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# A Study of Digging Productivity of an Electric Rope Shovel for Different Operators

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**Abstract:** A performance monitoring study of an electric rope shovel operating in an open pit coal mine was conducted. As the mining industry moves toward higher productivity, profitability and predictability, the need for more reliable, productive and efficient mining shovels increases. Consequently, it is critical to study the productivity of these machines and to understand the effect of different operational parameters on that. In this paper a clustering analysis is performed to classify shovel digging effort and behaviour based on digging energy, dig time and payload per pass. Then the influence of the operator on the digging efficiency and productivity of the machine is analyzed with a focus on operator technique during digging. A statistical analysis is conducted on different cycle time components (dig time, swing time, return time) for different operators. In addition to time components, swing and return angles as well as loading rate and mucking rate are observed and analyzed. The results of this study help to understand the effect of different operators on the digging productivity of the shovel and then to set the best operator practice.

**Keywords:** electric rope shovels; productivity; digging energy; operator; digging time

## 1. Introduction

Loading efficiency has a critical role in the success of the mining process as the loading equipment is the source of ore supply [1] or waste removal. An efficient loading practice can help to increase production and reduce cost. For instance, according to Scott and Mackee [2], one million dollars can be saved in a surface coal mine with a 1% improvement in loading efficiency. Therefore, it is essential to study and monitor the performance of loading equipment.

The electric rope shovel is one type of mining equipment primarily used in most large, high volume operations as a loading unit. 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 [3,4]. However, in addition to muck-pile characteristics, operator proficiency and skill play a significant role in the productivity of loading equipment [5–12].

This paper investigates the digging efficiency and productivity of a shovel and the effect of different operators on its performance. The shovel is currently operating in an open pit coal mine in Canada and the data has been collected during a week of field trials in the summer of 2015. The machine used in the present study is a P&H4100XPB shovel with a nominal dipper capacity of approximately 90 metric tonnes or approximately 48.4 cubic meters of material volume. The shovel's main functions during loading haul trucks include digging, swinging and dumping. The digging component is a combination of hoist and crowd actions. These functions are mainly accomplished by two hoist, one crowd and two swing motors on-board the shovel. Additionally, 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.

It should be noted that the onboard monitoring system on the shovel provides real-time feedback to the operator. The system was implemented to improve operator productivity and ensure consistent shovel performance. With this system, the operators adjust their digging tactics to current digging condition to achieve the highest productivity.

## 2. Background

Shovel productivity and performance are strongly influenced by operator proficiency. A well-trained operator is essential to achieve maximum productivity [10]. 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 productivity assessment. Some research studies have reported the effect of operators on shovel performance.

Hendricks [5] 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 [6], 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 [6] concluded that operator's style affects shovel productivity and duty loading.

In contrast to blasted muckpile digging, Patnayak *et al.* [8] 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" [8] (p. 133). Comparing average shift hoist and crowd motor power during different shifts and for different teams, Patnayak *et al.* [8] 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 [5] and Patnayak *et al.* [8], 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 [13] similar to Jessett [6] stated that operator style has a significant effect on shovel productivity. Similarly, Onederra *et al.* [7] , 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 [10] 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 [14] 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.* [15] 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 [16] 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.

## 3. Approach

### *3.1. Field Studies*

In this study data was collected during a one-week period using a commercially available fleet management and health monitoring system on-board the shovel. This monitoring system records data from sensors mounted on the shovel and processes them to estimate a comprehensive set of key shovel performance indicators (KPIs) per cycle. These KPIs include dig time, swing time, return time, swing angle, return angle, payload, and equivalent digging energy. This data is stored in a MySQL database and can be queried. In addition to the mentioned system, an embedded computer system, Octagon (Octagon Systems, Westminster, CO, USA) (Figure 1), has been installed in the shovel house to capture on-board shovel signals such as electrical motor responses and joystick reference signals. The Octagon computer records the data using an OPC (Open Platform Communications) interface. There is OPC bridge software installed on the two computers on the shovel. The software makes a connection to these bridges to collect the signals from digital side of the programmable logic controller (PLC). The signals pertaining to this paper include the hoist and crowd joysticks references as well as the hoist rope retraction and crowd arm extension. The sampling rate for these signals has been set at 20 Hz. Finally, in parallel to all of these data sets, the entire operation shift has been recorded using a USB camera mounted in the operator cab. These digital video records help to interpret collected data.


**Figure 1.** Octagon computer installed in the shovel house.

During the monitoring trial, four different operators worked the shovel; throughout the paper they are identified as ''Operator A", "Operator B", ''Operator C" and ''Operator D". The shovel was loading 315 tons trucks (930 E) from both sides (left and right) in 3 to 5 passes. Digging conditions were also assessed based on the operator comments, the blast engineer comments and the authors' field observations. Figure 2 shows the digging sequence of the shovel with different colours representing different dates during the field trial. As this figure displays, the shovel was mainly digging two blast patterns (1905-04 and 1905-06) and the edges of another one (1905-05) (Default blast design parameters for mentioned patterns include: Burden: 9.5 m; Spacing: 11 m; Bit Size: 13 inch; Bench Height: 15 m; Sub-drilling: 2 m). Two zones have also been identified in Figure 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 shifts and the authors couldn't make a conclusive statement about digging conditions while these operators were working.

