Evaluating Productivity Management of Materials Handling System at Mempeasem Gold Mine

Desmond B. Munyadzwe, Nonduduzo B. Mamba and Raymond S. Suglo

Abstract—Productivity management in materials handling is critical to mining operations. Most open pit mines use modular dispatch systems to control and monitor the movement of their materials handling equipment and operations. Statistical methods can be used on the data collected by the dispatch systems to identify major losses in time, tonnage and finances in productivity management. In this study, three ranking methods (a base case and two modified ranking methods) were used to evaluate the significance of the deviation and correlation parameters in productivity losses. A load and haul productivity loss ranking model was developed using data obtained from Mempeasem Gold Mine’s from January to October 2018 and tested with data obtained in November 2018. The results show that the ranking model can be used in the analysis of production data over any period of time and that the model is applicable in the analysis of the performance of all types of discrete load and haul equipment (trucks and excavators), either operating individually or in combination. The ranking based on deviation values is useful for comparative purposes. However, the ranking based on reduced values is more useful in decision making processes as it enables mine operators to take mitigation measures according to the level of priority of each item. Decision makers could also use the suggested colour coding for easy identification of the priority losses.

Index Terms—Modular Dispatch System, Open Pit Mine, Productivity Management, Ranking Model

I. INTRODUCTION

Productivity management has developed to be one of the major aspects of engineering management in mining largely because productivity has been declining significantly in the mining industry since the year 2000 [1]. From the mining value chain, ore production has a major impact on the total productivity of a mine. Therefore, it is necessary to improve productivity in primary mining operations such as drilling, blasting, loading, hauling and dumping. From a study carried out at Mempeasem Gold Mine, most of the bottlenecks in the mining cycle directly affect the load and haul (L&H) operations. Thus, focusing on L&H operations will give a clear picture of where the mine is possibly losing resources. Mempeasem Gold Mine requires high levels of productivity due to its high stripping ratios and escalating operating costs. Several efforts have been put in place to monitor and manage operational productivity of load and haul operations at Mempeasem Gold Mine. These include commissioning of a modular dispatch system, training of operators on how to use the system and deployment of a section responsible for managing productivity issues. The Modular Dispatch System (MDS) at Mempeasem Gold Mine is the main system used for measuring and processing L&H productivity data at the mine.

Though the MDS collects data very well to inform management on the operations, there are still possible analytical gaps due to the extraction and interpretation of limited useful information from the data. These gaps may largely be due to selection of inappropriate statistical methods and limited interpretation capabilities of the collected data. This results in inadequate determination of the root causes of many of the losses. Thus, more deterministic approaches to data optimisation are required. This paper reviewed the L&H productivity management system at Mempeasem Gold Mine using statistical methods to identify the major losses in time, tonnage and money. It also adopted a modified process of productivity management by introducing correlation and deviation parameters in analysing and interpreting the data.

II. OBJECTIVES OF RESEARCH

The objectives of this paper are to analyse major time and tonnage losses, and costs in the L&H processes at Mempeasem Gold Mine using the Anglo-American Time model and MDS data at Mempeasem Gold Mine; run correlation analyses on the major losses relative to corresponding key performance indicators (KPIs); develop and test an integrated ranking metrics for interpreting productivity losses and compare the results from the metrics model with the results from traditional methods of productivity data analyses.

III. RESEARCH METHODOLOGY

Data used in this study was collected from the Modular Dispatch System at Mempeasem Gold Mine, GEMS strategic planning data, Mempeasem Gold Mine’s Oracle System and Motion-metrics Fragmentation Analysis data. The data was obtained from actual mine production reports from January to November 2018. The data was extracted from the databases in .csv and .xlsx file formats. The data was processed in two software platforms, MS Excel (Data Analysis extension) and R-software to develop the model, while the data for November 2018 was used to test the model. Microsoft Excel
was used to sort, classify and analyse the data while R-software was used to determine the correlations for analysis. The prototype was built using MS Excel and the data was analysed in four stages (i.e. Stages 1 to 4).

