Statistical methods for evaluating the effect of operators on energy efficiency of mining machines

Maryam Abdi Oskouei*1 and Kwame Awuah-Offei2

Research has recognised operators’ skill as important factors affecting performance and energy efficiency of mining equipment. Modern monitoring tools generate large, highly variable, and, often, skewed energy efficiency data sets. Well-conceived statistical tests should be used to assess the effect of operators on energy efficiency in such situations. However, in many cases in the mining literature, the choice of statistical tests to evaluate operator effects has not been systematic and rigorous and, often, the underlying assumptions of these tests have not been examined before their use. This work provides a systematic method, synthesised from the statistical literature, to rigorously evaluate the effect of operators on energy efficiency of mining equipment. Mine engineers and managers can use this method to evaluate whether differences exist in energy efficiency of their operators given sample data and focus on operator training, if they find cause to improve operator performance.

Keywords: Energy efficiency, Mining equipment, Operators’ effect, Mining equipment performance, Statistical tests

Introduction

US Department of Energy (DOE) energy bandwidth analysis shows that the US mining industry consumes about 365bn kW h year⁻¹ (1246tn Btu year⁻¹) and there is a potential to reduce the annual energy consumption to 169bn kW h (579tn Btu), which is about 46% of current annual energy consumption. Digging equipment such as hydraulic shovels, cable shovels, draglines, continuous mining machines, and long-wall mining machines consume about 23bn kW h (79tn Btu) annually and, using a practical minimum (the so-called 2/3 rule), about 44% of this can be saved (U.S. Department of Energy (DOE), 2007). The high potential for energy savings in mining operations, particularly digging operations, has motivated mining companies to identify opportunities for improving performance and energy efficiency.

Different indicators, such as energy efficiency and specific energy, are used to describe the performance of digging equipment and operators. Generally, energy efficiency of an equipment or operation is defined as the ratio of useful work done (energy output) to the input energy (Zhu and Yin, 2008). In cases where either energy output or input cannot be measured easily, proxy parameters are used in their place. Table 1 shows several examples of this approach in the literature (Muro et al., 2002; Awuah-Offei et al., 2011; Acaroglu et al., 2008; Iai and Gertsch, 2013).

Specific energy (energy required to produce unit volume/mass of rock/soil) is widely used in excavation, tunnel boring, and soil cutting to measure efficiency of excavation, boring, or cutting processes (Muro et al., 2002; Acaroglu et al., 2008). For instance, Muro et al. (2002) in designing an experiment to estimate the steady state cutting performance, for varying cutting depth for a disc cutter bit, used specific energy as the measure of performance. Acaroglu et al. (2008) also used specific energy of a disc cutter for predicting the performance of tunnel boring machines (TBMs). Specific energy has also been used in drilling (Teale, 1965; Dupriest and Koederitz, 2005), shovel excavation (Awuah-Offei et al., 2005; Karpuz et al., 1992), and ripping (Iai and Gertsch, 2013). Specific energy is the inverse of energy efficiency, where material produced (payload) is used as a proxy for energy output. Hence, higher specific energy (or lower energy efficiency) is undesirable.

Operating conditions, mine planning and design, equipment characteristics and operator’s practice are factors that can affect the performance of digging equipment (Lumley, 2005; Bogunovic and Kecojevic, 2011; Awuah-Offei et al., 2011; Hettinger and Lumley, 1999; Kizil, 2010) (Fig. 1). In a given mine, maximising energy efficiency by changing the operating condition is difficult (e.g. changing blasting practices to change fragmentation) and sometimes impossible (e.g. climatic conditions). Also optimising the equipment mechanism can be costly. Mine planning and design is a viable way to maximise equipment efficiency. However, it is not always possible to achieve this objective. Of all these factors, operator’s practice and performance is,
probably, the most inexpensive factor to change. Training operators to improve their performance is a relatively cheap and valid approach in many cases. Before embarking on this type of improvement, it is critical to first establish that operators actually have an effect on energy efficiency (i.e. different operators have different energy efficiency numbers). This is not trivial in the presence of high data variability and asymmetry.

Often, large data on the indicator of performance (in this case, energy efficiency) can be acquired from machine monitoring systems. As these data are highly variable and, often, skewed, care must be taken not to draw conclusions on the effect of operators on energy efficiency just from comparing the sample means or performing statistical tests without considering the limitations of such tests. Such analysis can result in drawing incorrect conclusion and making poor decisions. Statistical analysis of data collected from monitoring systems is a common and valid tool that can be used to study the effect of operators on equipment performance. Many authors have assessed and compared operator’s performance using different criteria and statistical methods to identify best strategies to improve the efficiency of operations (Patnayak et al., 2007; Komljenovic et al., 2010; Awuah-Offei et al., 2011).

Patnayak et al. (2007) used one-way analysis of variance (ANOVA) and Tamhane’s T2 pairwise test to compare the average hoist and crowd motor power of four teams of operators to assess the effect of operators’ skills on shovel performance. They did not check the normality of the data and the equality of variances (the two conditions for ANOVA test) prior to conducting the ANOVA test. Komljenovic et al. (2010) presented an operator performance indicator (OPI) that specifically evaluates dragline productivity and energy consumption. OPI was defined as the dragline production divided by the dragline energy consumption in a given period of time. By assuming that the OPIs follow the t-distribution (when number of operators are less than 30) different confidence intervals were used to create a classification system to evaluate operators’ performance based on OPI (Komljenovic et al., 2010). This is essentially the t-test, which requires the data to be normal and equal variances – both assumptions were not verified. Awuah-Offei et al. (2011) used t-tests to study the differences in the fuel consumption and total cycle time of operators. Similar to Komljenovic (2010), they did not test for normality and equality of variance between operators.

The suggested methods in these works are limited to certain conditions because of assumptions made of the nature of the data (e.g. Komljenovic et al. (2010) assuming OPI follows a t-distribution). The authors could not find any work that provides general guidance on how to quantitatively evaluate (test) the effect of operators on energy efficiency of mining equipment. Data collected from digging equipment tend to have high variability. Making accurate inferences on whether different operators have significantly different energy efficiencies using the digging equipment in the presence of high variability and data skewness can be challenging.

In this work, a process to evaluate the effect of operators on energy efficiency of mining equipment is formulated. This process suggests the best statistical test for comparing the operators considering the properties of the data set.

**Proposed approach**

Any statistics based approach to study the effect of operators on energy efficiency relies on adequate and reliable data. Such data are available, these days, from equipment monitoring systems, provided care is taken to document who is running the machine at any time and the operating conditions. However, the data are often highly variable and skewed. Any approach to study the effect of operator practice on the energy efficiency of digging equipment should be able to handle the high variability in the measured data of the performance metric. For example, a simple comparison of the sample means of the metric is invalid because it does not address whether the difference in means of the metric for the operators is by chance (due to the sample) or is significant.

The metric could be any of the examples described in the previous section, which includes t kW⁻¹ h⁻¹ for draglines, tons/gal for truck and shovel systems, and specific energy for drilling and TBM operations. The analytical approach should be a function of the characteristics of the observed data. The specific measure of energy efficiency is of little consequence. The approach presented in this section can be applied to any mining machine so long as adequate and reliable data can be acquired for a suitable metric for energy efficiency.

The t-test and ANOVA are the two most common tests for comparing the means of different samples. The t-test is a pairwise test to compare average hoist and crowd motor power of four teams of operators to assess the effect of operators’ skills on shovel performance. They did not check the normality of the data and the equality of variances (the two conditions for ANOVA test) prior to conducting the ANOVA test. Komljenovic et al. (2010) presented an operator performance indicator (OPI) that specifically evaluates dragline productivity and energy consumption. OPI was defined as the dragline production divided by the dragline energy consumption in a given period of time. By assuming that the OPIs follow the t-distribution (when number of operators are less than 30) different confidence intervals were used to create a classification system to evaluate operators’ performance based on OPI (Komljenovic et al., 2010). This is essentially the t-test, which requires the data to be normal and equal variances – both assumptions were not verified. Awuah-Offei et al. (2011) used t-tests to study the differences in the fuel consumption and total cycle time of operators. Similar to Komljenovic (2010), they did not test for normality and equality of variance between operators.