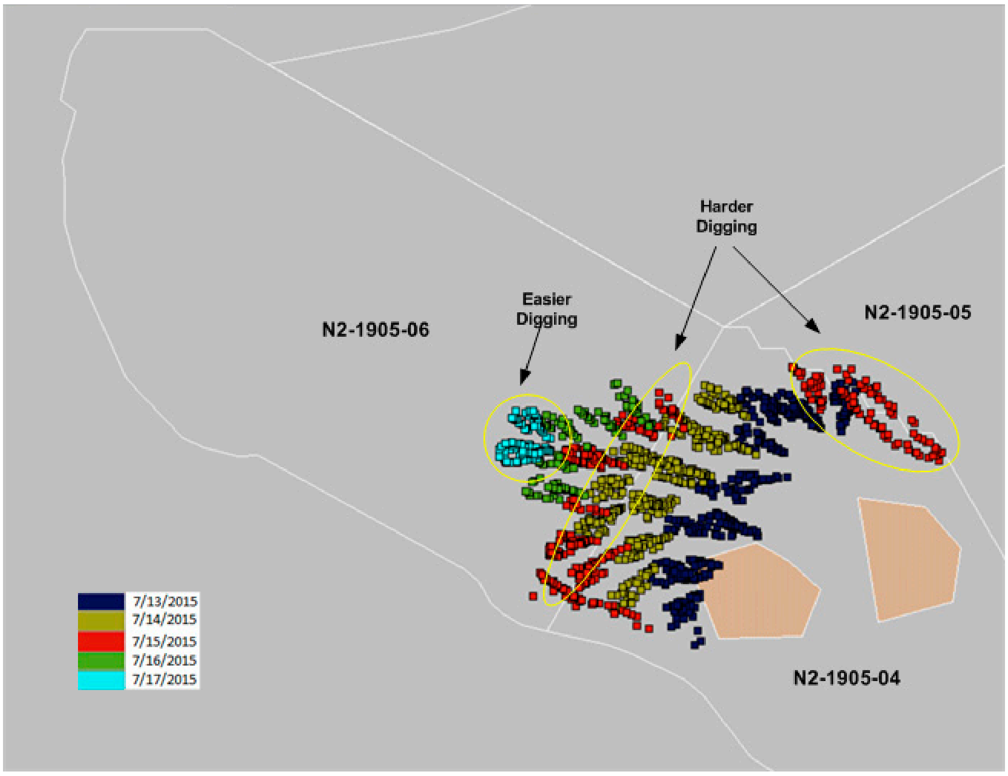


**Figure 2.** Shovel dig playback during the field trial (provided by mine).

### 3.2. Statistical and Clustering Analysis

As the first step in the analysis of the data collected during field studies, different shovel key performance indicators recorded by the commercial monitoring system on-board the shovel 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.

As the next step, to further investigate the effect of different operational parameters on the shovel performance, a clustering analysis is performed based on digging energy, dig time and payload per pass. 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 paper, to solve the clustering problem, K-means clustering technique is used because of its simplicity and speed in dealing with large datasets.

K-means [17] 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 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.

$$J = \sum_{x \in X}^{n} \mathrm{d}\,(x, c)^2 \tag{1}$$

where $c \in C$ and $\mathrm{d}\,(x, c)$ denotes the Euclidean distance between data points and each center. The details of K-means algorithm have been presented in [17].

In this paper, the number of clusters has been set as $k = 4$ to allow for the results from this work to be integrated into a diggability algorithm that is a subject of ongoing research. Additionally, Euclidian distance, the most common metric used for clustering, has been chosen to assign data points to each cluster.

Finally, K-means++ algorithm [18] has been used to initialize cluster centers. According to Arthur and Vassilvitskii [18], this algorithm improves the speed and quality of clustering of K-means.

In this paper to ascertain 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. The results of productivity analysis, as well as clustering analysis are presented next.

## 4. Analysis of Results

### 4.1. Productivity

A total of 4791 shovel cycles were monitored during the course of the field trial. As discussed in Section 3.1 a commercial monitoring system was used to record different shovel activities such as digging, swinging and returning. Additionally, the monitoring system detects and records activities that are not associated with loading the truck such as cleaning up the face. In this paper, such activities are not included in the analysis. As the current study mainly focuses on the digging part of each loading cycle, Figure 3 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 paper 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.

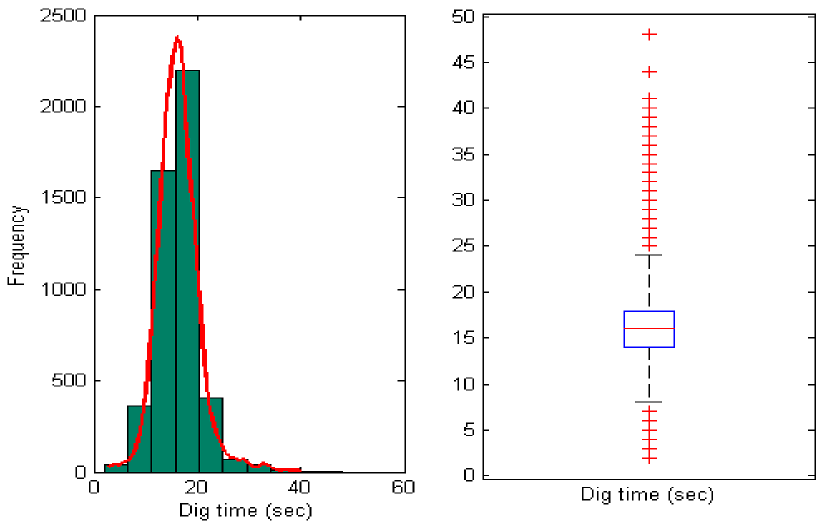


**Figure 3.** Dig time distribution.

Outliers were removed from the data and statistics for different KPIs were calculated. The KPIs include payload, cycle time components, swing and return angles, equivalent digging energy, loading rate and mucking rate. In this paper, 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 (The shovel monitoring system has been coded in this way). Equivalent digging energy, loading rate and mucking rate are also given by Equation (2) to Equation (4), respectively:

