How do operators and environment conditions influence the productivity of a large mining excavator?

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Abstract: This paper considers the sources of variation in the operation of hydraulic mining excavators to shed light on the benefit of tighter control of the excavation process. An observational study is conducted, collecting operational data from a Liebherr R996 mining shovel for a number of equipment operators and environments. The methodology assesses the significance of the operator, material diggability, and bench height on variation in productivity. The paper finds that these three factors are important, with operator variation identified as the dominant factor. There is evidence that skilled operators may marginalise the influence of variation in environment conditions on productivity. The paper's contribution is the quantification of the influence of bench height, digging conditions and the operator on productivity. The significance is that the findings give clarity to the prospective benefit that the automation of excavators would achieve.

Keywords: mining excavators; hydraulic shovels; mining shovels; productivity study; production rate; operators; human factors; bench height; diggability; excavation environment conditions; sources of variation; automation; precision mining.

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1 Introduction

In mining operations, excavators work at a critical point in a production chain that transforms mineral-rich earth into mineral products through a process that starts with mining and extracting, followed by processing for beneficiation, through to managing inventory levels and their quality, and ultimately the delivery of products to customers. As excavators work at the beginning of this process, variation in their operation has the potential to impact on the downstream activities.

At any time, excavators are operated by a single operator working in an environment that is specifically constructed for the purpose of excavation using excavation methods that are intended to optimise performance. The scope of optimisation can be as narrow as the extraction process itself, or as broad as the full production chain.

The outcome of this optimisation process defines the environment for excavation through the mine design (e.g., bench height) and the level of material fragmentation which determines the ease of digging and transport. It also defines the selection of equipment including the choice of excavator.

We subscribe to a philosophy we call *precision mining*, a phrase that is intended to describe the conduct of excavation in a very organised and exact manner. The tenets of this philosophy are set down in McAree (2018); at the core is the principle that efficiencies are derived from carefully planned actions that are faithfully and methodically executed with exactness and meticulousness. The creation of mining environments through appropriately fragmented rock, the organisation of the environment into well-laid-out blocks and benches, the design of machines involved in excavation, and the identification of mineral grade boundaries that distinguish what is considered ore from waste all serve to increase the precision of mining.

From where will the next level of precision come? The existing controls still result in variability in production which dilutes precision. This paper seeks to gain insight into the sources of variation by studying the operation of a hydraulic mining excavator, see Figure 1. The purpose is to understand the effect of variations associated with the operator and the environment on machine performance and the potential for reducing these.

This work takes the structure of an observational study which has as its focus, the diggability of material and the bench height as characterisers of the environment and the skill and experience of the operator. This study involved collecting operational data from a Liebherr R996 hydraulic mining shovel, under control of equipment operators having different levels of skill and experience and working in various environments. The paper statistically analyses this data set with a view to gaining insight into the impact of variation. We claim this to be the first study that has systematically sought to do this.

Figure 1 A Liebherr R996 in face shovel configuration (see online version for colours)

1.1 Factors affecting excavator performance

It is generally accepted that a number of confounding factors influence the efficiency of excavators, including fragmentation and tightness of the muckpile, muckpile profile, truck scheduling, machine condition and operator skill (Williamson et al., 1983).

The fragmentation and tightness of the muckpile are controlled by drill-and-blast practices and the efficacy of these is often distilled into a 'diggability index' (Williamson et al., 1983; Hendricks and Scoble, 1990; Khorzoughi and Hall, 2016b). These indices have been proposed as guidance for equipment selection (Scoble and Muftuoglu, 1984) and as measures for quantifying the impact of the muckpile properties on the performance of loaders. The index of Scoble and Muftuoglu (1984) is based on four dominant rock mass characteristics: rock strength, joint spacing, bedding spacing and rock weathering. This takes into account that digging conditions improve as the rock weathers, and also as intact rock strength, block joint and bedding spacing are reduced. The proposed use for this index is to guide drill and blast based on the capabilities of the excavator to be used.

Several studies have sought to characterise diggability by the distribution of rock size. Allen et al. (1999) conducted a laboratory and field study examining the influence of muckpile size distribution on fill factors and dig times. This work characterised the particle-size distributions by a 63rd percentile measure, termed P_{63}, and observed that as the size of the 63rd percentile rock increased, so did bucket payloads at the cost of longer dig times.

Brunton et al. (2003) examined the effect of several fragmentation parameters on the operation of a Liebherr 944 hydraulic shovel and found that characterising size distributions by P_{80} had the strongest correlation with dig time. Consistent with these findings, Osanloo and Hekmat (2005) noted that material fragmentation P_{80} had a significant impact on shovel productivity and observed that shovel production could drop by as much as 38% when the particle size increased from 40 cm to 80 cm. These studies give insight into how variation in the fragmented rock affects dig times and bucket fills.

Operators have also been recognised to be an important factor in productivity. Hendricks (1990), in seeking to develop an index to assess digging conditions for rope shovels, found that the index was sensitive to operator behaviours. Specifically, the index considered high frequencies in the hoist armature current signal. These were observed to have larger amplitudes when digging conditions were harder. However, the work also observed that the operator practices influenced the index, with significant differences among the operators.

Several studies have observed that operator skill impacts both the loading cycle time (Taksuk and Erarslan, 2000; Osanloo and Hekmat, 2005; Yaghini et al., 2020) and bucket fills (Osanloo and Hekmat, 2005; Khorzoughi and Hall, 2016a). Good operating practices have also been shown to result in lower dig energies without compromising the loading rate (Khorzoughi and Hall, 2016a), and operator training has been shown to result in increased efficiency and reduced variability in operator performance (Branscombe, 2015).

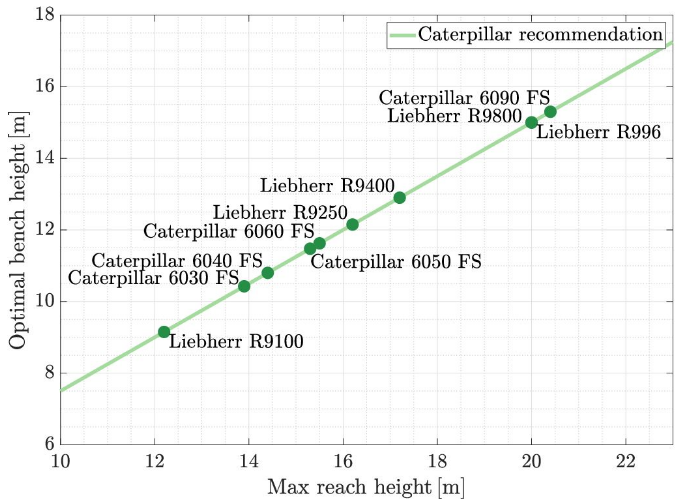
Hall and McAree (2005) investigated the variation in excavation technique by analysing dig trajectories for an O&K RH200 hydraulic excavator. The work found significant differences across operators, in both productivity and technique. Hall and McAree identified two distinct operating styles based on trajectory with differing cycle times and duty impacts on the machine. The two styles were analysed with respect to the mechanical capabilities of the machine to identify a preference, however, the work concluded that the machine was equally effective for both methods.

Patnayak et al. (2008) conducted a monitoring study to investigate the influence of operators, machine type and tooth configuration on electric mining shovel performance. The data set was collected from eight shovels over a 12-month period and included hoist and crowd motor armature current and voltage, truck payload as well as geological and geotechnical information. The work showed a difference in hoist motor power consumption of up to 25% and production rate of 50% across operators. It has been estimated that the flow-on effect of the variation in operator performance can impact the overall mine production rate by as much as 20% (Yaghini et al., 2020).

It is also recognised that the geometry of the working environment, in particular, the bench height has an influence on machine performance. Hustrulid et al. (2013) observe that rope shovels require a bench height sufficient to provide the vertical travel needed to achieve dipper fills and that shorter benches require deeper bank penetration. In tough conditions where the shovel can not penetrate into the face, a taller bench is required to fill the dipper in a single pass. Hustrulid et al. provides a method for estimating shovel cycle times which includes a correction factor for bench height based on the work of Atkinson (1973). The 'bench correction factor' increases cycle times by 25% when working on benches at 40% of the optimal height.

For hydraulic face shovels, equipment manufacturer Caterpillar advises a bench of 75% of the maximum reach height (Caterpillar Inc., 2019). Figure 2 plots a number of popular excavators against this recommendation. Another estimate of optimal bench height is derived by Vylomov and Kovalev (1982) as part of an investigation into the application of hydraulic shovels for selective mining. Here, the optimised bench height is based on machine reach and dig face angle, however, the work is theoretical and does not provide any validation of the estimate.

Figure 2 The optimal bench height for various hydraulic shovels estimated by applying the recommendation from Caterpillar Inc. (2019) to manufacturer reach specifications (see online version for colours)



The case studies of Scoble and Muftuoglu (1984) provide further evidence of the relationship between bench height and performance. Hendricks et al. (1988) examine this in more detail, noting that halving the bench height resulted in an increase in dig cycle times. Similarly, Onederra et al. (2004) found that hydraulic shovel productivity was dependent on not only operator skill, but also the muckpile profile. Reduced production rates were observed in 'flatter regions' of the muckpile that corresponded to a smaller dig face.

The literature has identified rock fragmentation, pit geometry and the human factor as key contributors to performance. The gap that we seek to address here is the relative contribution of these three factors to variation in excavator productivity.

2 Methodology

The method of this study was to observe the operation of a Liebherr R996 hydraulic face shovel working in an open-cut nickel mine over a four-week period, with a view towards establishing the influence of operators, bench height and material diggability on production rates. The site employed a conventional drill-and-blast and load-and-haul mining method. A fleet of Caterpillar 793C dump trucks serviced the loading equipment.

The excavator was instrumented with sensors to provide:

1 shovel location using single-antenna GPS

2 boom, stick, and bucket cylinder extensions

3 boom, stick and bucket cylinder pressures

4 machine house yaw rate

5 operator commands, comprising motion commands from joystick signals, foot pedals and binary inputs such as the horn signal.

Data sources 2 to 5 are referred to as *machine data* and were collected at 50 Hz; GPS information was collected at 1 Hz.

The machine data stream was combined with an additional channel indicating the shovel operational state, i.e., dig, swing, dump, return, wait for truck, propelling, and idle, which was manually annotated. Annotation was conducted in a 90-minute session for each day and night shift, for the purpose of capturing the spread of operator variation over the four weeks of the trial. Although day and night-time operation data was collected, day and night were not considered as factors in this study. This amounted to 80 hours of machine operation.

This collected data was further augmented with truck payload information from the site fleet management system (Caterpillar MineStar, Caterpillar Inc., 2019).

The operator cohort who operated the machine during the trial comprised 11 operators with varying experience, see Table 1.

Table 1 The cohort of 11 operators had a range of experience from trainee to expert

Operator	*Experience*	*Rating [1–5]*
A	Beginner	2
B	Moderately experienced	3
C	Expert	5
D	Experienced	4
E	Experienced	4
F	Experienced	4
G	Expert	5
H	Moderately experienced	3
I	Experienced	4
J	Trainee	1
K	Experienced	4

Note: Ratings were assigned by the production superintendent as a subjective judgement.

Bench heights were assigned into one of three categories for each production block: 10 m, 15 m and 20 m. Different bench heights were the consequence of both design and post-blast conditions, e.g., material swell and cast.

Material diggability for each excavation block was rated by the site geotechnical team into one of three categories:

1 easy

2 normal

3 difficult.

This diggability rating (DR) was a subjective judgement that took into account the block geology, structural trend, the blast powder factor, the number of blast holes, the blast hole pattern, blast drill penetration, the blast initiation, and visual inspection post-blast. Photos of digging conditions for each rating are shown in Figure 3.

Figure 3 Muckpiles with differing DRs, (a) diggability 1 – easy conditions (b) diggability 2 – normal conditions (c) diggability 3 – difficult conditions (see online version for colours)

(a) (b) (c)

3 Analysis of data

The following sections detail the analysis of the collected data set. Subsection 3.1 covers the estimation of production rates for the trial. Subsection 3.2 examines linear correlations between the operational factors. Subsection 3.3 presents statistical analyses of the impact of operators, DR and bench height on productivity.

3.1 Productivity

The measure of machine productivity to be used in subsequent analyses is the loading cycle productivity (LCP) measured in tonnes per hour. This is determined from the payload for each excavator loading cycle divided by the corresponding cycle time. The duration of an excavator loading cycle is the time from the start of the excavator dig, through swing, dump and return, up to the start of digging in the next loading cycle. In this analysis, factors such as truck delays and machine downtime are accounted for as lost production time and do not affect LCP, however, a truck delay may still impact how the operator performs the first loading cycle knowing they are not time restricted by a waiting truck. The payload for each loading cycle in the LCP computation is the average bucket payload for the truck loaded in that cycle.

The uncertainty in LCP is based on the uncertainty in the truck payload reported by the Caterpillar truck payload system. Bender (2005) estimates this to be in the range of 3% to 5% of the reported payload. Given a truck capacity of 223 t (Caterpillar Inc., 2019), an average loading cycle time of 31.5 s, and an average number of passes per truck of 5.8, the uncertainty on this productivity measure is in the range of $\pm$135 (3%) to $\pm$222 (5%) t/h.

3.2 Correlation analysis of operational factors

A summary of operational factors is given in Table 2 where for each environmental condition (bench height, DR), the average performance of each operator is computed. Environments where there was only one operator have been removed from the analysis. Linear correlations between the various operational factors are given in Figure 4.

The following observations are made:

- Operator experience shows moderate positive linear correlation with production rate and moderate negative linear correlation with cycle time and dig time, suggesting operator experience is linked with excavator performance.
- Diggability rating shows a moderate negative correlation with mean payload and production rate, suggesting that difficult digging conditions negatively affect excavator performance.
- Diggability rating shows a strong positive correlation with return time. This speculatively suggests that in harsher digging conditions operators spend longer choosing the point they will commence digging, and therefore greater care in their positioning of the bucket.
- Mean payload shows a positive correlation with production rate, which is expected.

Table 2 A summary of the collected data for the operators and environmental conditions

Op.	*Op. exp. [1–5]*	*Mean payload [t]*	*Mean LCP [t/h]*	*Mean cycle time [s]*	*Mean dig time [s]*	*Mean swing time [s]*	*Mean dump time [s]*	*Mean return time [s]*	*Mean max dig reach [m]*	*DR [1–3]*	*Bench height [m]*
A	2	41.5	4,309	35.1	15.3	6.6	4.1	8.9	13.94	1	15
B	3	42.7	4,645	32.3	15.2	6.2	4.1	6.6	14.08	1	15
C	5	54.6	5,321	38.4	18.1	7.4	4.0	8.8	14.52	1	15
D	4	51.0	5,603	33.7	16.8	6.8	4.0	6.6	14.74	1	15
E	4	44.2	4,668	35.8	15.9	6.9	3.8	9.2	14.47	2	15
F	4	45.2	4,708	35.7	14.3	8.1	4.3	9.6	14.59	2	15
G	5	41.8	4,961	30.9	11.3	6.8	3.3	9.5	13.76	2	15
H	3	-	-	35.8	16.9	7.3	4.3	7.8	14.00	3	20
I	4	45.7	4,745	35.9	16.8	6.4	4.0	9.5	14.46	3	20
J	1	43.2	3,801	42.9	21.8	6.7	4.4	11.0	14.74	3	20
K	4	38.6	4,129	35.3	13.4	7.0	4.2	11.0	13.50	3	20
F	4	40.6	4,426	33.9	11.5	8.1	3.8	10.7	14.30	3	20
G	5	32.7	4,173	31.7	13.1	6.2	3.4	9.1	13.95	3	20

Notes: Payload estimates for the truck were not available for operator H. Operators F and G appear twice as they worked in two different environments. The standard error of mean LCP using the per-truck precision of LCP given in Subsection 3.1 is less than 1% of the mean LCP values. It is therefore not a significant contributor to uncertainty in this measure.

3.3 Impact of operational factors on excavator performance

A one-way ANOVA (Montgomery, 2019) is used for each operational factor to assess if it statistically impacts LCP at a significance level of 0.05. The following hypotheses are used as the basis for testing the equality of means:

$$H_0: \quad \mu_1 = \mu_2 = \ldots = \mu_n,$$

$$H_1: \quad \text{the means are not all equal.}$$

Here μ_k corresponds to the mean LCP for condition k, for a specific operational factor. Table 3 shows the operational factors and their corresponding conditions. Operators are grouped by the environment conditions (DR and bench height).

Figure 4 The correlation coefficient matrix (see online version for colours)

	Operator experience	Mean payload	Mean LCP	Mean cycle time	Mean dig time	Mean swing time	Mean dump time	Mean return time	Mean maximum dig reach	Diggability rating	Bench height
Operator experience	1.00										
Mean payload	0.06	1.00									
Mean LCP	0.54	0.76	1.00								
Mean cycle time	-0.58	0.38	-0.28	1.00							
Mean dig time	-0.58	0.52	-0.03	0.84	1.00						
Mean swing time	0.20	0.27	0.15	0.17	-0.23	1.00					
Mean dump time	-0.67	0.35	-0.20	0.70	0.62	0.20	1.00				
Mean return time	-0.12	-0.37	-0.65	0.43	-0.07	0.39	0.09	1.00			
Mean maximum dig reach	-0.22	0.65	0.33	0.55	0.67	0.26	0.39	-0.18	1.00		
Diggability rating	0.02	-0.59	-0.64	0.16	-0.14	0.07	-0.11	0.78	-0.15	1.00	
Bench height	-0.11	-0.52	-0.64	0.22	0.01	-0.07	0.03	0.64	-0.14	0.90	1.00

Note: Correlations corresponding to a p-value < 0.1 are coloured green.

Table 3 The variables and their conditions tested for equality of means with one-way ANOVA

Explanatory variable	*Conditions*
Diggability rating	1, 2 and 3
Bench height	10 m, 15 m, 20 m
Operator – group 1	Operator A, B, C and D
Operator – group 2	Operator E, F and G
Operator – group 3	Operator H, I, J, K, F and G

Notes: The operational factors are treated as explanatory variables and the response variable is mean LCP. Operators are divided into groups based on the excavation environment.

The Tukey-Kramer (Kramer, 1957) test is used to indicate which conditions result in a mean LCP that differ significantly from others. The output from a multiple comparison test is visualised by plots of the condition means and confidence intervals in the subsections below. In general, if the mean confidence interval for one condition overlaps the mean confidence interval of another, there is insufficient evidence in the data to assume that the two means are statistically significantly different.

In Table 2 describing the LCP mean and variance for each condition, an *observed mixture* measure is included. This is determined by the *pro rata* allocation of LCP based on the number of loading cycles for each condition in the analysis. The table also includes the range of values across the conditions.

3.3.1 The effect of operators on production rate

The impact of the operator on excavator performance was examined within condition-groups. The condition-groups give a subset of the data where there were sufficient operators working within the same environment conditions to be statistically meaningful. This allows for a control over the influence of the environment on the production rates. Table 4 shows the grouping of operators, under three different environmental conditions (DR, bench height).

Table 4 The three operator groups and their environment

	Group 1	*Group 2*	*Group 3*
Digging environment	easy	moderate	difficult
Diggability rating	1	2	3
Bench height [m]	15	15	20
Operators	A	E	H
	B	F	I
	C	G	J
	D		K
			F
			G

Notes: The digging environments are classified as easy, moderate and difficult based on the combination of bench height and DR. Note that operators F and G are in two different environments.

ANOVA indicates that the operator has a significant effect on mean LCP for all groupings: group 1 $[F(3, 896) = 76.93, p < 10^{-8}]$, group 2 $[F(2, 1{,}411) = 8.73, p = 0.0002]$, and group 3 $[F(3, 939) = 34.13, p < 10^{-8}]$.

Figures 5 and 6 present the LCP for operators in each of the three condition-groups. Table 5 gives the LCP mean and variance by operator.

Within group 1, the two most experienced operators, C and D, have the highest LCPs. Operator C has the slowest average cycle time of the group but achieves a high LCP through greater bucket fills. Operator D has the lowest variance with faster cycle times and a reduced bucket load. The maximum difference between the mean LCP of operators in group 1 is 1,295 t/h.

Group 2 has the smallest spread of mean LCP of all operator cohorts, with a range of just 293 t/h between the lowest and highest performing operators. This could be attributed to the spread of operator ability levels: all are experienced or expert operators. Operator G is the most experienced in the group, with the shortest cycle times and highest LCP.

Figure 5 A box plot presenting the effect of operator on LCP (see online version for colours)

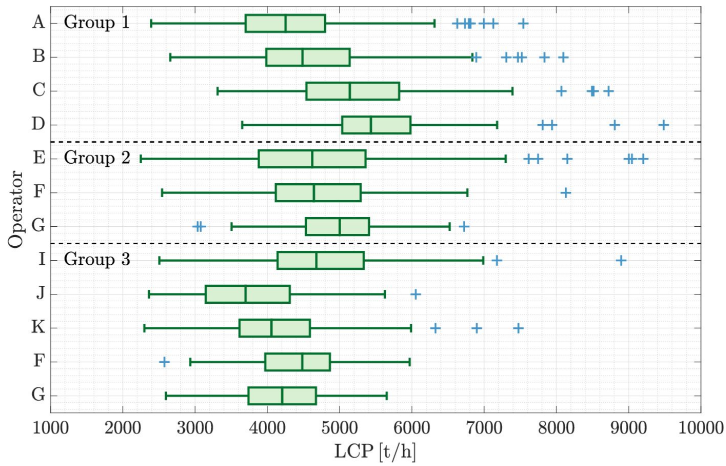
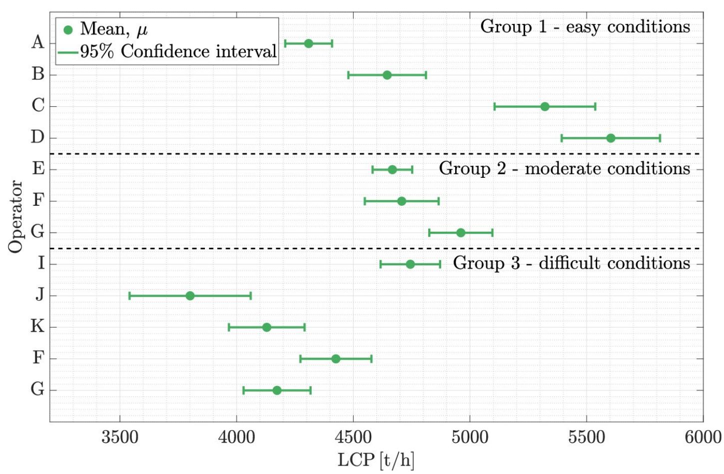


Figure 6 A comparison of means using the Tukey-Kramer method showing the 95% confidence on estimates of the mean LCP for different operators.



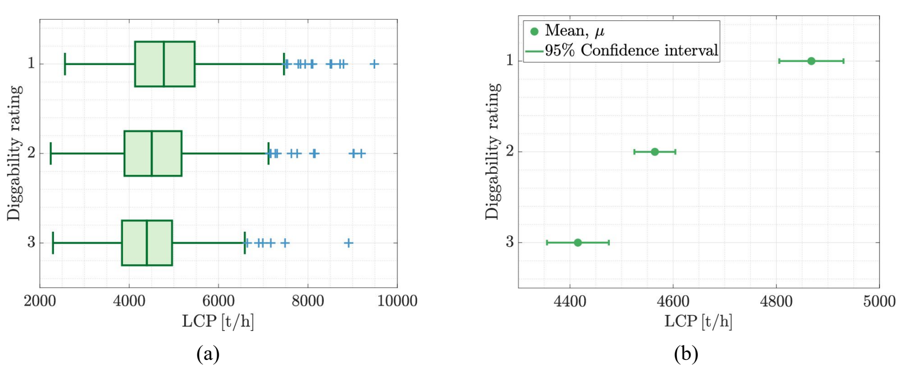
Group 3 excavate in the conditions with the highest DR and average the lowest LCP of all groups. The variation in mean LCP between experienced operators is 616 t/h, with operator I achieving the highest LCP and bucket fills. The comparison of means in Figure 6 shows there is insufficient evidence to indicate a significant difference in the performance of the most and least experienced operators – operators G and J, respectively. The maximum effect of varying operators in group 3 on the mean LCP is 944 t/h. Some of the more experienced operators are more sympathetic to the trade-off between production rate and machine duty, which may be an influencing factor in the LCP variation observed in this group as it has the highest DR.

This analysis supports the hypothesis that operator experience is an important factor in determining LCP.

Table 5 The LCP distributions for operators in each group

Group	*Case*	μ_{LCP} *[t/h]*	σ_{LCP} *[t/h]*
1	Operator A	4,309	,1099
	Operator B	4,645	1,152
	Operator C	5,321	1,283
	Operator D	5,604	944
	Observed mixture	4,822	1,234
	Range	1,295	339
2	Operator E	4,668	1,477
	Operator F	4,708	1175
	Operator G	4,961	873
	Observed mixture	4,754	1,302
	Range	293	604
3	Operator I	4,745	1,192
	Operator J	3,801	1163
	Operator K	4,129	974
	Operator F	4,425	894
	Operator G	4,173	934
	Observed mixture	4,373	1,106
	Range	944	298

Figure 7 The Tukey-Kramer post-hoc analysis shows that the mean LCP for the diggability ratings are all significantly different, (a) a box plot of the LCP observed for each DR (b) a comparison of means using the Tukey-Kramer method showing the 95% confidence on estimates of the mean LCP for each diggability rating (see online version for colours)



Notes: The condition with the lowest rating of 1 has the highest mean LCP of 4,868 t/h while the highest, 3, has the lowest LCP of 4,415 t/h.

3.3.2 Effect of DR on production rate

Results of the ANOVA show that the effect of DR on mean LCP is significant for the three digging conditions $[F(2, 3255) = 39.88, p < 10^{-8}]$. This is not surprising, and is consistent with prior work demonstrating the influence of muckpile diggability on excavator performance (Scoble and Muftuoglu, 1984; Hendricks, 1990; Brunton et al., 2003; Osanloo and Hekmat, 2005; Giltner and Koski, 2010). The comparison of means in Figure 7 shows that a lower DR corresponds with higher LCP and the difference is statistically significant.

Table 6 indicates that the most difficult digging (DR = 3) results in the lowest mean LCP and variance. The easiest conditions (DR = 1) result in the highest mean LCP and also the highest variance. The difference between the mean LCP of the best and worst diggability conditions is 453 t/h.

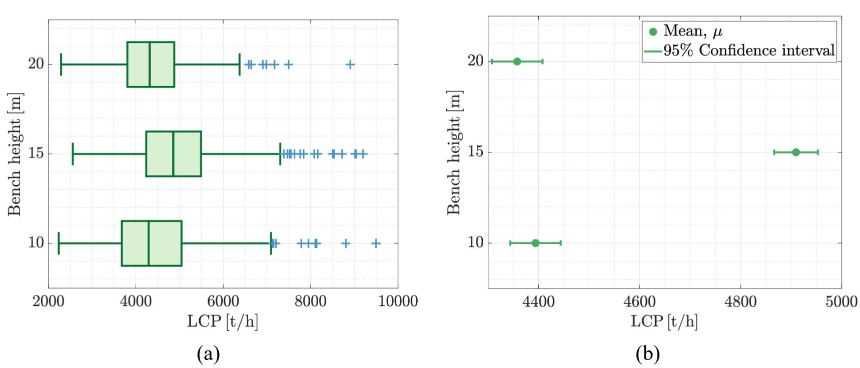
Table 6 The LCP distributions for different DRs

Case	μ_{LCP} *[t/h]*	σ_{LCP} *[t/h]*
Diggability rating 1	4,868	1,332
Diggability rating 2	4,565	1,275
Diggability rating 3	4,415	1,121
Observed mixture	4,579	1,251
Range	453	211

3.3.3 Effect of bench height on production rate

ANOVA identifies the effect of bench height on production rate is significant for the three conditions $[F(2, 3255) = 125.2, p < 10^{-8}]$. Figure 8 presents the post-hoc Tukey-Kramer test together with the production rates for each bench height. The LCP for the 15 m bench is approximately 500 t/h greater than the other two cases. This fits closely with the bench height recommended for the Liebherr R996 based on the maximum cutting height (Caterpillar Inc., 2019) shown in Figure 2.

Figure 8 The mean LCP for the 15 m bench is significantly greater than the other conditions, while there is insufficient evidence to show a difference between the 10 m and 20 m benches, (a) a box plot of the LCP observed for each bench height (b) a comparison of means using the Tukey-Kramer method showing the 95% confidence on estimates of the mean LCP for each bench height (see online version for colours)



The LCP distributions indicate that the 20 m bench corresponds with the lowest mean LCP of 4,358 t/h as well as the lowest variance, see Table 7. However, the majority of data for a 20 m bench is in conditions with high DR, and this may skew results.

Comparing the distributions of the highest and lowest performing conditions indicates that the maximum effect of controlling BH on mean LCP is 552 t/h.

Table 7 The LCP distributions for varied bench height.

Case	μ_{LCP} *[t/h]*	σ_{LCP} *[t/h]*
10 m bench	4,394	1,365
15 m bench	4,910	1,255
20 m bench	4,358	1,074
Observed mixture	4,612	1,257
Range	552	291

4 Discussion

4.1 The influence of operational factors on production rate

In this study, the operational factor that most affects the LCP is the operator. Table 8 gives a summary of the results. Operator group 2 serves as a post-hoc control, this group comprising experienced and expert operators, whilst their mean LCP is impacted by working in moderately difficult digging conditions, the range of their mean LCP, $R(\mu_{\text{LCP}})$, is 6.2% of the group mean.

The environmental conditions rank next in terms of operational factors in their influence on $R(\mu_{\text{LCP}})$. The $R(\mu_{\text{LCP}})$ for DR is 9.9% of the group μ_{LCP}; $R(\mu_{\text{LCP}})$ for BH is 12.0% of the group μ_{LCP}.

An operator crew with a wide spread in experience is observed to be the most influential factor on $R(\mu_{\text{LCP}})$. The $R(\mu_{\text{LCP}})$ for operator group 1 is 26.9% of the group μ_{LCP} LCP; for group 3 it is 21.6%. Both groups are characterised by a broad range of operator experience.

To the extent that this dataset allows, it is concluded that the effect of the operators on excavator performance, viz., their experience, is the most significant factor. It is arguably also the one most open to influence through better training or technology to support better dig-by-dig decisions by the operator. This conclusion that operators are important is not new (Hendricks, 1990; Taksuk and Erarslan, 2000; Osanloo and Hekmat, 2005; Khorzoughi and Hall, 2016a; Yaghini et al., 2020). What this study has provided is an assessment of the magnitude of their contribution to the sources of uncertainty.

The analysis suggests that the contribution of the operators to variation in LCP for a crew of mixed experience is roughly twice as large as the influence of the environment. In contrast, environment conditions are the significant sources of variation when skilled operator crews are used. The caveat on this discussion is of course that these observations apply only to a single site over a short period of time. However, they do not seem unreasonable observations to make on the basis of the data.

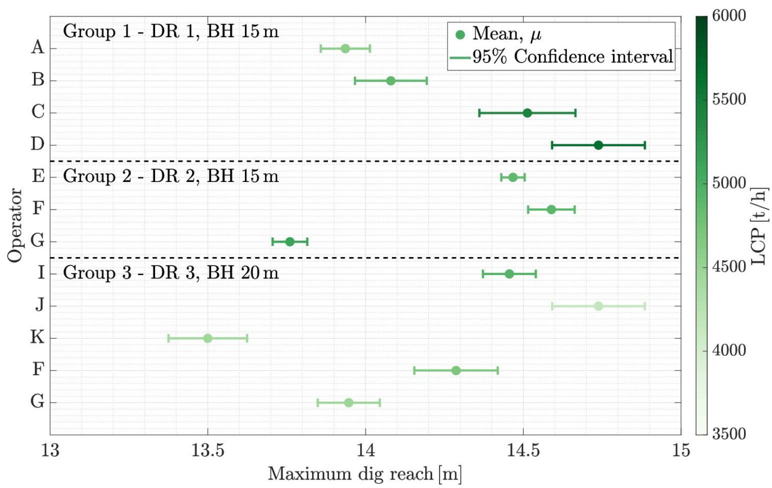
Table 8 The range of mean LCP for the conditions within each operational factor

Operational factor	*Range of mean LCP* $R(\mu_{LCP})$ *[t/h]*	$R(\mu_{LCP})$ *as percentage of group mean LCP*
Diggability rating	453	9.9%
Bench height	552	12.0%
Operator – group 1	1,295	26.9%
Operator – group 2	293	6.2%
Operator – group 3	944	21.6%

4.2 *Why do experienced operators perform better?*

It is not surprising that experienced and expert operators should perform better than the less skilled trainees, beginners and moderately experienced operators. Ultimately performance will come down to operator judgement. However, the essence of what constitutes good operator judgement is by no means clear. Hall and McAree (2005) for example, identified distinct dig styles in the operation of a hydraulic excavator, but found no inherent production benefit to either.

Figure 9 The comparison of means for maximum dig reach between operators is presented and coloured by LCP (see online version for colours)



Note: The confidence intervals are obtained using the Tukey-Kramer method and represent the 95% confidence interval of the mean maximum dig reach.

A plausible hypothesis is that operator skill manifests in the efficacy of decisions around where to position the machine, what material to dig from that position, and how to plan a sequence of these decisions to have sustained productivity. These decisions must necessarily account for the environment conditions. For example, in difficult digging conditions an operator may stand the machine close to the dig face in order to achieve maximum mechanical advantage from the front-end machine geometry. Equally, they position further back from the face in easy conditions to maximise the kinematic advantage of the machine, taking longer, broader sweeps to fill the bucket.

Figure 9 shows how the mean maximum dig reach and mean LCP varies between operators under different environment conditions. Here, the mean maximum dig reach is taken as an indicator of excavator positioning relative to the face and measures the furthest distance from the machine house to the bucket teeth during a loading cycle. In this sense, it is a measure of the excavator's distance from the digging face.

Figure 9 indicates that positioning varies by 1.25 m between operators and environment conditions. For group 1 where digging conditions are easy, the highest LCPs are achieved when positioning further from the face, consistent with the hypothesis. This is the strategy of the two most experienced operators. For group 2 where digging conditions are moderate, the operator who positions closest to the face achieves the highest LCP. For group 3, where digging conditions are difficult, the trainee operator positions furthest from the face and has the lowest LCP, consistent with the hypothesis. If this operator is not considered, there is a trend between positioning and LCP: the further from the face, the higher the LCP. This is not consistent with the hypothesis that in difficult digging conditions operators should position close to the face to maximise mechanical advantage. However, there is a correlation in the results, and arguably there is an optimal position to place the machine which may be consistent with operator I.

What is clear is that operator LCP is not solely a function of maximum reach, and that machine positioning likely involves a complex set of factors worthy of further investigation.

5 Conclusions

It is recognised that the study covers a single type of excavator, operating in a limited range of environment conditions with a moderately small set of operators. The extent to which the analysis and discussion of data generalises to a broader set of machines, operators and environments is not clear.

However, within the scope of this study, a clear picture emerges, and that is that variation in operator experience is the largest contributor to operational variance. Operator experience can, to some extent, be taken as a proxy for operator skill and the conclusion that these analyses lead us to is that if operator skill can be equalised and brought to the level of experts, there is the possibility for effective management of not only the variance introduced by operators, but also that introduced by environmental conditions.

There is scope for further and broader studies to understand the potential for improved productivity, but equally, the results suggest that automation of excavator function is a means to control the sources of variation with benefits to the productivity. Whilst the experienced operator group appears to have demonstrated that they are able to reduce variations in productivity, it is also clear that the highest productivity is achieved when the digging conditions are easy and the bench height is consistent with the capabilities of the machine.

The possibility of automating mining excavators has been explored for many years by equipment manufacturers (Komatsu, 2016; Grayson, 2018; Gleeson, 2020) and researchers (Singh, 1995; Beasley, 2013; Jud et al., 2017; McAree et al., 2007, 2011, 2013, 2015). Many of the technical complexities of automation have been addressed and it would appear that creating an autonomous mining excavator is feasible. The results presented in this paper suggest there is benefit in doing so, but equally, there are still problems to solve *vis-à-vis* understanding the triple question of where to position, what material to take at that position, and when and where to move in the future so as to maximise productivity. Beasley and McAree (2010, 2012a, 2012b, 2013) and Beasley (2013) have made progress to the address of these questions, but there is manifestly much more to do.

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