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of type I error. ANOVA is a parametric analysis, which tests the hypothesis of equality of means between two or more sets. The null hypothesis is that the mean values of the data sets are the same against the alternate hypothesis that at least two sets have different means. For example, ANOVA can help infer whether all operators at a mine have essentially the same mean energy efficiency (null hypothesis) or at least two of the operators have different mean energy efficiencies (alternate hypothesis).

Each statistical test has specific assumptions and violating these assumptions can lead into misapplication of the test (Herberich et al., 2010; Ankara and Yerel, 2010). It is critical to choose a statistical test that is compatible with the nature of the data set. Preliminary data analysis can help to better understand the data and check for the assumptions of the tests. The best statistical test should be chosen based on the result of preliminary data analysis. The importance of preliminary data analysis and checking the assumptions before performing the test has been overlooked when comparing the performance of mining equipment (Patnayak et al., 2007; Komljenovic et al., 2010).

In the case of comparing the means between groups using ANOVA or t-test, preliminary data analysis includes estimating summary statistics, testing for normality, and testing for equality of variances. Figure 2 shows the suggested approach in this work, which can be used as a guideline to choose the optimal statistical test that is compatible with the data.

Both ANOVA and t-test require three assumptions. First, the observations should be independent. This assumption seems reasonable as we assume that performance of one operator does not affect the performance of other operators. However, the mine engineer should ensure this assumption is true through good data collection practices and experimental design. Second, the observations should follow a normal distribution. Graphical methods and quantitative methods can be used to test for normality of the data. Graphs such as histograms and quantile–quantile (Q–Q) plots, can be used to compare an empirical distribution and a theoretical normal distribution. Quantitative methods look at skewness and kurtosis of data and also the result of statistical tests of normality (such as goodness-of-fit tests) to check the normality of the data (Park, 2008). The Shapiro–Wilk (SW) (Shapiro and Wilk, 1965), Kolmogorov–Smirnov (KS), Anderson–Darling (AD) (Anderson and Darling, 1952), and Cramer–vol Mises (CM) (Anderson, 1961) tests are some of the common tests that are used to test for normality of a data set. SW test is the most powerful test; however, it is limited to sample sizes greater than or equal to 7 and less than or equal to 2000 (Shapiro et al., 1968; Stephens, 1974). For data collected from digging equipment monitoring systems, even for short periods of observation, the sample sizes are likely to exceed the range of support of the SW test. KS, AD, and CM tests are recommended for larger (>2000 samples) data sets. These tests are based on the empirical cumulative distribution (Park, 2008; Schlotzhauer, 2009). When the KS test is rejected it can be concluded that the data do not follow the normal distribution with the sample mean and sample variance; however it can be normal at other values of the mean and variance. AD and CM tests also share this weakness (Stephens, 1974; Drezner et al., 2010). Given the weakness of these statistical tests, it is helpful to consider the results of both quantitative and graphical methods when testing for the normality. It is probable that the data violate the assumption of normality. One approach to handle the violation of the normality assumption is to transform the data (typically using a natural log transformation).

The third assumption requires equal variances of the samples. Several statistical tests, including F-test, Bartlett’s test and Levene’s test, examine the differences in variation among two or more samples. The F-test and the related Bartlett’s test are too sensitive to normality of the data (Schultz, 1983). Levene’s test (Levene, 1960; Van Valen, 1978), which is an alternative to the F-test, is robust even when the data are not normally distributed (Levene, 1960; Van Valen, 1978). Hence, the authors suggest the Levene’s test to analyze the equality of variances in this work.

Welch ANOVA and Welch t-test, in which the third assumption (equality of variances) is relaxed (Welch, 1947), can be used to address the problem caused by violating the third assumption. Welch’s test is a practical, simple and accurate test. It is based on Student’s distribution with degree of freedom depending on both sample size and sample variance. In some cases, Welch’s test is recommended as a replacement of t-test even when the variances are equal (Rodgers and Nicewander, 1988; Krishnamoorthy et al., 2007).

To reduce the chance of misusing statistical tests, non-parametric tests can be used alongside parametric tests. Non-parametric tests have fewer assumptions compared to parametric tests. However, they are less powerful in detecting differences (Schlotzhauer, 2009). The Kruskal–Wallis test, which is a non-parametric equivalent test for the ANOVA, can be used instead of ANOVA (Wilcoxon–Mann–Whitney a replacement for the t-test) (Cody, 2011). The null hypothesis of this test is that all sets (more than two sets) have identical cumulative distribution function and the alternative hypothesis is that at least two of the sets differ only with respect to location (median). In this test, the assumption of normality is relaxed. When performed on log-transformed data the results may be invalid in the case of extremely skewed data (McEllduff et al., 2010).

To sum up, it is critical to check the assumptions of statistical tests before using them. The proposed approach (Fig. 3) presents a systematic means to study...
the effect of operators on energy efficiency. The \( t \)-test and ANOVA are the two common tests for comparing the means of two or more than two data sets, respectively. Data should follow a normal distribution for valid results of ANOVA and \( t \)-test. Quantitative and graphical methods can be used to test for normality. Non-parametric tests, such as Kruskal–Wallis and Wilcoxon–Mann–Whitney, can replace ANOVA and \( t \)-test when the data are not normal. Equal variance between groups is another assumption of the ANOVA and \( t \)-test. Welch ANOVA and Welch \( t \)-tests are not sensitive to equality of variances and can be used in place of ANOVA and \( t \)-test when the assumption of homogeneity (equality of variances) is violated. Figure 3 describes the suggested algorithm of choosing the statistical test compatible with the data set, for both cases of two and more than two operators. The result of valid statistical tests can be used to investigate the effect of operator practice on the performance of digging equipment.

### Case study

Data collected from a Bucyrus-Erie 1570w dragline with bucket capacity of 85 yd\(^3\) are used here to illustrate the suggested method. The main duty of the dragline in this mine is to remove the overburden above the coal seam(s). During the 1-month data collection period, the material type remained, essentially, constant as the dragline was operating in one pit. During the period, 13 operators worked on this dragline. Five of these operators, with sufficient working hours, were selected for this analysis (Abdi Oskouei and Awuah-Offei, 2014). Accuweigh (Tyler, TX, USA) monitoring system on this dragline was modified (the programmable logic controllers were reprogrammed) to record energy consumption of drag, hoist, and swing motors. In this study, dragline energy efficiency is introduced as an indicator of an operator’s performance. Energy efficiency of dragline can be determined using the following equation

\[
\eta = \frac{P}{E_t} \tag{2}
\]

where \( \eta \) is the energy efficiency, \( P \) is the weight of material moved by the dragline (payload), and \( E_t \) is the total energy consumed by drag, hoist, and swing motors during the cycle.

The energy efficiency of the five operators under review was calculated for each productive cycle using equation (3). Table 2 shows the summary of operator performance (after removing outliers) during the data collection period

\[
\eta(i) = \frac{P(i)}{E_d(i) + E_s(i) + E_h(i)} \tag{3}
\]

where \( \eta(i) \) is the energy efficiency for cycle \( i \); \( P(i) \) is the payload for cycle \( i \); \( E_d(i) \) is the drag energy for cycle \( i \); and \( E_s(i) \) and \( E_h(i) \) is the hoist energy for cycle \( i \).

Figure 4 shows the boxplots of the energy efficiency of the five operators. Obviously, the data are highly variable. As with the mean energy efficiency data (Table 2), one can rank the operators in decreasing order of median energy efficiency as E, A, C, D and B. Although, the mean and median energy efficiencies vary from operator to operator, it is difficult to conclude from summary statistics and plots (e.g. Figure 4) alone whether this variation is significant or not (i.e. because of sampling). This requires further analysis, which is the scope of this paper.

### Normality

Preliminary data analysis includes testing for normality and testing the equality of variance as described in the methodology section. KS, CM, and AD tests were carried out at significant level of 0.05 to examine the normality of data. Table 3 shows the results of these tests. The results of these tests show that the null hypothesis in all these tests (data follow normal
distribution) is rejected and energy efficiency of none of the operators follows the normal distribution (all \( p \)-values are less than 0.005). Log transformation is commonly used to reduce the skewness of the data (Zhou et al., 1997). Even after log transformation, the results (Table 4) of the statistical tests indicate that the transformed data are not normal.

Given the weakness of these statistical tests, it is important to also use graphical methods to gain a better understanding of the nature of the data. Figure 5 shows histograms of energy efficiency for the five operators. It can be seen that the data have right skewness and non-normal. Figure 5 shows that the transformed data are closer to the normal distribution. \( Q-Q \) plots were also used to study the effect of log transformation of the data. These plots compare ordered values of a variable with quantiles of a normal distribution. The closer the data are to the normal distribution, the closer the points will be to the linear pattern passing through the origin (Johnson and Wichern, 2007). Figure 6 displays these \( Q-Q \) plots of the original data and the log-transformed data. The comparison between the \( Q-Q \) plots and histograms indicates that log transformation made the data more normal.

Equality of variance

The results of the statistical tests show that neither the original data nor the log-transformed data follow normal distribution. These statistical tests cannot always be trusted. Graphical methods were utilised to confirm the results of the statistical tests. Histograms and \( Q-Q \) plots indicate that the assumption of log-transformed data following normal distribution may be valid.

Levene’s test was performed to examine the equality of variances between the log-transformed data from the different operators. A \( p \)-value of 0.0008 was estimated, which indicates that, at a significance level of 0.05, the null hypothesis of equal variances was rejected. The result of the Levene’s test showed that the third assumption will be violated by this data set. Performing the Levene’s test on the original data also indicated that the variances between energy efficiency of operators are significantly different (\( p \)-value<0.0001).

**Evaluating operator effects**

This case study compared the energy efficiency of five operators. Considering that \( t \)-tests can handle pairwise comparisons, 10 runs would be needed to compare all five operators. Therefore, the chance of committing type 1 error was 40% (equation (1)). It was concluded that the results of the \( t \)-test cannot be trusted because of the high risk of committing type 1 error. Also, the assumption of homogeneity (equality of variances) between energy efficiency of operators (original and log-transformed data) is violated in this case. The final conclusion was drawn based on the result of the Welch ANOVA and Kruskal–Wallis test. The Welch ANOVA is valid if one assumes the log-transformed data to be normal and will handle the fact that the variances are unequal. The non-parametric Kruskal–Wallis test does not require the data to be normal nor have equal variances. It is important to note that these two tests, which are probably the most

<table>
<thead>
<tr>
<th>Table 1 Examples of proxy use in mining energy efficiency literature</th>
</tr>
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<tbody>
<tr>
<td><strong>Reference</strong></td>
</tr>
<tr>
<td>Acaroglu et al. (2008)</td>
</tr>
<tr>
<td>Muro et al. (2002)</td>
</tr>
<tr>
<td>Awuah-Offei et al. (2011)</td>
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<tr>
<td>Iai and Gertsch (2013)</td>
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</tbody>
</table>
optimal in a lot of mining situations have never been used in the mining literature to review the effect of operators on energy efficiency or performance. The systematic approach suggested in this work will lead mine engineers to the most appropriate test and, hence, reliable conclusions.

The results of the Welch ANOVA test at significance level of 0.05 showed that energy efficiency is significantly different between operators ($p < 0.0001$). The Kruskal–Wallis test also confirmed the results of Welch ANOVA test and indicated that energy efficiency of operators is significantly different between operators (Table 5). The mine can, therefore, conclude with confidence that operator practices affect energy efficiency. The reasons for this are explored elsewhere (Abdi Oskouei, 2013).

This example illustrates many of the challenges and pitfalls in analysing the effect of operators on energy efficiency of mining equipment. The data are highly variable (coefficient of variation more than 25%) and

Table 2 Summary of operators’ performance during the data collection after removing outliers

<table>
<thead>
<tr>
<th>Opr</th>
<th>No. of cycles</th>
<th>Time/h</th>
<th>Material weight/t</th>
<th>Energy consumption/kWh</th>
<th>Production/t h⁻¹</th>
<th>Energy efficiency/t kW⁻¹ h⁻¹</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3897</td>
<td>56.91</td>
<td>496.173</td>
<td>44.850</td>
<td>8719</td>
<td>11.063</td>
</tr>
<tr>
<td>B</td>
<td>3611</td>
<td>54.62</td>
<td>450.217</td>
<td>43.894</td>
<td>8243</td>
<td>10.257</td>
</tr>
<tr>
<td>C</td>
<td>3350</td>
<td>49.60</td>
<td>427.226</td>
<td>39.827</td>
<td>8613</td>
<td>10.727</td>
</tr>
<tr>
<td>D</td>
<td>3058</td>
<td>45.64</td>
<td>383.552</td>
<td>36.879</td>
<td>8404</td>
<td>10.400</td>
</tr>
<tr>
<td>E</td>
<td>2211</td>
<td>32.77</td>
<td>277.554</td>
<td>23.395</td>
<td>8469</td>
<td>11.864</td>
</tr>
</tbody>
</table>

Table 3 Result of statistical test on energy efficiency of operators

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Opr A p-Value</th>
<th>Opr B p-Value</th>
<th>Opr C p-Value</th>
<th>Opr D p-Value</th>
<th>Opr E p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>KS</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
</tr>
<tr>
<td>CM</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
</tr>
<tr>
<td>AD</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
</tr>
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</table>


Table 4 Result of statistical test on transformed energy efficiency of operators

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Opr A p-Value</th>
<th>Opr B p-Value</th>
<th>Opr C p-Value</th>
<th>Opr D p-Value</th>
<th>Opr E p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>KS</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
<td>&lt;0.010</td>
</tr>
<tr>
<td>CM</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
</tr>
<tr>
<td>AD</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
<td>&lt;0.005</td>
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skewed (non-normal), even after removing outliers. A simple \(t\)-test will have a significant (40\%) risk of type 1 error. This risk will increase to 98\% (equation (1)), if all 13 operators at the mine were included in the analysis. In any case, the use of a \(t\)-test cannot be justified in this case because the data violate the assumption of equal variances. The data are not normal but approaches normal upon log transformation, although the evidence is inconclusive. Depending on whether one assumes normality of the transformed data or not, the Welch ANOVA and Kruskal–Wallis tests, respectively, are optimal based on the process presented in Fig. 3. Both tests result in the same inference: the mean energy efficiency differs among operators (they have an effect on energy efficiency).

**Conclusion**

This research proposes a two stage process to evaluate the effect of operators on performance of digging equipment in mines. The first stage involves evaluating the validity of three basic assumptions – independence, normality, and equality of variances. It is assumed that performance of one operator is independent of the others. Graphical and quantitative tests are suggested for testing the normality of data. Levene’s test is suggested for analysing equality of variances due to low sensitivity to the normality of the data set. The second stage of the suggested process involves tests for equality of means. Depending on the number of pairs of operators to be compared, this work recommends two different processes for determining the appropriate tests. Both parametric and non-parametric tests are considered, based on the stage one analysis (test for independence, normality, and equality of variances). The goal is to draw the right inference about the effect of operators on energy efficiency, given the data properties and to reduce type 1 errors.

The proposed method is illustrated with a case study of a dragline operation. In the case study, 1-month’s data were collected for 13 operated, with five operating long enough to be included in the analysis. Based on the mean and median of the energy efficiencies of productive cycles, the operators can be ranked as follows: E, A, C, D and B with operator E being the most energy efficient. However, to establish with confidence whether the variation in energy efficiencies is independent of sampling randomness, the proposed approach was applied to these operators. Preliminary data analysis shows that the data were non-normal. The analysis was inconclusive with respect to whether log transformation makes the data normal or not. The results of analysis, based on the proposed approach, suggest that the variances of energy efficiencies for the five operators are not equal. The Welch ANOVA and Kruskal–Wallis tests were found to be optimal depending on whether one concludes that the log-transformed data are normal or not. Both tests confirm, in this case, that the means of the energy efficiencies are significantly \((p<0.0001)\) different. The authors conclude then that, at this mine, the energy efficiency of dragline operations differs from operator to operator. Mine engineers and management can, therefore, proceed with continuing operator training efforts to improve energy efficiency and reduce energy consumption.

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References
Abdi Oskouei, M. 2013. Methods for evaluating effect of operators on dragline, Missouri University of Science and Technology, Rolla, MO.
Abdi Oskouei, M. and Awuah-Offei, K. 2014. A Method to Identify the Key Causes of Differences in Efficiency of Operators. SME Annual Meeting. Salt Lake City, USA
Welch, B. L. 1947. The generalization of ’student’s’ problem when several different population variances are involved, Biometrika Trust, 34, (1), 28–35.