$$\text{Equivalent Digging Energy} = \int_{t_0}^{t_1} F_b \times \text{Crowd Rate}\, dt \tag{2}$$

$$\text{Loading Rate} = \frac{\text{Payload}}{\text{Dig time}} \tag{3}$$

$$\text{Mucking Rate} = \frac{\text{Payload}}{\text{Productive Cycle Time}} \tag{4}$$

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 all these KPIs are being estimated by the commercial monitoring system on-board the shovel using a suit of sensors such as load cells and gyro sensors. As Equation (2) shows the digging energy estimated by the monitoring system on-board the shovel is an equivalent mechanical energy (tons $\times$ rad) 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. This energy is provided by electrical DC motors on-board the shovel. A summary of the aforementioned KPIs for all of the operators is presented in Table 1.

Table 1 shows that the largest component of the cycle is the dig phase which on average accounts for about 50% of the productive cycle time. Swing time and return time each accounts for 25% of the productive 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 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 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 digging 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 PLC 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 component, a clustering analysis is performed and operators' techniques during digging are compared. The results are presented next.

**Table 1.** Key shovel performance indicators.

| Operator | Statistics | Payload (tons) | Dig Time (s) | Swing Time (s) | Swing Angle (°) | Return Time (s) | Return Angle (°) | Productive Cycle Time (s) | Waiting Time (s) | Equivalent Digging Energy (tons × rad) | Loading Rate (tons/s) | Mucking Rate (tons/s) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Operator A 589 Cycles | Mean | 98.3 | 16.4 | 8.2 | 68.8 | 8.6 | 62.3 | 33.3 | 18.9 | 266,265.5 | 6.2 | 3.0 |
| | COV | 0.17 | 0.20 | 0.31 | 0.36 | 0.24 | 0.36 | 0.15 | 1.94 | 0.36 | 0.26 | 0.19 |
| | Min | 13 | 8 | 2 | 9 | 1 | 0 | 21 | 0 | 36,461 | 1 | 0 |
| | Max | 133 | 24 | 18 | 180 | 27 | 173 | 53 | 373 | 588,114 | 15 | 6 |
| Operator B 1629 Cycles | Mean | 104.1 | 16.5 | 8.5 | 66.8 | 8.1 | 61.8 | 33.1 | 18.9 | 231,875.7 | 6.5 | 3.2 |
| | COV | 0.14 | 0.18 | 0.33 | 0.32 | 0.33 | 0.43 | 0.16 | 2.18 | 0.32 | 0.20 | 0.16 |
| | Min | 11 | 8 | 2 | 1 | 0 | 0 | 18 | 0 | 6717 | 1 | 0 |
| | Max | 139 | 24 | 30 | 166 | 36 | 175 | 67 | 411 | 617,241 | 15 | 6 |
| Operator C 1633 Cycles | Mean | 98.6 | 15.7 | 8.5 | 70.8 | 8.5 | 64.6 | 32.7 | 17.0 | 204,946.2 | 6.5 | 3.1 |
| | COV | 0.16 | 0.20 | 0.32 | 0.32 | 0.30 | 0.38 | 0.15 | 2.03 | 0.34 | 0.22 | 0.19 |
| | Min | 17 | 8 | 1 | 2 | 1 | 0 | 16 | 0 | 19,629 | 1 | 0 |
| | Max | 137 | 24 | 23 | 172 | 46 | 161 | 70 | 540 | 491,753 | 15 | 6 |
| Operator D 671 Cycles | Mean | 97.0 | 15.3 | 7.6 | 66.8 | 8.5 | 58.8 | 31.4 | 12.8 | 253,197.2 | 6.4 | 3.1 |
| | COV | 0.21 | 0.21 | 0.31 | 0.37 | 0.31 | 0.37 | 0.16 | 2.46 | 0.37 | 0.22 | 0.19 |
| | Min | 11 | 8 | 2 | 4 | 1 | 0 | 19 | 0 | 22,938 | 1 | 1 |
| | Max | 139 | 24 | 23 | 165 | 32 | 131 | 59 | 476 | 557,642 | 17 | 5 |
| All Data 4522 Cycles | Mean | 100.3 | 16.0 | 8.3 | 68.5 | 8.4 | 62.5 | 32.7 | 17.4 | 230,100.6 | 6.4 | 3.1 |
| | COV | 0.16 | 0.20 | 0.32 | 0.34 | 0.31 | 0.40 | 0.16 | 2.14 | 0.36 | 0.22 | 0.18 |
| | Min | 11 | 8 | 1 | 1 | 0 | 0 | 16 | 0 | 6717 | 1 | 0 |
| | Max | 139 | 24 | 30 | 180 | 46 | 175 | 70 | 540 | 617,241 | 17 | 6 |

### 4.2. Clustering of Shovel Cycles

To classify shovel digging behavior and effort, first a 3D space of digging energy, dig time and payload for total of 4522 cycles is built. These three parameters or a combination of them have been widely used as a measure of digging efficiency or shovel performance [4,5,7,8,16]. Then, using the K-means method [17], this space is divided into four clusters. Figure 4 shows different clusters in the 3D space.

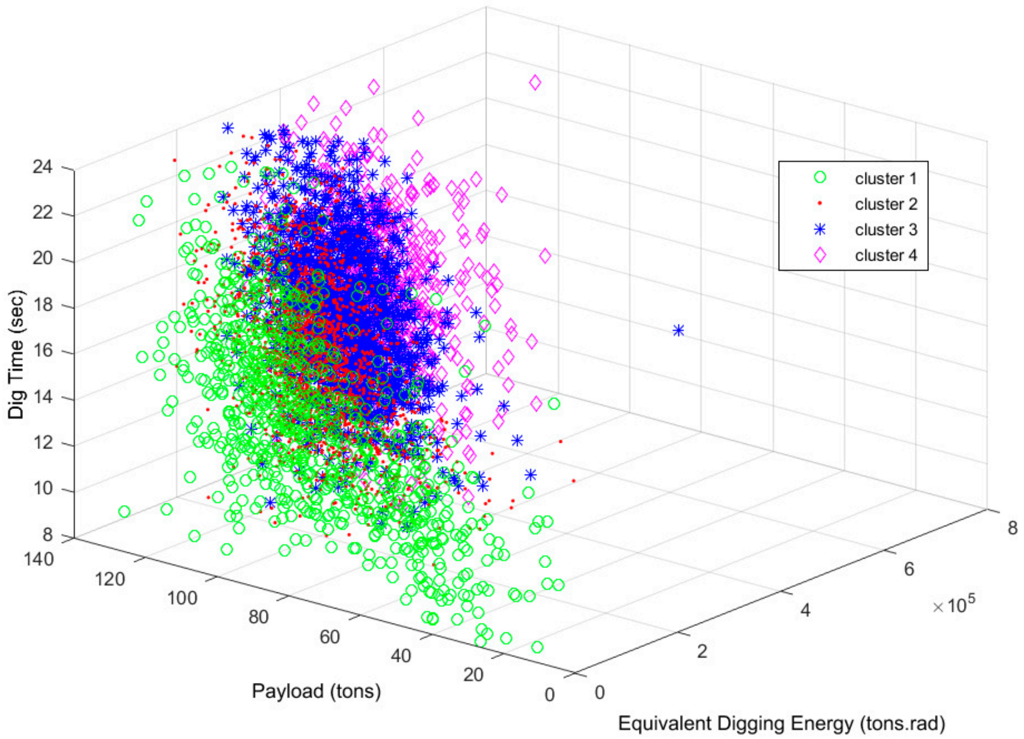


**Figure 4.** Generated clusters using K-means clustering method.

As the results of clustering show (Figure 4), clusters have been generated based on the digging energy which means that digging energy explains the majority of variability in the data. Therefore, a classification for digging energy based on the results of clustering analysis is presented in Table 2. This table illustrates that most cycles are within the range of average to high 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 2.** Digging energy classification.

| Digging Energy Class | Energy Range ($\times 10^5$) (tons $\times$ rad) | Percentage of Cycles (All Data) | Percentage of Cycles (Operator A) | Percentage of Cycles (Operartor B) | Percentage of Cycles (Operator C) | Percentage of Cycles (Operator D) |
|---|---|---|---|---|---|---|
| Low Energy | <1.57 | 18 | 14.2 | 14.4 | 24 | 15.2 |
| Average Energy | 1.57–2.36 | 37 | 22.6 | 39.1 | 44 | 25.4 |
| High Energy | 2.36–3.23 | 33 | 34.2 | 36.2 | 27 | 37.5 |
| Extremely High Energy | >3.23 | 12 | 29 | 10.3 | 5 | 21.9 |

In order to further investigate the relationship between digging energy, payload and dig time, Figures 5 and 6 compare dig time and payload for the different classes of digging energy from Table 2.

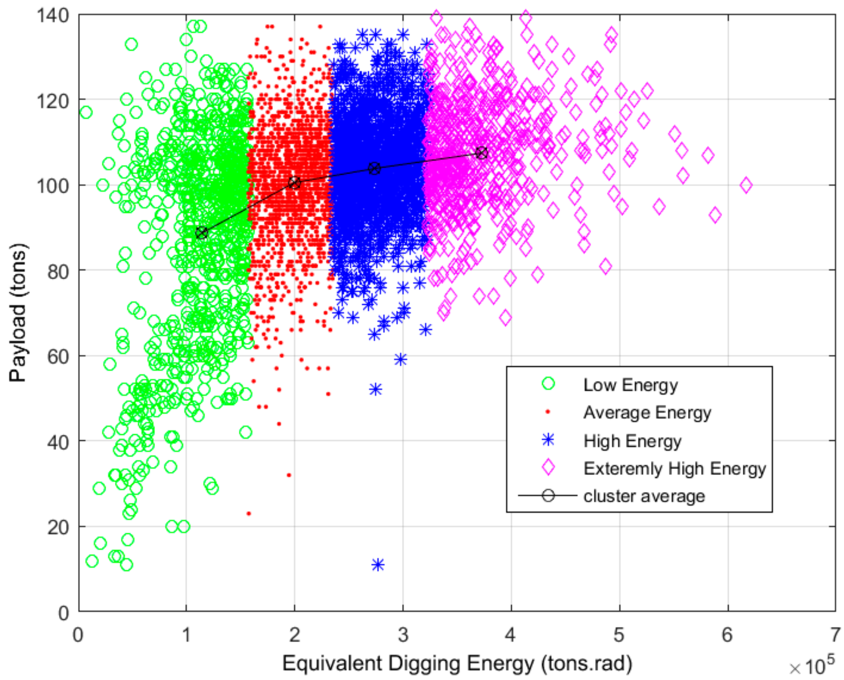


**Figure 5.** Result of clustering analysis for comparison of payload and equivalent digging energy.

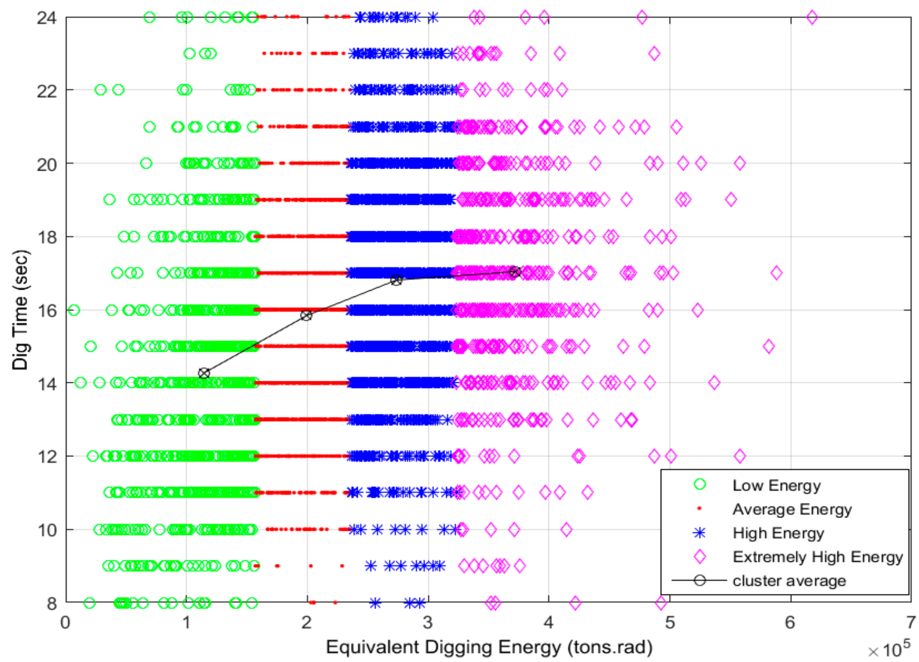


**Figure 6.** Result of clustering analysis for comparison of dig time and equivalent digging energy.

As the above figures show, dig time and payload vary widely across all the clusters, but Figure 5 indicates that the average payload increases with increasing digging energy. Similarly, Figure 6 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) is analyzed.

Figure 7 shows how loading rate changes as digging energy increases. This figure indicates that there is no relationship between loading rate and digging energy (correlation coefficient = 0.0302). In addition, average loading rate is almost the same for all of the clusters (all digging energy classes).

Therefore, one would conclude that variations in 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), 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 8 compares loading rate values for different digging energy classes for Operator A. These results indicate that for this case the loading rate is independent of operator or digging condition.

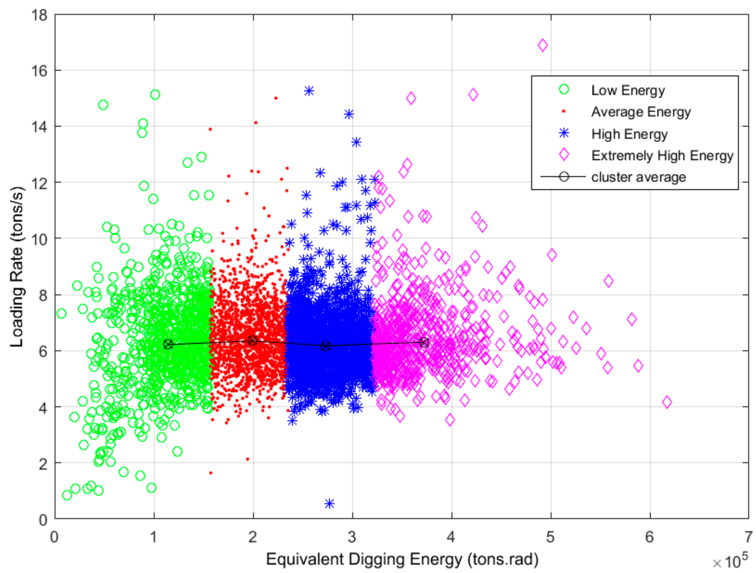


**Figure 7.** Loading rate *vs.* digging energy for all operators.

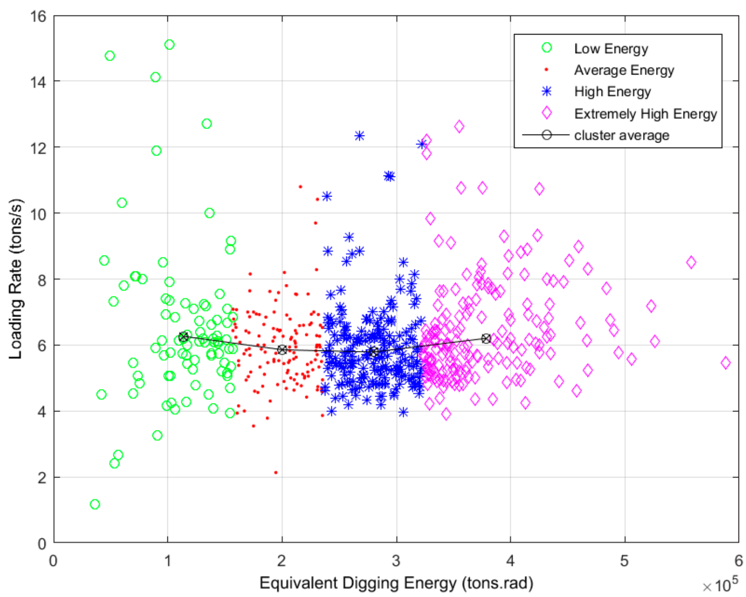


**Figure 8.** Loading rate *vs.* digging energy for Operator A.

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 commercial monitoring system), 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

As mentioned in Section 1, 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, an evaluation of their hoist and crowd practices based on joystick signals is done. Figure 9 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 10 shows the crowd joystick reference signals for Operators A and B for the same period of time.

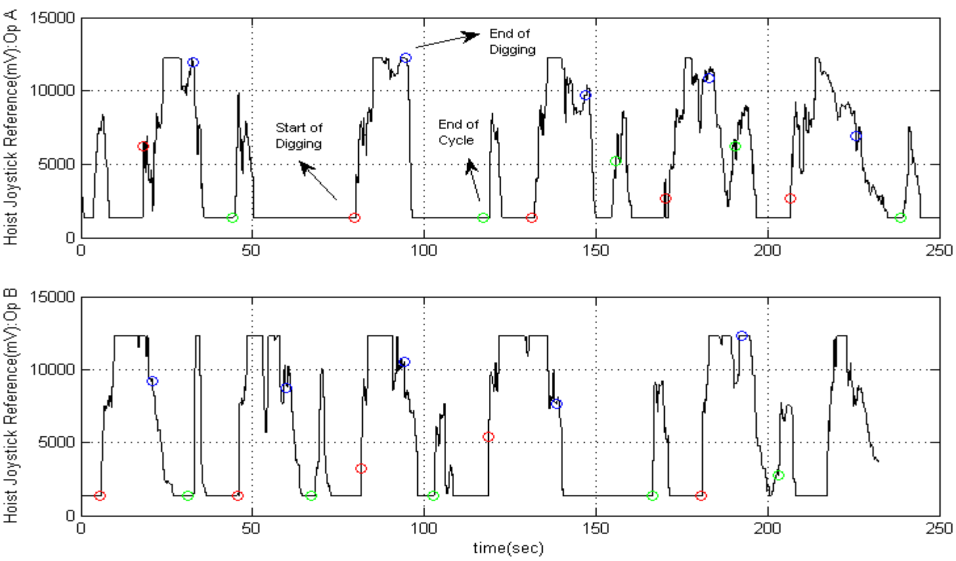


**Figure 9.** Hoist joystick reference.

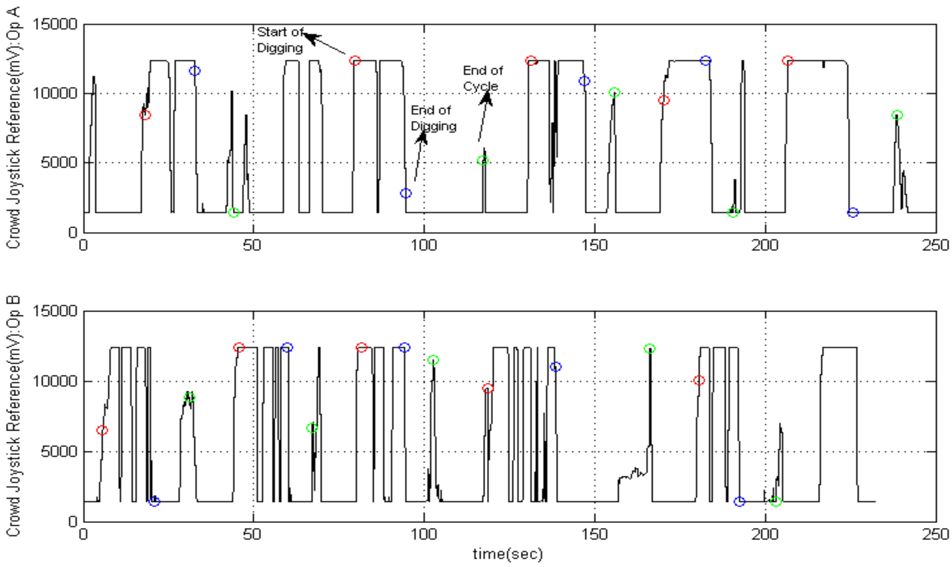


**Figure 10.** Crowd joystick reference.

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 11 and 12 compare the average dig time and payload respectively for the different digging energy classes presented in Table 2. These figures show that average dig time and payload increase with higher digging energy classes. Figure 11 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.

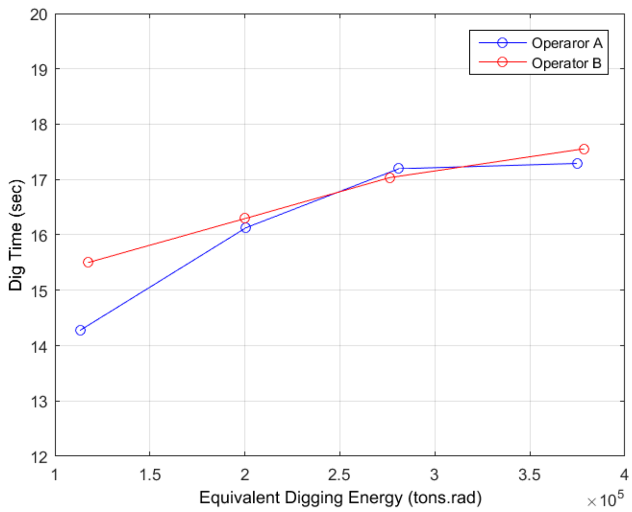


**Figure 11.** Average dig time for different digging energy classes.

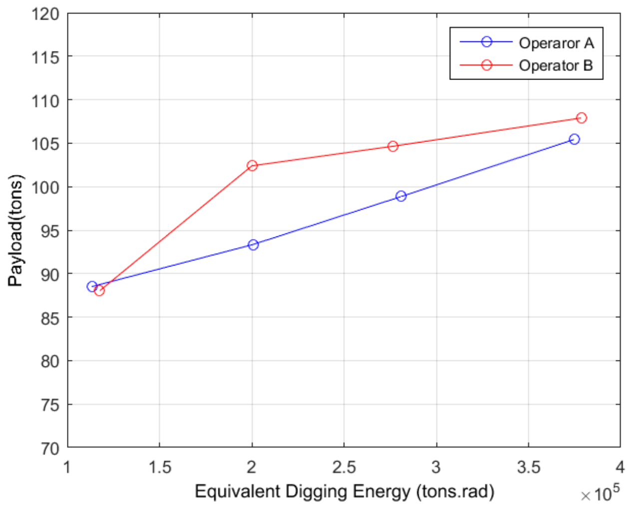


**Figure 12.** Average payload for different digging energy classes.

In contrast to dig time, Figure 12 shows that for average to extremely high 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 (Figure 12); however, based on the authors' field observations, the blast engineer's comments and operators comments, as mentioned in Section 3.1, muck-pile digging conditions were easier for Operator A. Therefore, to understand the differences in digging energy, Figure 13 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.

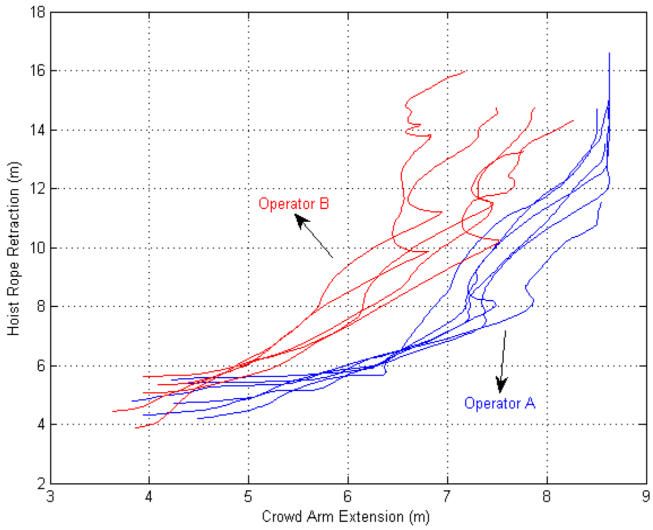


**Figure 13.** Digging trajectory for Operators A and B

According to past studies [16,19] 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 4.1 it was shown that there is no relationship between 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. Additionally, digging energy can be affected by other factors, such as muck-pile digging conditions and machine type and conditions.

To demonstrate how operators control the machine during digging, Figure 14 shows the crowd arm extension and hoist rope retraction during digging for 5 consecutive cycles for Operators A and B. In this figure, the slope of hoist rope retraction represents hoist speed and the slope of crowd arm extension represents crowd speed.

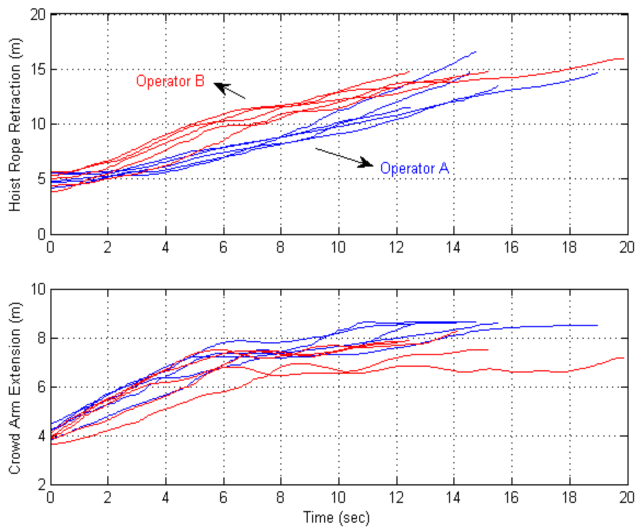


**Figure 14.** Hoist rope retraction and crowd arm extension for Operators A and B.

Figure 14 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. Comparing the two operators, Operator A has a lower hoist speed. The hoist speeds and associated R-squared values for cycles in Figure 14 are presented in Table 3. In contrast to the hoist rope retraction, Figure 14 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.

**Table 3.** Crowd and hoist speed values.

| Operator | Cycle # | 1 | 2 | 3 | 4 | 5 | Mean | Standard Deviation | Coefficient of Variation |
|---|---|---|---|---|---|---|---|---|---|
| Operator A | Crowd Speed (m/s) | 0.460 | 0.523 | 0.567 | 0.599 | 0.402 | **0.510** | 0.080 | 0.157 |
| | R-squared | 0.994 | 0.986 | 0.986 | 0.989 | 0.959 | | | |
| | Hoist Speed (m/s) | 0.692 | 0.816 | 0.518 | 0.528 | 0.571 | **0.625** | 0.127 | 0.204 |
| | R-squared | 0.954 | 0.966 | 0.992 | 0.983 | 0.995 | | | |
| Operator B | Crowd Speed (m/s) | 0.379 | 0.654 | 0.553 | 0.462 | 0.493 | **0.508** | 0.103 | 0.202 |
| | R-squared | 0.988 | 0.996 | 0.986 | 0.992 | 0.947 | | | |
| | Hoist Speed (m/s) | 0.782 | 0.617 | 0.766 | 0.591 | 0.792 | **0.709** | 0.097 | 0.137 |
| | R-squared | 0.983 | 0.961 | 0.978 | 0.942 | 0.970 | | | |

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 on the crowd arm extension values in the first part of the digging. Crowd speeds and the associated R-squared values are presented in Table 3.

Table 3 shows that the average hoist speed is higher for operator B while the average crowd speeds are almost the same for both operators. The R-squared values indicate that a straight line is the best fit to describe the data. A combination of crowd and hoist speeds generates different digging trajectories, as shown in Figure 13, 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 paper, a rating system similar to surface excavating classification systems [20–22] developed in the past is proposed based on the product of digging energy, loading rate, crowd speed and hoist speed:

$$N = a_1 \times a_2 \times a_3 \times a_4 \quad (5)$$

where $a_1$, $a_2$, $a_3$, $a_4$ are the numerical ratings of digging energy, loading rate, crowd speed and hoist speed, respectively. Because of high variability in 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 ($a_1$):

$$a_1 = p_1 \times 5 + p_2 \times 4 + p_3 \times 3 + p_4 \times 2 \quad (6)$$

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 4.1 that loading rate is independent of the operator, to have a more generic equation it has been included in this approach. Additionally, digging energy is influenced by not only operator practices (crowd and hoist speeds) but also digging conditions and machine type and conditions. Therefore, to ensure that other factors such as digging conditions don't 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 (5) 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 suggests an example of the rating system based on the observed data during the 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 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 mine senior 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 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 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.** Operator rating system.

| **Parameters** | **Class** | | | |
|---|---|---|---|---|
| | **Rating** | | | |
| Loading Rate (tons/s) | <5.4<br>4 | 5.4–6.9<br>6 | 6.9–8.8<br>8 | >8.8<br>10 |
| Digging Energy | Low<br>5 | Average<br>4 | High<br>3 | Extremely High<br>2 |
| Hoist Speed (m/s) | <0.6<br>1 | 0.6–0.7<br>2 | 0.7–0.8<br>3 | >0.8<br>4 |
| Crowd Speed (m/s) | <0.3<br>0.5 | 0.3–0.4<br>0.4 | 0.4–0.5<br>0.3 | >0.5<br>0.2 |

**Table 5.** $N$ values for Operators A and B.

| **Patarameters** | **Loading Rate (tons/s)** | **Digging Energy** | **Hoist Speed (m/s)** | **Crowd Speed (m/s)** | $N$ |
|---|---|---|---|---|---|
| | **Average Value** | | | | |
| | $a_i$ | | | | |
| Operator A | 6.2<br>6 | 266,265.5<br>3 | 0.625<br>2 | 0.510<br>0.2 | **7.2** |
| Operator B | 6.5<br>6 | 231,875.7<br>4 | 0.709<br>3 | 0.508<br>0.2 | **14.4** |

## 5. Conclusions

This study presented the results of performance monitoring of an electric rope shovel operating in an open pit coal mine in Canada. The effect of operator on shovel productivity was studied. The performance of four operators was compared. 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 the operator's response to the payload monitoring system.

A clustering analysis was performed to classify shovel digging effort and behaviour based on digging energy, dig time and payload. It was found that 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 digging energy was presented. It was shown that most of the cycles during the monitoring trial were in the range of average to high digging energy. The best operator practice should result in a higher percentage of cycles in the lower digging energy classes while maintaining a proper loading rate. Furthermore, average dig time and payload for different clusters were compared. It was concluded that average dig time and average payload increase toward higher digging energy classes. It was also shown that digging energy is independent of loading rate. Average loading rate was almost constant along different energy classes.

Furthermore, to demonstrate the effect of operator digging practice on shovel performance, two cases were selected and compared. It was found that the joysticks reference signals can be used to compare the operators' styles. It was shown that digging energy is not only a function of muck-pile digging conditions but also mainly is a function of 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.

To compare the operators' 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.

It is believed that a properly determined digging energy, which has been compensated for the effect of operator digging practice, can be part of an approach to measure muck-pile diggability and indirectly blast quality. Future work will study the effect of muck-pile digging conditions to develop a diggability index based on the shovel performance and independent of operator practice.

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