A. Stage 1:

General productivity key performance indicators (KPIs), classified according to tonnage, cost and time were calculated. These indicators are the availability, utilisation, machine output, overall equipment effectiveness (OEE), production tonnage and mining costs. The general equations for calculating the parameters are summarised in Table I [2]-[4]

<table>
<thead>
<tr>
<th>Losses/Factors</th>
<th>OEE Loss Category</th>
<th>OEE Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unscheduled maintenance</td>
<td>Down time losses</td>
<td>Availability (A) = Operating time \times 100</td>
</tr>
<tr>
<td>Scheduled maintenance</td>
<td></td>
<td>Net available time</td>
</tr>
<tr>
<td>Operational stops</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consequential time loss</td>
<td>Speed losses</td>
<td>Utilisation (U) = Net operating time \times 100</td>
</tr>
<tr>
<td>Delays</td>
<td></td>
<td>Scheduled operating time</td>
</tr>
<tr>
<td>Standby</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loading rate</td>
<td>Defects losses</td>
<td>Quality (Q) = Payload Bucket capacity x 100</td>
</tr>
<tr>
<td>Diggability</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

B. Stage 2:

Losses and factors associated with each KPI were measured and the correlations between the losses and KPIs were then determined. These factors include loading rate, loadability, degree of fragmentation, costs, consequential time losses, delays, standby losses, scheduled and unscheduled maintenance, and operational stops. For each analysis the Pearson correlation factor, r, was determined.

C. Stage 3:

Based on the calculated correlation parameters, a ranking metrics model was developed that ranks losses and other factors according to the degree of loss or level of impact on the materials handling system. The ranking is in a simple order of values (1 ≤ n ≤ ∞). The factor with the highest impact in terms of losses is assigned a value of 1 while the larger the value of ∞, the smaller its impact in terms of losses. The model utilises three main statistical parameters in generating the results (i.e. deviation, correlation and rank parameters). The deviation parameter is used to standardise the values that are to be ranked, by reporting the difference between the measured (actual) values and the target values. The rank is then calculated based on the deviation between the measured and target values. The correlation parameter helps to improve the accuracy and precision of the results by multiplying the standardised results by the correlation factor to obtain the reduced values. The correlation factor shows the degree to which two variables are related. Therefore, the reduced value gives a clearer picture of which loss has a greater impact on productivity. The reduced value ranking is then used to identify the losses that need attention and prioritisation when taking mitigation measures.

D. Stage 4:

In this stage, the model was tested using data collected from the mine in November 2018. Comparison of the results between original ranking (using measured values) and modified ranking using deviation and correlation were made.

IV. GENERAL INFORMATION ABOUT THE MINE

Mempeasem Gold Mine is a hypothetical mine in Democratic Republic of Congo. It produces over 54.32 million grams of gold per year from an average recoverable ore grade of 6.87 per ton. The mine operates using both conventional and dip-slope open pit mining methods to recover diamonds from a large auriferous reef [5]. The mine produces about 9.3 million tons of ore per year and has an average stripping ratio of 3.98:1. The mine life is estimated to be 55 years.

V. LITERATURE REVIEW

The following sections contain the relevant literature reviewed in this study.

A. Productivity Management

As mining managers work to increase the profitability of their mines, improving productivity is high on the agenda [6]. Productivity in a mining company can be analysed at the macroeconomic or operational level [7]. Managing operational productivity requires the identification of actionable items. The widely applied approach is the lean management concept, which was founded by Kiichiro Toyoda, founder of Toyota Motor Corporation. This approach allows companies to achieve small, incremental changes in the processes to improve efficiency and quality by measuring key performance indicators and interpreting the indicators by determining the losses that are attributable to each indicator. Many mining companies are failing to capture productivity improvements mainly due to limited information on the major operating factors and losses that affect productivity in the mining industry [8]. Usually the overall equipment effectiveness (OEE) is reported to indicate productivity of extraction activities, which reflects the level of equipment performance [2]. The method is only limited to assessing time effectiveness and does not measure the other key performance indicators like the tonnages mined and costs incurred. In addition, the reliability of the method is heavily dependent on accurate data which poses a serious challenge to companies that either do not collect data on the key operations at all or collect data manually. Though these challenges are magnified in junior mining companies due to lack of advanced systems to capture data, large companies have enough data to use in their productivity management.

Unfortunately, most of the large companies are not using all the data they are capturing from operational systems to their maximum benefit in productivity management. This leads to limited data optimisation and utilisation. Some mine managers have realised that capturing and managing the right data and using the latest analytical tools can provide significant improvements to the operational productivities of their mines [9]. The challenge today is simplifying data

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interpretation to the required level of understanding for end users at different levels of decision making. A report on business risks and opportunities facing mining puts data optimisation as the third highest risk for two years in a row [10]. Though it is more of an opportunity than a risk now, the main challenge to most mines is data optimisation. Data is useless when not interpreted correctly and proper actions are not taken.

Data optimisation is integral to productivity management. To achieve data optimisation each step in the information cycle as shown in Fig. 1 must be properly executed. There is the need for proper use and interpretation of data to optimise its value - the last steps in the information cycle [10]. Therefore, the gap largely lies in interpretation, which could be largely attributed to the type of analytical techniques used.

VI. DATA ANALYSIS

The evaluation is centred around data optimisation through the analysis and interpretation capabilities of different statistical methods. Ranking, summation, correlation and deviation parameters were applied on the sample data to evaluate the significance of each parameter on data optimisation in a materials handling productivity management system.

A. Correlation Analyses

The Pearson’s correlation factor analysis was run using Microsoft Excel with data from the mine’s Modular Dispatch System and verified using the R-software. Fig. 2 is a scatter graph generated to determine the correlation factors summarised in Table II for each KPI and corresponding losses.

![Fig. 2. Scatter Graph for Daily Tonnage and Loading Rate.](image)

TABLE II: CORRELATION FACTORS AND R-VALUES FROM CORRELATION ANALYSIS

<table>
<thead>
<tr>
<th>KPI Associated Factor</th>
<th>Tonnage</th>
<th>Loading Rate</th>
<th>Total Mining Costs</th>
<th>Availability</th>
<th>Utilisation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loading Rate</td>
<td>0.7147</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Truck Loads</td>
<td>-</td>
<td>0.4122</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Particle Size</td>
<td>-</td>
<td>-</td>
<td>0.9998</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Business Expenses</td>
<td>-</td>
<td>-</td>
<td>0.9906</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Fuel Costs</td>
<td>-</td>
<td>-</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Labour Costs</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Repair &amp; Maintenance</td>
<td>-</td>
<td>-</td>
<td>0.9815</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Tyres</td>
<td>-</td>
<td>-</td>
<td>1.0000</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Scheduled Maintenance</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.6125</td>
<td>-</td>
</tr>
<tr>
<td>Unscheduled Maintenance</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.4647</td>
<td>-</td>
</tr>
<tr>
<td>Operational Stops</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.1391</td>
<td>-</td>
</tr>
<tr>
<td>Consequential Loss</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.4308</td>
<td>-</td>
</tr>
<tr>
<td>Delay Loss</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.7501</td>
<td>-</td>
</tr>
<tr>
<td>Standby Loss</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.2678</td>
<td>-</td>
</tr>
</tbody>
</table>

B. Load and Haul Productivity Losses Ranking Model

The evaluation of statistical parameters used to identify losses was incorporated into a model based the actual operating data or parameters (the base case) and two modified cases (the correlation and deviation parameters). The model was developed and tested using Microsoft Excel software.

C. Prototyping

The correlation values were used to develop a prototype calculator to incorporate the new statistical parameters of correlation, deviation and rank. The model ranks losses from the largest loss to the smallest loss to enable decision makers detect which losses to focus on when developing mitigation plans.

D. Working Principle

The metric model was designed with 7 distinct columns in MS Excel as shown in Fig. 3. They are in the static, input and output columns. Static columns A and B have fixed values. The values in the input columns C and D can be changed by the user. The values in output columns E to H change automatically depending on the input values in the linked cells. Fig. 4 summarises the Excel formulae for the Model Columns.
Column A in Fig. 3 contains the losses and factors categorised under tonnage, cost and time losses. These losses are the ones that were ranked to determine which loss has the highest impact and should be given the highest priority when taking mitigation measures to improve productivity.

Column B is a static column of correlation factors calculated in this study and summarised in Table II. The correlation factors are used as multipliers to obtain the reduced values in column F of Fig. 3. The signs of the correlation values were ignored as they are catered for by the rank formula in MS Excel. The coefficients improve the accuracy and precision of the loss analysis, consequently they can be considered as optimising the data.

Columns C and D in Fig. 3 are input columns for measured and target values from the mine. The user enters the values for required parameters under tonnage loss, time lost and cost losses for a given period. The measured (achieved) values are the values that were obtained from the data sources like the mine’s Modular Dispatch System. The target values are the values that decision makers or mine planners set based on their own experience, discretion and understanding of their operations.

Column E in Fig. 4 has the deviation values (i.e. the numerical differences between the values in Columns D and E). The deviation values show the relative differences (gains or losses) between the target values and measured values. This is because compared to the measured values, the deviation values are standard to all the losses being ranked. For example, with reference to Fig. 3, delays which were expected to take 4.00 hr actually took 5.93 hr and operational stops which were expected to sum up to 1.00 hour took 4.95 hr. Thus, the time lost due to delays is ranked higher than the time lost due to operational stops when using the measured values. However, the actual avoidable time lost due to delays...
is 1.93 hr compared to 3.95 hr lost due to operational stops. Thus, using deviation values to rank losses gives a clearer picture of the actual situation and it improves data optimisation leading to more efficient mitigation measures.

In Column F of Fig. 4, the deviation values are standardised by reducing them by the correlation factor. Thus, the reduced values in Column F are the products of correlation factors (column B) and the deviation values in column E of Fig. 4. Disregarding the signs of correlation factors, the possible range of reduced values is between 0 and 1. A reduced value of 1 represents a strong correlation between the parameters while a 0 value represents a very weak or no correlation. A correlation factor closes to 0 (e.g. 0.2) reduces the deviation value by a much greater amount than a correlation factor close to 1 (e.g. a correlation factor of 0.9). Thus, the more related a loss is to a KPI, the higher it ranks as a priority loss, or the lower the relationship, the lower the loss ranking. For example, in Fig. 3 the deviation values for delays and operational stops are 1.93 hr and 3.95 hr respectively, but their respective correlation factors are 0.7501 and 0.1391, the ranking based on the reduced values regards delays as the higher priority loss with 1.45 hr as compared to operational stops with a reduced value of 0.55 hr.

Columns G and H in Fig. 4 are the output columns in which the rank formulae are used to prioritise the losses based on the deviations and reduced values. The rank formulae were applied to the values in the corresponding cells in Columns E and F (the rank deviation and rank reduced values) as shown in the embedded equations in the cells in Fig. 4. The rank deviation value has integer values ≥ 1 (i.e. from 1 to n), where the value n is the number of the losses per given category. For example, n = 6 for time loss because there are five losses for time loss. Each number is colour coded in a spectrum of red, yellow and green. The numbers are divided into 3 sets based on priority. Red colour corresponds to the numbers in the highest priority set, yellow to the numbers in the medium priority set and green to the numbers in the least priority set. Each set has a fading colour code intensity to highlight which loss is more prominent within the set. For example, in Fig. 3 various time losses were ranked from priority 1 to 6 of which the top 2 priority losses (priorities 1 & 2) are coded red, second set of time losses included priorities 3 and 4 which are coded yellow. The least priority set of time losses (priorities 5 and 6) are coded green (light green to green). For tonnage losses (see Fig. 3), truck loads are measured by the number of loads/shift, loadability in tons/hr and particle size in percent which makes it difficult to rank them. However, the comparisons are reflected in the deviations and reduced values which can be used in decision making.

E. Testing

Actual operating data from January to October 2018 were considered as the base data and these were tested for functionality and accuracy in the model with data collected by the MDS in November 2018.

VII. COMPARISON OF MODEL GENERATED AND ORIGINAL RESULTS

The results of correlation and deviation parameters generated by the model were compared with the original results and are presented in this section.

A. Costs Ranking

Table III summarises the comparison of ranking metrics for major costs in the load and haul operations. The categories of costs are ranked based on the measured values (as is the current practice at Mmpeasem Gold Mine), the modified ranking based on the deviation and reduced values which were developed in this study.

1) Rank 1 – Ranking based on original cost values

From columns 2 and 3 of Table III, the ranking of the original cost values (from the highest to the lowest) is business expenses (BWP 15.11 × 10^3), fuel (BWP 10.52 × 10^3), repair and maintenance with BWP 10.43 × 10^3, labour with BWP 4.20 × 10^3 and tyre costs (BWP 1.87 × 10^3).

2) Rank 2 – Ranking based on modified deviation cost values

From columns 4 and 5 of Table III, using the modified ranking based on deviation cost values, from the highest to the lowest, the highest priority is fuel cost with BWP 15.30 × 10^3, tyre costs with BWP 8.33 × 10^3), repair and maintenance had BWP 7.70 × 10^3 deviation, labour (BWP 1.95 × 10^3) while business expenses have the lowest priority. The actual business expenses were less than the target costs (i.e. no cost overruns).

3) Rank 3 – Ranking based on reduced cost values

From columns 6 and 7 of Table III, using the modified correlation based on reduced cost values (from the highest to the lowest), the highest priority is to be given to fuel cost (BWP 15.30 × 10^3), tyres (BWP 8.33 × 10^3), repair and maintenance (BWP 7.56 × 10^3), labour (BWP 1.95 × 10^3) and business expenses with - BWP 88.07 × 10^3.

B. Time Loss Ranking

Table IV summarises the ranking metrics for the time losses in the load and haul operations. The categories of losses are ranked based on the measured value as is the current practice at Mmpeasem Gold Mine. The deviation values account for the deviation parameters and the reduced values account for the correlation factors.
1) Rank 4 – Original time loss ranking

Based on Table IV, the time loss categories are ranked according to the measured, deviation and reduced values. From columns 2 and 3 of Table IV, using the original ranking based on measured (original) values, the highest priority is to be given to scheduled maintenance with 23.91 hr, followed by unscheduled maintenance (20.65 hr), standby (6.00 hr), delays (5.93 hr), operational stops (4.95 hr) and consequential time loss (3.10 hr) in that order.

2) Rank 5 – Loss ranking of modified deviation time values

From columns 4 and 5 of Table IV, using the modified ranking based on the deviation in time values, the ranking (in descending order of priority) are scheduled maintenance (23.91 hr), unscheduled maintenance (20.65 hr), standby (6.00 hr), delays (5.93 hr), operational stops (4.95 hr) and consequential time loss (3.10 hr).

3) Rank 6 – Time ranking of modified correlation values

From columns 6 and 7 of Table IV, using the modified ranking based on the reduced time values, the ranking (in descending order of priority) are scheduled maintenance (3.01 hr), unscheduled maintenance (2.16 hr), delays (1.45 hr), standby (1.07 hr), consequential delays (0.90 hr) and operational stops (0.55 hr). Thus, time losses due to scheduled maintenance should be given the highest priority while time losses due to miscellaneous delays should have the lowest priority.

VIII. APPLICABILITY

The ranking model developed in this study can be used in the analysis of production data over any period of time. However, weekly production data analysis is currently done at Mempeasem Gold Mine. Also, the model is applicable in the analysis of the performance of all types of discrete load and haul equipment (trucks and excavators), either operating individually or in combination.

The user has to input the measured and the target values into the model to obtain the output values which can then be modified based on the deviations and correlation factors, and ranked based on the actual, deviation and reduced values. The ranking based on deviation values is useful for comparative purposes. However, as determined in this study, the ranking based on reduced values is more useful in decision making processes as it enables mine operators to take mitigation measures according to the level of priority of each item. Decision makers could also use the colour coding for easy identification of the priority losses. The red, yellow and green spectra shown in Fig. 4 are suggested because most mining engineers are very familiar with them.

IX. CONCLUSIONS

Statistical methods can be used in productivity management to deal with declining productivity trends. An important aspect of productivity management is collection and analysing data, interpreting the information obtained to make informed decisions and coming up with significant and practical mitigation measures.

In this study, statistical methods were used to identify and analyse major time, tonnage and cost losses in the L&H operations in an open pit mine. The parameters identified for analysis included loading rate, loadability, degree of fragmentation, costs, consequential time losses, delays, standby losses, scheduled maintenance, unscheduled maintenance and operational stops. The Pearson correlation factors and R2-values which measures the degree of relationship between data are sets were calculated from the data for each of the identified objective function parameters.

Three ranking methods (a base case and two modified ranking methods) were used to evaluate the significance of the deviation and correlation parameters in productivity losses. The values obtained from ranking methods were then compared with the base case to examine the level of significance of each parameter. The study has demonstrated the importance of correlation, deviation and rank parameters in productivity management. The calculated parameters reveal information about the root causes of productivity losses in a typical open pit mining operation and helps to improve the analytical ability of systems used for productivity management decisions.

It is recommended that open pit mining companies adopt the load and haul productivity losses ranking model presented in this study and that the model be used on weekly basis for more accurate results and that colour coding may also be used for easy identification of the priority losses as most mining engineers are very familiar with them.

REFERENCES


Desmond B. Munyadzwe graduated with an BEng (First Class) in Mining Engineering from Botswana International University of Science and Technology (BIUST), Palapye, Botswana in 2019. He is currently a Mining Engineer Trainee at Debswana Jwaneng Mine. His research interests are in mine management, mine economics, mine automation and materials handling. He is affiliated to Engineers of Botswana (ERB) and Botswana Institute of Engineers (BIE).

Nonduduzo B. Mamba graduated with BEng. (Second Class) Upper Division in Mining Engineering from Botswana International University of Science and Technology (BIUST), Palapye, Botswana in 2019. Her interests are in mineral economics, mine management, and mineral resources and sustainable mining. She is a registered member of the Botswana Institute of Engineers (BIE).

Raymond Suglo holds PhD and MSc in Mining Engineering from the University of Alberta, Edmonton, Canada and Postgraduate Diploma and BSc degrees in Mining Engineering from Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. He has over 32 years of professional experience in teaching, research and consultancy. He is currently a Professor and Head of Mining and Geological Engineering Department at Botswana International University of Science and Technology (BIUST), Palapye, Botswana. Before joining BIUST, he worked for 24 years at the University of Mines and Technology, Tarkwa, Ghana. His research areas are Mine Ventilation and Safety Engineering, Simulation of Mining Systems, Surface and Underground Mine Planning and Design, Mining Laws and Environmental Management. He has to his credit 64 publications (31 refereed journal publications, 33 conference publications). He is a Member of the American Institute of Mining, Metallurgical and Petroleum Engineers, Inc. (SME), the Canadian Institute of Mining, