential energy was incorporated into the diggability calculations. The mechanical calculations consider bail force, dipper position, payload, dig height, dig time and digging trajectory. To isolate the effect of operators, the results were normalized based on the digging trajectory and the variation in digging height was considered as a part of potential energy calculations.

8. The developed diggability index has been implemented on a fleet of shovels and the diggability values have been collected per pass on a real-time basis. This provides a unique opportunity for further studies on shovel operations as well as drill and blast optimization.

9. Different methods were suggested to report diggability values. It is suggested to report an average diggability value for the blocks of Burden × Spacing size with a blasthole in the centre. This will reduce the operational variability. Also, to report results, histograms, pdfs, contour maps, colour coded scattered plots and spatial plots have been suggested.

7.3. Future Work

The following points summarize some of the main recommendations for future work to build on the outcomes of the current research:

1. The proposed diggability index is new into mining operations, so it should be implemented on more shovels to study its behaviour and variations with respect to different materials such
as pushed coal, insitu coal, pushed waste, fill, blasted waste and frost. It will help to come up with a proper classification. Also, the index was developed in a coal mine, but it is expected to produce the same results in metal mines. Future studies should also focuses on the metal mines.

2. The size of the bucket and machine conditions and type might have an effect on the diggability. Additionally, the proposed index was developed on P&H shovels. The effect of machine size and type on the diggability index should be considered in the future studies. Also, although the potential energy has been integrated into calculations, payload may still have effect on the diggability values because of higher frictions caused by higher payload values. As such, future studies may consider further normalization of diggability for payload.

3. The main focus of this study was to monitor the performance of electric rope shovels, to study their digging behaviour and efforts, to study the effect of operators and to develop a diggability index. However, future studies should consider how to use this diggability index to improve the productivity and to reduce mining costs. It is essential to define the acceptable and then optimum ranges of diggability which does not reduce productivity, does not damage machines and does not hurt operators through excessive vibrations. To be able to conduct this optimization extensive field observations and collaborations of maintenance, engineering and operation departments in a mine are required.

4. The electrical approach was not implemented on any shovels for continuous collection of diggability data and for further analysis and adjustments. As such it is suggested to develop a platform for implementation of the electrical approach on a shovel for further studies. Also, the electrical approach was developed on a DC derived shovel. It should be tested and
modified if necessary for AC derived shovels. Additionally, other data collection techniques can be considered.

5. Diggability reports can be created in the future to present results for different machine and operators during different shifts and for different locations. This will help operations and training departments to improve the performance of operators and the machine. Additionally, the data can be integrated into mine planning software such as MineSight or SURPAC or GIS tools such as ArcMap or ArcSED for visualization, design and analysis. Figure 7.1 shows an example of diggability data imported into ArcMap.
Figure 7.1. Diggability data integration into the ArcMap
7. The vibration sensor was mounted on the shovel’s boom. Further studies on the vibration analysis of electric rope shovels can be done for operator health and safety as well as performance assessment. Also, it can help to define the optimum range of diggability based on the amount of vibrations that the machine and the operator sense during the operation.

8. Diggability index is eventually supposed to help to optimize drilling and blasting practices. Future work should consider how to optimize drilling and blasting practices using the diggability index. Also, the relationship between diggability and blast design parameters, Measurement While Drilling data and other indices such as blastability index should be studied. Finally, the relationship between diggability and fragmentation related factors such as P80 should be studied.

9. The proposed index was developed for electric rope shovels. Future studies may consider developing an index for hydraulic shovels or other excavators adopting the approach used in this research.

10. The results of this study provided a better understanding of how operators control the shovels and how these machines operate. This can be a basis for developing automated or semi-automated excavators in future. Also, with advancement in technologies such as LiDar and their integration into the operating shovels, this process will be facilitated. Having LiDar on shovels, future research may study the effect of face profile and shovel distance to toe on the machine performance and the diggability.
References


176


P&H Mining (2005), *Operator Manual*.

P&H Mining (2006), *Internal Communications*.


Appendix I – Rock Mass Diggability Classification

To establish a system for equipment and method of excavation selection, Franklin et al. (1971) proposed a graphical rock quality classification based on the fracture spacing and point load strength. Figure 1 shows the prepared chart for excavatability (diggability) classification by Franklin et al. (1971). As this figure shows, excavatability is grouped into the dig, rip, blast to loosen and blast to fracture classes.

Figure A1.1. Rock quality classification system (after Franklin et al., 1971)

Kirsten (1982) introduced an excavation index based on four parameters: mass strength, block size, relative ground structure and joint strength which could be related to the excavation effort. This index was given by:

\[ N = a_1 \times a_2 \times a_3 \times a_4 \] (1)

Where \( a_1, a_2, a_3, a_4 \) are the numerical ratings of the aforementioned parameters. This excavation index was aimed to provide a tool for selecting the appropriate equipment and excavation method.

Similarly, Scoble and Muftuoglu (1984) introduced a diggability metric based on both ground conditions and equipment capabilities. The goal in developing a diggability index in this study
was to predict the effect of ground conditions on loading equipment performance. Similar to Kirsten (1982), they proposed four geotechnical parameters to calculate a diggability index. These parameters included rock unit intact strength (S), extent of weathering (W), joint (J) and bedding (B) spacing. Finally, the summation of these four parameters as a diggability index was employed to connect machine type and performance and ground conditions to geotechnical features. The diggability index rating and the relevant classification are presented in Tables 1 and 2 respectively.

Table A1.1. Diggability index rating (after Scoble and Muftuoglu, 1984)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Class</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weathering</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rating (W)</td>
<td>Completely</td>
<td>&lt;0</td>
</tr>
<tr>
<td></td>
<td>Highly</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Moderately</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>Slightly</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>Unweathered</td>
<td>25</td>
</tr>
<tr>
<td>Strength Mpa (UCS)</td>
<td>&lt;20</td>
<td>20-60</td>
</tr>
<tr>
<td></td>
<td>40-60</td>
<td>60-100</td>
</tr>
<tr>
<td></td>
<td>&gt;100</td>
<td></td>
</tr>
<tr>
<td>Is Mpa (50)</td>
<td>&lt;0.5</td>
<td>0.5-15</td>
</tr>
<tr>
<td></td>
<td>15-20</td>
<td>20-35</td>
</tr>
<tr>
<td></td>
<td>&gt;35</td>
<td></td>
</tr>
<tr>
<td>Rating (S)</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td></td>
</tr>
<tr>
<td>Joint Spacing m</td>
<td>&lt;0.3</td>
<td>0.3-0.6</td>
</tr>
<tr>
<td></td>
<td>0.6-1.5</td>
<td>1.5-2</td>
</tr>
<tr>
<td></td>
<td>&gt;2</td>
<td></td>
</tr>
<tr>
<td>Rating (J)</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>Bedding Spacing m</td>
<td>&lt;0.1</td>
<td>0.1-0.3</td>
</tr>
<tr>
<td></td>
<td>0.3-0.6</td>
<td>0.6-1.5</td>
</tr>
<tr>
<td></td>
<td>&gt;1.5</td>
<td></td>
</tr>
<tr>
<td>Rating (B)</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td></td>
</tr>
</tbody>
</table>
Table A1. 2. Diggability classification (after Scoble and Muftuoglu, 1984)

<table>
<thead>
<tr>
<th>Class #</th>
<th>Ease of Digging</th>
<th>Index ((W+S+J+B))</th>
<th>Plant which could be used without blasting</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Very Easy</td>
<td>&lt;40</td>
<td>Hydraulic Backhoe &lt;3 m³</td>
</tr>
<tr>
<td>2</td>
<td>Easy</td>
<td>40-50</td>
<td>Hydraulic Shovel &lt;3 m³</td>
</tr>
<tr>
<td>3</td>
<td>Moderate</td>
<td>50-60</td>
<td>Hydraulic Shovel &gt;3 m³</td>
</tr>
<tr>
<td>4</td>
<td>Difficult</td>
<td>60-70</td>
<td>Hydraulic Shovel &gt;3 m³</td>
</tr>
<tr>
<td>5</td>
<td>Very Difficult</td>
<td>70-95</td>
<td>Hydraulic Shovel &gt;3 m³</td>
</tr>
<tr>
<td>6</td>
<td>Extremely Difficult</td>
<td>95-100</td>
<td>Hydraulic Shovel &gt;7 m³</td>
</tr>
<tr>
<td>7</td>
<td>Marginal without Blasting</td>
<td>&gt;100</td>
<td>Hydraulic Shovel &gt;10 m³</td>
</tr>
</tbody>
</table>

Hadjigeorgiou and Poulin (1998) summarized various classifications that can be related to diggability. In this study an empirical ground classification for excavation in surface mines was presented which could be used for equipment selection. Table 3 shows different rock classifications for excavation purposes presented by Hadjigeorgiou and Poulin (1998).
Table A1.3. Rock classification schemes for excavation purposes (after Hadjigeorgiou and Poulin, 1998)

<table>
<thead>
<tr>
<th>Classification</th>
<th>Franklin et al.</th>
<th>Weaver et al.</th>
<th>Read et al.</th>
<th>Kristen et al.</th>
<th>Scoble &amp; Mouftouglou al.</th>
<th>Singh et al.</th>
<th>Smith et al.</th>
<th>Scoble et al.</th>
<th>Karpuz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uniaxial Comp. Strength</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Point Load Strength</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Schmidt Hammer</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Tensile Strength</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>No of Joint Sets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
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<tr>
<td>Volumetric Joint Count</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tbody>
</table>
To develop a comprehensive classification, data was collected from several mines in Canada about their equipment, geology and operating conditions. Hadjigeorgiou and Poulin (1998) defined ease of excavation as a characteristic of rock mass determined by its strength, structural features and weathering severity. As a result, point load strength of material and block size, derived from the number of joints per cubic meter or from visual review, as well as variation in weathering conditions and relative ground structure were chosen to derive an excavation index (EI). Different classes of EI values show different degrees of ease of excavation from easily excavated to ground conditions necessitating blasting. Tables 4 and 5 show the EI rating and the relevant classification respectively.

Table A1.4. Excavating index rating (after Hadjigeorgiou and Poulin, 1998)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Class</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Completely</td>
<td>Highly</td>
</tr>
<tr>
<td>Weathering Rating (W)</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td>Rock Strength Is Mpa (50)</td>
<td>0.5</td>
<td>0.5-1.5</td>
</tr>
<tr>
<td>Rating (Is)</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Block Size</td>
<td>Very small</td>
<td>Small</td>
</tr>
<tr>
<td>Volumetric Joint Count (Joint/m³)</td>
<td>30</td>
<td>10-30</td>
</tr>
<tr>
<td>Rating (Bs)</td>
<td>5</td>
<td>15</td>
</tr>
<tr>
<td>Relative Ground Structure</td>
<td>Very favorable</td>
<td>Favorable</td>
</tr>
<tr>
<td>Rating (Js)</td>
<td>0.5</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Table A1.5. Excavating classification (after Hadjigeorgiou and Poulin, 1998)

<table>
<thead>
<tr>
<th>Class #</th>
<th>Ease of Digging</th>
<th>Excavating Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>( ((I_s + B_s) \times W \times J_s) )</td>
</tr>
<tr>
<td>1</td>
<td>Very Easy</td>
<td>&lt;20</td>
</tr>
<tr>
<td>2</td>
<td>Easy</td>
<td>20-30</td>
</tr>
<tr>
<td>3</td>
<td>Moderate</td>
<td>30-45</td>
</tr>
<tr>
<td>4</td>
<td>Difficult</td>
<td>45-55</td>
</tr>
<tr>
<td>5</td>
<td>Blasting Required</td>
<td>&gt;55</td>
</tr>
</tbody>
</table>

The EI developed in this study was applied to 49 case studies which showed that if material diggability could be estimated to a desirable degree of confidence, the excavation equipment then would be properly sized and fully utilized.

In addition to experimental classifications, some diggability indices and classifications have been proposed in the past decade using data processing techniques such as fuzzy logic and artificial neural network. Iphar and Goktan (2006) applied fuzzy theory set to the diggability classification system developed by Scoble and Muftuglo (1984). They showed that fuzzy set theory could overcome the uncertainties associated with conventional classifications. Haghir Chehreghani et al. (2011) used artificial neural network to estimate rock mass excavatability. They aimed to establish a predictive relationship between rock mass and intact rock properties and excavatability of rock mass. This relationship could be a tool to predict rock excavatability and performance of machine at the design and planning stage. Input parameters to the model in this study were uniaxial compressive strength, tensile strength and discontinuities spacing of rocks and the output was volume of extracted rock (in cubic meter) per unit of power as the productivity indicator.

Rock mass classifications such as those mentioned in this appendix can only help to gain an initial understanding of actual conditions and they are mainly used at the preliminary stages for
equipment selection. However, to assess muck-pile digging conditions for operational activities, other methods such as shovel instrumentation and loading equipment performance assessment are required.
Appendix II – P&H4100XPB Shovel Specifications

### Operating Specifications

<table>
<thead>
<tr>
<th>Metric</th>
<th>Equivalent</th>
</tr>
</thead>
<tbody>
<tr>
<td>19.7 m</td>
<td>64.1 ft</td>
</tr>
<tr>
<td>39.4 m</td>
<td>129.2 ft</td>
</tr>
<tr>
<td>59.1 m</td>
<td>193.8 ft</td>
</tr>
<tr>
<td>78.7 m</td>
<td>258.3 ft</td>
</tr>
</tbody>
</table>

#### Capacity

<table>
<thead>
<tr>
<th>Description</th>
<th>Metric 1</th>
<th>Metric 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal Dipper Capacity</td>
<td>55.8 m³</td>
<td>73 yd³</td>
</tr>
<tr>
<td>Optimum Truck Size</td>
<td>172-363 m ton</td>
<td>190-400 ton</td>
</tr>
</tbody>
</table>

#### Performance

<table>
<thead>
<tr>
<th>Description</th>
<th>Metric 1</th>
<th>Metric 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nominal Cycle Time</td>
<td>29 s</td>
<td>29 s</td>
</tr>
<tr>
<td>Peak Propel Speed</td>
<td>1.6 km/h</td>
<td>1.0 mile/h</td>
</tr>
<tr>
<td>Gradability (Continuous)</td>
<td>17%</td>
<td>17%</td>
</tr>
</tbody>
</table>

#### Working Ranges

<table>
<thead>
<tr>
<th>Description</th>
<th>Metric 1</th>
<th>Metric 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Height of Cut (Max)</td>
<td>18.06 m</td>
<td>59 ft 3 in</td>
</tr>
<tr>
<td>Radius of Cut (Max)</td>
<td>23.80 m</td>
<td>78 ft 1 in</td>
</tr>
<tr>
<td>Depth of Cut (Max)</td>
<td>1.93 m</td>
<td>5 ft 4 in</td>
</tr>
<tr>
<td>Dumping Height (Max)</td>
<td>10.44 m</td>
<td>34 ft 3 in</td>
</tr>
<tr>
<td>Floor Level Radius</td>
<td>16.34 m</td>
<td>55 ft 7 in</td>
</tr>
<tr>
<td>Tail Swing Radius</td>
<td>9.83 m</td>
<td>32 ft 3 in</td>
</tr>
<tr>
<td>Operator Eye Level</td>
<td>10.08 m</td>
<td>33 ft 1 in</td>
</tr>
</tbody>
</table>
MACHINERY DECK PLAN

ELECTRICAL

INCOMING SUPPLY REQUIREMENTS

<table>
<thead>
<tr>
<th>Supply Voltage</th>
<th>7200 or 13800V</th>
<th>6000, 6600 or 11000V</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 Phase, 60 Hz</td>
<td>3 Phase, 50 Hz</td>
<td></td>
</tr>
</tbody>
</table>

Supply Transformer (Minimum) 3750 kVA
Minimum Short Circuit VA Available at Shovel 30 MVA
*Voltage per customer requirements.

TRANSFORMER

| Main Armature Transformer | 3000 kVA |
| Auxiliaries-Field Transformer | 435 kVA |
| Relays/Lighting Supply Winding | 50 kVA |

Note: Transformer capacities may vary depending on options.

P&E ELECTROTORQUE PLUS® AUTOMATIC REACTIVE POWER COMPENSATION

| Switched Steps | 60 Hz (9 step) | 50 Hz (8 step) |

P&E ELECTROTORQUE PLUS® STATIC DC POWER CONVERSION

<table>
<thead>
<tr>
<th>Component</th>
<th>Hoist/Propel</th>
<th>Swing</th>
<th>Crowd/Propel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Continuous Armature Converter KW Rating &amp; 600 VDC *</td>
<td>2x1000 kW</td>
<td>2x1000 kW</td>
<td>1000 kW</td>
</tr>
<tr>
<td>15 Sec. Armature Converter Current Rating</td>
<td>3700 amp.</td>
<td>3700 amp.</td>
<td>3700 amp.</td>
</tr>
<tr>
<td>150 amp.</td>
<td>150 amp.</td>
<td>150 amp.</td>
<td></td>
</tr>
</tbody>
</table>

1 Based on outside ambient temperature of 60°C or 122°F.
2 Cascaded hoist converters.

P&E DC FAST RESPONSE MAIN MACHINERY MOTORS

<table>
<thead>
<tr>
<th>Component</th>
<th>Continuous @ 600 volts</th>
<th>Peak developed power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hoist Motor (Two used)</td>
<td>Total 1857kW/2530hp</td>
<td>2880kW/3873hp</td>
</tr>
<tr>
<td>Swing Motor (Three used)</td>
<td>Total 1119kW/1500hp</td>
<td>1725kW/2313hp</td>
</tr>
<tr>
<td>Crowd Motor (One used)</td>
<td>Total 537kW/720hp</td>
<td>867kW/1162hp</td>
</tr>
<tr>
<td>Propel Motor (Two used)</td>
<td>Total 1074kW/1440hp</td>
<td>1372kW/1833hp</td>
</tr>
</tbody>
</table>

*Specifically designed for Electrotorque Plus® system.
CONTROL AND DIAGNOSTICS

ELECTROTORQUE PLUS® DIGITAL CONTROL
• Digital controls allow constant horsepower characteristics to be programmed for increased motion speeds which reduce overall cycle time.
• Programmable electrical parameters provide one-time setup and consistent optimum operation.
• New R.C delivery for the latest productivity enhancing P&H Smart Systems and Technologies, as well as for traditional sequencing, lube system, hoist and crow motion limit functions.
• Automatic Boom Soft Setdown and Boom Profile Protection Envelope guards against structural impact.

DIAGNOSTIC FUNCTIONS
• Touch Screen Monitors provide built in reference and fault tree diagnostic information with informational help screens accessed with touch screen convenience.

MECHANICAL

HOIST
• All gearing housed in single enclosed gear case with filtered oil circulation for reliable splash lubrication, ease of maintenance, and extended component life.
• Large 68” diameter hoist drum for extended rope bending life. Female becket system and electric tugger are standard for efficient rope change.
• Two spring set air release disc brakes - one per motor.

CROWD
• Powerband V-belt drive between motor and gear case absorbs shock loads.
• First and second reduction gearing in enclosed gear case for reliable splash lubrication, ease of maintenance, and extended component life.
• Twin leg dipper handle with tension box and rear and pinion drive has inherent stability in the bank for optimal digging.
• Single spring set air release disc brake.

SWING
• Three modular planetary gear cases of proven design and the single piece forged swing gear provide the torque for faster cycle times.
• Three spring set air release disc brakes - one per motor.

PROPEL
• Two rugged planetary gear cases of proven design transmit torque to the drive sprockets, producing the tractive effort required for fast, efficient propel and positioning operations contributing to greater digging time.
• Low tension sprocket drive system for improved lower works availability and life.
• Two spring set air release disc brakes - one per motor.

DIPPER
• OPTIMA™ PLUS dipper provides nominal 115 ton (104 metric ton) capacity.
• OPTIMA™ PLUS 80 and 90 dippers are interchangeable when lower nominal capacity is required.

DIPPER TRIP
• Adjustable torque electric motor with sealed planetary drive unit for reliable trip and slack take up operation.
• Both female becket and clamp system on drum with two part sheave arrangement on dipper for ease of maintenance.

OPERATOR’S STATION

MAN MACHINE INTERFACE
• Mounted on adjustable arm, on board side.
• System parameter display.
• Motion limit settings via touch screen.
• Lube and air system displays.

WALL CONSOLES (RH & LH)
• Ample panel space for various P&H productivity enhancing tools, communication systems, depiction systems, and fire suppression controls.

SIDE CONSOLES (RH & LH)
• Push button controls for start, stop, neutral and brake set/release.
• Climate controls, wipers, lights and other optional equipment control.
• Dimmable panel lights.

RH JOYSTICK (ARM MOUNTED)
• Hoist (propel).

LH JOYSTICK (ARM MOUNTED)
• Crow (propel).
• Dipper trip, horn.

AMPLE AREA FOR CUSTOMIZATION