Development of a Prototype Key Performance Indicator in Large-Scale Drilling Operations

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DEVELOPMENT OF A PROTOTYPE KEY PERFORMANCE INDICATOR IN LARGE-SCALE DRILLING OPERATIONS

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ABSTRACT: The significant increase of rotary blasthole drilling technology in recent years requires enhanced utilisation tactics of the “Big Data” being produced, to gain insight into operator performance and increase drilling efficiency. An area often overlooked by production is the drill cycle, due to the delayed nature of the downstream effects resulting from poor drilling. The project objective was to develop a prototype Key Performance Indicator (KPI) scorecard model to assess and rank drill operator performance, and provide a two-way feedback mechanism for training and development. Furthermore, to identify applications of the KPI scorecard model to enhance utilisation of Big Data in large-scale drilling operations. The prototype scorecard model was based on three main KPIs - rate of penetration, accuracy to plan, and cycle time. The dataset used to develop the scorecard was based on four different through-seam drill patterns. A main component of the scorecard model is a ranking system that enables feedback on an operator’s proficiency based on these indicators and supporting parameters. By analysing the established scorecard model and ranking system it was found that 13 operators, of the 37 in the dataset, had sufficient data to produce a scorecard and rank them. The results reflect trends in the raw data and provided a strong indication of operator proficiency, identifying areas for improvement.

INTRODUCTION

Many mining operations currently face increasing challenges due to more complex deposits, intensified environmental restrictions and fluctuating commodity prices. These challenges, which will be intensified in the future, urge mining operators to increase efficiency of the operations in order to cut costs. Because drilling has a significant effect on unit operations, i.e. blasting, loading, haulage, crushing and processing, improving the drilling performance is considered a key factor in increasing mining operational efficiency (Hustrulid et al., 2013).

At present there has been a shift in the hard rock mining industry towards a “Mine-to-Mill” or “Drill-to-Mill” optimisation approach. This encompasses a focus on each process, not as separate operations (e.g. drill and blast, production, or the processing plant) but the system as one combined unit and making changes within the system that influence downstream processes, in order to improve the system as a whole (Vynne 2001). By improving drill performance from the base level (i.e. the operator), the flow on effect will be noticed in the downstream process, resulting in productivity improvements across the entire system (Liu and Karen 2001).

As autonomous drilling technologies emerge in the mining industry there is a need for improved operating tactics of drills to deliver increased productivity, drill hole quality and accuracy, improve operator safety, and gaining the maximum benefit from the large amounts of data produced by the drills - often referred to as “Big Data” Knights and Liang (2011). It is therefore essential to utilise these large datasets to gain the maximum benefit through improved identification of root causes, training and performance development and monitoring to improve drilling performance.

PROJECT

This research paper describes the development of a prototype KPI scorecard model to gain more value from “Big Data” provided by the drills. It includes findings of main KPIs, an appropriate and
comprehensive scorecard layout, the development of a meaningful scoring system to provide unbiased performance rankings, and investigates the application of this scorecard to assess operator performance on automated drills.

Background

The project was conducted at an open cast coal mine in North West New South Wales, Australia. The multi-pit operation uses a dragline, truck and shovel operation, assisted by drilling and blasting, or dozers for rock breakage of thin partings and coal seams. The company is currently seeking a tool to better utilise the “Big Data” produced by their drills to evaluate drilling performance. “Big Data” is a broad term for large complex datasets that present new challenges for traditional data processing methods. Advancements in machine monitoring technology have resulted in vast datasets being produced, yet they are too often left underutilised. The large datasets produced by the drill monitoring system provide potential opportunities to gain more value and operational insight, but require extensive manipulation and processing to produce a useable format from which these benefits can be drawn. A scorecard identifying Key Performance Indicators (KPI) was proposed as a potential method to evaluate and rank operator performance. Presently a drill operator’s performance is largely based on metres drilled per shift or rate of penetration per operating hour. This is decidedly incomplete due to:

- Varying drill pattern layouts and depths;
- Inconsistent geological domains, and rock strata;
- Different models of drill and drill bits used; and
- Whether or not the operator is entering the correct delays into the system.

Prior to carrying out the research the company’s measure for drill performance were directed primarily toward the drill rig and not the individual operator. As such this meant that limited information relating to optimum operating ranges or performance targets were available from the company besides the somewhat crude measures of metres drilled per shift and rate of penetration per operating hour. Consequently, acceptable operating ranges would need to be derived from historical data in order to provide an initial baseline for the prototype scorecard model.

The majority of studies investigating drill performance focus heavily on drill parameters and often overlook the influence of the operator on performance. Liu and Karen (2001), Anon (2010) and Patnayak and Tannant (2005), assist in re-emphasising the importance of the operator on drill performance. A method of comparing operator performance is required to identify a range of operator specific KPIs, bring them into one place, and provide a two-way feedback mechanism for training and development to occur. The ‘Balanced Scorecard’ (BSC) developed by Kaplan and Norton (1992), is a method of tracking and managing company performance to ensure alignment with key targets and long-term strategy. As the BSC approach is more focused on strategic management, a variation of this approach was employed to assess performance from a tactical perspective. Although BSCs do not appear to be widespread in mining, Richard (2004) identifies significant value in adopting this approach for production monitoring and development at an operational level.

The approach taken to introduce a scorecard into the work place should be treated carefully to ensure a positive attitude towards its use is created. This requires the scorecard to maintain a fair and unbiased scoring system and allow active involvement in the development of measures from both management and the operator’s perspectives. Subsequently, the method of ranking operators based on their respective performance scores is intended as a measure to assist the manager with a performance review and used to judge where a particular operator sits in relation to their peers. Although performance rankings may foster competitiveness amongst the operators to improve, it has the potential to be viewed in a negative manner and should be used by managers at their own discretion.
METHODOLOGY

Investigation of operator KPIs

Discussions with experienced drill operators, drill and blast engineers, drill supervisors and management were undertaken to cross-reference a diverse range of viewpoints with the findings in the literature. A range of questions were prepared with the key focus to ascertain the following:

1. Current KPIs
2. Maintenance measures
3. Technical factors
4. Extrinsic/Environmental factors
5. Challenges
6. Variables

It was then necessary to identify targets, upper and lower control limits, and measures of importance set by the company and likewise accepted in industry. A review of the various databases was carried out to determine the available data and its specific format. This included a variety of MS Excel workbooks used to extract data from each of the databases. This data is primarily received from the Aquila Drill System (ADS) installed on the drill rigs. Based on the investigation and comparisons between the literature, experienced mine site personnel and available data, the following variables were chosen to develop the KPI scorecard. It should be noted that these chosen indicators may vary from site to site and are related to the company’s targets for drilling performance and quality.

Chosen KPIs (influenced by the operator)

Dependent variables:

a. Instantaneous Rate of Penetration (ROP) (m/dr.hr);

b. Cycle time (min/hole drilled) (this measure is not inclusive of drilling time or operating delays); and

c. Accuracy to design (m) (this includes two separate measures for the drill hole collar and toe accuracy to the drill pattern design in easting and northing, x- and y-planes respectively).

Supporting parameters (influenced by the operator)

Independent variables:

a. Weight On Bit (WOB) (kN); rotary speed (RPM); torque (TRQ) (kNm); Air Pressure (AP) (Pa);

b. Difference in bearing from design (angle°), difference in mast angle from design (angle°);

c. Shift change (hr), lunch break (hr), water or fuel – refilling (hr), fatigue break (hr), machine checks (hr), and accident damage events and duration (hr).

Dependent variables:

a. Operating time (OT), operating delay (OD), operating standby (OS), no scheduled production (NSP), scheduled loss (SL), unscheduled loss failure (ULF), unscheduled loss other (ULO) - all measured in (hr); availability (% calendar time), utilisation (% of available time), and use of availability (% of available time).

Experimental controlled variables were implemented in the data selection process to reduce variability and minimise errors in the development and analysis of the prototype scorecard model. These are listed as follows:

Controlled variables:
a. Geological domain;
b. Drill pattern design;
c. Drill rig; and
d. Drill bit.

Furthermore, parameters that were seen to be of importance but were either not captured in the data, or found to be unsuitable for application in the scorecard:

Excluded Parameters:

- Drill bit failure modes;
- MTBF (mean time between failure); and
- MTTR (mean time to repair).

These parameters were excluded as they cannot be associated with an individual operator and have been influenced by multiple operators using the same drill. Therefore, cannot be used as objective measures of an operator’s performance in these areas.

Database review

It was apparent that the data stored in each database is setup to assess the performance of individual drill rigs and the drill fleet, which had been done to fulfil company reporting measures as opposed to an operator focused approach. This meant that a significant amount of manipulation was required to extract, filter and organise the data into a usable format for the prototype scorecard development.

Aquila (ADB)

The Aquila Database (ADB) was not directly accessed for the purposes of this project, but it delivers the vast majority of drill data utilised in the production databases. The on-board ADS user interface is used by the operator (Figure 1) to align the drill to the design holes via the screen, align the mast angle, drill heading, drill level in relation to varying floor grades, and a variety of other controls (Caterpillar 2005).

Figure 1: ADS operator interface (Bucyrus 2011)
Production databases

The production databases are primarily used for specific drill information (e.g. hole ID, hole depth, number of holes drilled, drilling time, etc.) and all the time metrics (e.g. OT, OD, OS, NSP, SP, delay reasons and duration).

A range of Structure Query Language (SQL) queries were coded to select and filter data for the specified drill patterns, dates, equipment ID, and to remove various outliers in the data where possible. Testing and validation was required to ensure the SQL queries returned the correct data and to remove errors in the coding.

Performance database

The performance database is setup for the drill fleet and contains a large amount of performance data used in the scorecard development and analysis. The KPI – instantaneous ROP, and supporting parameters – RPM, WOB, TRQ, and AP are recorded at small time intervals in the database for each drill hole and provide a high accuracy of measurement.

Development of KPI scorecard

As no prior scorecard model or similar tool was available from the company or could be found in the literature, a prototype scorecard model had to be developed. This made it challenging to define objective operating ranges for many of the parameters, as limited company targets were available. Subsequently, historical data was required in order to determine a baseline from which to judge performance. Due to this some of the measures may not be entirely objective, although were suitable for the purposes of developing a prototype model to prove the potential benefits of the approach and the dataset was of a significant sample size to justify statistical methods.

The data records used for the scorecard development are from four through-seam drill patterns. Each pattern consisted of over 1000 drill holes with the same burden (m) and spacing (m). Drill holes were angled with typically 15 degrees, with an average depth of 30-50 m; and located in the same geological domain. The three drill-rigs in the dataset were all Bucyrus SKSS model rotary blast-hole drill-rigs, equipped with 270 mm diameter rotary roller tricone drill bits.

A basic layout for the prototype scorecard model was created, shown in Figure 2. The colour code displayed in the diagram indicates the main ‘KPIs’ (i.e. ‘Accuracy’, ‘Cycle Time’, and ‘ROP’) - green, ‘Reference parameters’ - dark blue, ‘Ranking’ - purple, ‘Additional information’ - yellow (e.g. ‘Time metrics’), and ‘Qualitative feedback’ - light blue.

Rate of penetration (ROP)

ROP was chosen as one of the KPIs due to its significance in the literature and as a key company measure in assessing operator productivity. The main ROP units are typically metres per operating hour (m/op.hr). Because ROP per operating hour is influenced by variables such as hole depth, the proficiency of an operator to enter the correct delays and cycle time between drill holes, instantaneous ROP (m/dr.hr) was chosen as the first KPI measure. In doing so a more reliable measure for ROP can be determined and the cycle time (i.e. time taken from when the operator has finished drilling, tramming to the next hole and setting up) can be assessed individually.

Cycle time

Cycle time was previously not recorded by the company but was found to be an important KPI following the research and review with experienced mining personnel. Measuring the cycle time would allow a manager to assess the efficiency of an operator moving between drill holes, setting up the drill and identify any trends in operator behaviour that require further investigation. The defined cycle time per hole does not include the actual drilling time, since this is highly dependent on the depth of hole and ROP. Instead, it was decided to analyse the time taken for jacking, tramming, repositioning and setting up to start drilling the next drill hole. This provides a good indication of the operator’s productivity between drill holes and was deduced from the available data. Equation 1 shows how the cycle time is calculated.
Cycle Time [min] = \frac{(Dur - DT)}{\text{#holes drilled in period}} \tag{1}

where, Dur = operating time (sec) and DT = drilling time (sec).

This KPI is a useful measure to compare against drill-hole accuracy, to determine the balance between accuracy and productivity. This can become a useful comparison if an operator spends too much time lining up the drill to achieve an accurate hole at the expense of productivity, and vice versa.

Figure 2: Prototype KPI Scorecard model layout

Accuracy

The final KPI was chosen to be accuracy to plan. An inaccurately drilled pattern can lead to poor blast fragmentation, which has a significant impact on downstream processes such as loading and haulage cycles. In order to achieve effective fragmentation and promote an efficient production cycle, it is imperative to produce accurate drilling.

The accuracy is measured in 2-dimensions (2D) by comparing the actual x-coordinate (easting) and y-coordinate (northing) of the collar and toe to design coordinates. The z-coordinates (RL – reduced level) were intentionally omitted due to the unreliable nature of the z-coordinates in the model’s coal seam and bench levels when compared to the actual seam and bench levels. By doing so the variability in measurements are significantly reduced.

The term ‘collar’ refers to the x-, y-, and z-coordinate where the drill hole is started, and the ‘toe’ refers to the x-, y- and z-coordinate where the drill hole finishes. To calculate the specific coordinates, geometry and trigonometric functions were used to ensure an accurate projection was made to the design collar coordinates, as they were previously determined incorrectly in the database. Equation 2 and Equation 3 show how the design collar x- and y-coordinates are calculated, respectively.
\[ CD_X = TD_X + |CA_Z - TD_Z| \times \tan(DM) \times \sin(DH) \] (2)

\[ CD_Y = TD_Y + |CA_Z - TD_Z| \times \tan(DM) \times \cos(DH) \] (3)

where, \( TD_X \) = Toe X Design (m) – Easting, \( TD_Y \) = Toe Y Design (m) – Northing, \( TD_Z \) = Toe Z Design (m) – RL, \( CD_X \) = Collar X Design (m) – Easting, \( CD_Y \) = Collar Y Design (m) – Northing, \( CA_Z \) = Collar Z Actual (m) – RL, \( DH \) = Design heading (degrees - from toe to collar) and \( DM \) = Design Mast Angle (degrees - angle from vertical).

Similar difficulties were encountered with the 2D difference measurement at the toe found in the database. Consequently, the actual toe x- and y-coordinates were projected to the designed z-coordinate (depth) to eliminate inaccuracy created by the difference in z-coordinates between actual and design. Equation 4 is the vector equation for 3D coordinates where, subscripts TD = design toe, TA = actual toe and R = resultant vector (toe to collar).

\[
\begin{pmatrix}
X_{TD} \\
Y_{TD} \\
Z_{TD}
\end{pmatrix} = \begin{pmatrix}
X_{TA} \\
Y_{TA} \\
Z_{TA}
\end{pmatrix} + t \begin{pmatrix}
X_R \\
Y_R \\
Z_R
\end{pmatrix}
\] (4)

Therefore the actual toe x- and y-coordinates may be determined at the design depth using \( t \) from Equation 4; the calculations are shown in Equation 5 and Equation 6 respectively.

\[ X_{TA@D} = X_{TA} + t \times X_R \] (5)

\[ Y_{TA@D} = Y_{TA} + t \times Y_R \] (6)

**Development of a ranking system**

A ranking system was developed to indicate the proficiency of an operator across the main KPIs. This is done by translating drill data into a tangible score and then ranking the respective scores. The rank identifies an operator’s relative performance and allows comparison with the supporting parameters on the scorecard to highlight where improvements can be made. It is intended to assist the manager with the performance review and can be used to monitor the progress of training and development. An individual score is assigned to each KPI, as an operator may excel in one area but need to improve in another. The best total score achievable is 100 points, whereas the worst-case score is zero points. The KPIs were weighted based on their meaning and importance in order to maintain a balance between company targets, the literature, and interview findings.

The weighting for ROP, cycle time and accuracy are somewhat arbitrary but reasonable and reflect the findings and recommendations from management at the particular site for the purposes of developing the prototype scorecard. These are by no means fixed but provide a model to describe how weightings can be assigned to each chosen KPI. Sensitivity analysis was carried out to identify the influence of adjusting these weightings. It was found that the ranking scores do change when the weightings are changed, although they can be easily adapted to suit the preferences of a specific site or at any time during trial implementation of the scorecard. Figure 3 shows the weighting associated with each KPI selected for the ranking system.

The scorecard KPIs, ROP (m/dr.hr) and Cycle Time (min/hole), are typically measured as a combined unit of ROP (m/op.hr), inclusive of cycle time, ROP (m/dr.hr) and OD. Therefore, it was decided to separate ROP (m/dr.hr) and cycle time (min/hole) to better identify trends and root causes.

The accuracy and cycle time scoring ranges aim to achieve the minimal value possible. The scoring system to determine the ranks was ascertained through an iterative process to identify upper and lower control limits, while maintaining a suitable spread that correlated with trends in the raw data and company targets.
Rate of penetration scoring

All ROP data was reviewed and as company targets were previously based on metres drilled per shift there was no baseline or defined range with which to compare the instantaneous ROP data. Subsequently, a baseline was developed using the data provided from the four through-seam drill patterns. The average and Standard Deviation (SD) of the ROP was determined for all the operators and was used as a standard from which to develop the scoring system. There were two components of the ROP score:

- A score based on the difference from the baseline ROP average (representing a target ROP), and
- A score based on the difference from the baseline ROP standard deviation (representing the target range).

The two scores were evenly weighted across the score of 35 with the overall average and standard deviation of the dataset representing a mid-range score.

Using the standard deviation provided a good indication of the variation in the observed ROP when an operator is drilling. Based on the recommendations from site personnel a wider spread of ROP is ideal, as the operator must adjust the WOB and RPM to account for variations in the rock strata and to ensure minimal occurrence of drill bit wear and failure. These supporting parameters directly influence the ROP and this was cross-referenced between the data of known experienced drillers versus an inexperienced trainee driller. Once again this measure is not entirely objective as it is based on the average and standard deviation of historical data, but served as a reference range. As the scorecard is a prototype to convey the benefits that such a model can provide, this was accepted as a suitable approach. It must be noted that during a trial implementation of the KPI scorecard model these baseline target values and optimal operating ranges can be determined to provide objective values from which to base the scoring.

K-factor adjustment for the rate of penetration KPI

Particular adjustments were required for the ROP KPI, as excessive WOB, RPM, TRQ, and AP can have detrimental effects on the drill rig in terms of damage. Therefore, a score system for the reduction of the ROP was developed using the Cramér-von Mises (CVM) test.

The CVM test is a statistical test, also known as the ‘Goodness-of-fit’ test, and is used to find the similarity between two continuous distribution curves shown in Figure 4 (EOM 2011). If the critical value \( w^2 \) is greater than the critical value at a particular significance level alpha (\( \alpha \)) the null hypothesis is rejected. The null hypothesis is that the curves are from the same distribution with a certainty defined by the significance level. Therefore if an operator was operating well outside the normal range a factor can be derived from the critical value.
The theoretical Cramér–von Mises’ integral equation is approximated by Equation 7 and applied to the empirical dataset to determine the Goodness-of-fit (EOM, 2011).

\[ w_i^2 \approx \sum_{i=0}^{n-1} (F_n(x_{i+1}) - F^*(x_{i+1}))^2 \times [F^*(x_{i+1}) - F^*(x_i)] \]

\[ 0 \leq w_i^2 \leq 1 \]

where, \( F_n(x) \) = empirical distribution function (i.e. average of all operators); \( F^*(x) \) = cumulative distribution function (i.e. operator function), \( w_i^2 \) – critical value (CVM test statistic).

This was used to determine the difference from the average that an operator performed for the specified operational variables RPM, WOB, AP and TRQ, known as the critical value \( (w_i^2) \). The smaller the critical value determined, the less similarity between the curves. Following the determination of these factors, a K-factor \( (K) \) was determined and is shown in Equation 8.

\[ K = \gamma_{RPM} \times \gamma_{AP} \times \gamma_{TRQ} \times \gamma_{WOB} \leq 1 \]

where, \( \gamma_{RPM}, \gamma_{AP}, \gamma_{TRQ}, \gamma_{WOB} \) are adjustment factors for RPM, AP, WOB, TRQ respectively derived from \( w_i^2 \).

The K-factor was used to reduce the operator’s ROP ranking score if their ROP was deemed significant by CVM’s test. The adjustment factor may be used in the scorecard with varied significance levels as desired by the user.

RESULTS

Operator rankings and KPI scorecard model

The results of applying the scoring system to the 13 operators are shown in Table 1, with the score and associated rank achieved in each category. The total ranks show that an operator does not necessarily have to be amongst the best operators in each individual category to achieve a high total rank. This can be seen in the rankings of the three highest ranked operators. For example Operator A ranks first overall, and only ranked fourth in the accuracy; also Operator M ranked second overall, yet only ranks seventh in the ROP category.

The total scores of the operators are well spread. One operator achieved a ranking of 79 points, indicating excellent drill performance based on the developed scoring system. The prototype scoring scale shown in Table 2 could be used to rate the operator overall performance scores.
Most operators scored average (50 points) or above average. Only four operators have a score below the average and two out of these four operators are very close to the average performance score of 50; namely Operator K and Operator F at 49 and 48 points respectively. Only Operator H and Operator C have a score well below average. The results of the rankings look reasonable and could be attributed to the large dataset that was analysed. This is a good sign in terms of reducing potential errors. But it has to be considered that this system is only a prototype model, which requires implementation and an iterative development process of refinement. The total ranking shows that the system balances out potential bias and assesses performance based on multiple weighted parameters. As an example, Operator B was selected to discuss the prototype KPI scorecard and how it may be used for a performance review in detail with reference to the associated ranking. Operator B ranks highly (1st rank) in regards to accuracy, although there shows poor performance in terms of cycle time (11th rank).

Table 1: Final rankings summary of results

<table>
<thead>
<tr>
<th>Operator</th>
<th>Accuracy</th>
<th>ROP</th>
<th>Cycle Time</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Score</td>
<td>Rank</td>
<td>Score</td>
<td>Rank</td>
</tr>
<tr>
<td>Operator A</td>
<td>28</td>
<td>4</td>
<td>27</td>
<td>2</td>
</tr>
<tr>
<td>Operator M</td>
<td>32</td>
<td>1</td>
<td>17</td>
<td>7</td>
</tr>
<tr>
<td>Operator E</td>
<td>26</td>
<td>5</td>
<td>24</td>
<td>4</td>
</tr>
<tr>
<td>Operator G</td>
<td>31</td>
<td>3</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>Operator I</td>
<td>16</td>
<td>12</td>
<td>28</td>
<td>1</td>
</tr>
<tr>
<td>Operator D</td>
<td>24</td>
<td>7</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>Operator L</td>
<td>25</td>
<td>6</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>Operator B</td>
<td>32</td>
<td>1</td>
<td>18</td>
<td>6</td>
</tr>
<tr>
<td>Operator J</td>
<td>23</td>
<td>8</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Operator K</td>
<td>21</td>
<td>9</td>
<td>17</td>
<td>7</td>
</tr>
<tr>
<td>Operator F</td>
<td>20</td>
<td>11</td>
<td>26</td>
<td>3</td>
</tr>
<tr>
<td>Operator H</td>
<td>21</td>
<td>9</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Operator C</td>
<td>12</td>
<td>13</td>
<td>9</td>
<td>13</td>
</tr>
</tbody>
</table>

Review of rankings against KPI scorecard model

Operator B’s scorecard is based on 15 shifts within the period from 24th of January to the 19th of August 2014, three Bucyrus SKSS model drill rigs were operated during the drilling of four associated through-seam drill patterns. Operator B drilled 175 holes in this period with an average depth of 40.14 m. A total 7,025 m were drilled during the 15 shifts, which equates to about 470 m/shift on average (Figure 6). Referring to the company goals, this is just a bit under the target of 500 m/shift.

The graphs ‘Collar Accuracy’ and ‘Toe Accuracy’ indicate average 2D difference of the actual collar and toe positions compared to design. In both graphs it can be seen that Operator B is more accurate than the average. Furthermore, the standard deviation of Operator B is relatively small compared to the overall standard deviation. A similar trend can also be seen in the ‘Bearing’ and ‘Mast Angle’ charts. The accurate adjustment of the bearing and mast angle support the high accuracy results of the toe location and is reflected in the rankings.

Operator B ranks sixth for the ROP ranking. In Figure 6 the cumulative frequency plots for RPM, WOB, TRQ and AP, show Operator B very close to the average. Although the ROP of Operator B appears to be a bit below the average a mid-rank 6th out of 13 (seen in Figure 6) is a reasonable result.

By looking at the graph ‘Cycle time per hole’ (Figure 6), it is found that Operator B’s average cycle time per hole exceeds the average cycle time of the dataset. The numbers reveal that Operator B requires around 30% more time to drill a hole compared to the average. These numbers may indicate that Operator B spends too long tramming and lining up the drill, decreasing productivity. The utilisation of available time is slightly below the average, which could be attributed to the poor cycle time performance. Operator B is ranked 11th in the Cycle Time category (Figure 5). Based on the results it is observed that
Operator B’s cycle time is an area for improvement. The poor cycle time performance could be connected to excessive attention to achieve excellent drilling accuracy. One approach could be to analyse the operating delays and standbys (seen in Figure 5) in order to prove if Operator B had been recording delays properly (e.g. lunch break which appears inconsistent on the charts, or other delays not listed). Any feedback from Operator B could be helpful to identify reasons for the cycle time performance in order to provide training and development, if required.

Table 2: Operator proficiency scores for ranking system

<table>
<thead>
<tr>
<th>Total Score</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>81-100</td>
<td>Outstanding</td>
</tr>
<tr>
<td>71-80</td>
<td>Excellent</td>
</tr>
<tr>
<td>61-70</td>
<td>Very Good</td>
</tr>
<tr>
<td>46-60</td>
<td>Average</td>
</tr>
<tr>
<td>35-45</td>
<td>Poor</td>
</tr>
<tr>
<td>&lt;35</td>
<td>Very Poor</td>
</tr>
</tbody>
</table>

Figure 5: Operator B’s prototype KPI scorecard (page 2)

Figure 6: Operator B’s prototype KPI scorecard

ANALYSIS

Scorecard and rankings

The KPI scorecard was able to identify operator performance and substantiate some potential reasons for each KPI ranking based on the supporting parameters. This is in contrast to the majority of literature, which appears to relate successful operating performance primarily on ROP and associated drill parameters such as WOB and RPM. It was found that a consistent performance across the board is the main key in gaining a high total score.

The analysis of the operator rankings based on the developed scoring system show clearly that operators have strengths and weaknesses in the various areas of performance. This verifies the need for a
balanced scoring system to assess the performance based on multiple parameters. By comparing the operator ranks across the different KPIs it was found that the ranks varied between ROP, accuracy and cycle time. This finding supports the proposed assumptions and methodology that a scorecard can provide a more encompassing view on operator performance, and that the ranking system can eliminate bias towards a specific KPI measures, such as ROP. The detailed example review of Operator B’s scorecard revealed that the prototype KPI scorecard model is a strong tool to identify areas for improvement and development, which may lead to enhanced productivity.

The scorecard approach brings the large amounts of data, referred to as “Big Data”, into one place where a supervisor, manager and also operator can look at various aspects of the operator’s performance. It also incorporates company targets and strategy in order to align and compare an operator’s performance in relation to these measures and the other operators. This is further supported by the views of Knights and Liang (2011) who mention that effective utilisation of production data can provide a key insight into a mining operation if managed correctly. Furthermore, the KPI scorecard model provides a mechanism to allow a two-way feedback process to occur between manager or supervisor and the operator. It should be used as a constructive tool and not considered as a negative thing by the operator. This is important to ensure that successful implementation is achieved. Mooraj et. al (1999) highlight the importance of a constructive learning environment based around the use of a performance scorecard. The scorecard is also an important tool to enhance key themes such as communication and engagement between both leader and operator, which are often found to be lacking in employer-employee relationships. Increased levels of engagement can lead to increased productivity in most cases.

CONCLUSIONS

The purpose of developing a prototype KPI scorecard model was to demonstrate the potential applications to enhance drilling performance influenced by the operator, improve the feedback and development process, and thereby decrease the impact of poor drilling on blasting, loading haulage and even downstream processes. By reviewing and comparing all available resources, both qualitative and quantitative, it was found that the main KPIs for the development of the prototype scorecard are accuracy (i.e. 2D collar and 2D toe accuracy), adjusted ROP (considering RPM, WOB TRQ, and AP), and cycle time (operating time excluding drilling time and delays).

The established scorecard shows the KPIs in a graphical representation, contains general information, and provides reference parameters that are used to draw conclusions based on the findings from the indicators. This was found to be very useful as it provided an initial indication of the operator’s strengths and weaknesses in these areas. The ranking is intended as a measure to give an initial indication of the performance in each KPI. The reviewer should still use their judgement and apply discretion based on experience when providing operator feedback. Clear communication and engagement is essential to ensure successful implementation. It is also important that operator feedback regarding the measures on the scorecard, and any areas where the model could be improved, are taken into consideration to maintain the iterative development of the KPI scorecard model.

RECOMMENDATIONS

During the process of developing the prototype scorecard, various areas for potential improvement were identified. The developed scorecard is only a prototype and was not trialled in operation. In order to validate the benefit of the scorecard in terms of improving the performance based on feedback provided from the scorecard, it is recommended to introduce trial scorecards in the field. The prototype scorecard model can be tailored to site and company specific targets, and specified operating ranges as these vary between different mining operations and between different drill rig models and specifications. Feedback from the operators and insight from manager and supervisors should then be used to adapt and improve the scorecard model where required. It is also recommended to investigate whether the ranking system weighting is appropriate. This is highly dependent on company targets and may change with time. The KPI scorecard layout could be slightly adapted to show only the raw score and the manager could look at
the rankings separately from the scorecard.

It could be beneficial to implement a measure for drill bit consumption and failure modes attached to an operator’s name and relate this to the ROP measure and supporting parameters. This would provide an additional method to relate the operator’s influence on the supporting parameters WOB, RPM, TRQ and AP to excessive drill bit wear and failure mechanisms, to establish acceptable operating ranges and incorporate these into the ROP scoring system. A financial measure could also be included to give an indication of an operator’s cost per drilled metre to allow management to gauge the costs associated with each operators drilling proficiency.

Finally, it is recommended that the KPI scorecard model has the potential for application across any mine site that has rotary drills. This would require minor changes and development to tailor the scorecard to a specific site or company, but by and large in large the fundamental concept would remain similar. Furthermore, not only could this concept be applied to drilling operations to improve and develop operator performance from a tactical level, but it could also be applied to a vast number of operational roles in mines and other industries, with relevant modifications.

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REFERENCES

EOM - see Encyclopedia of mathematics.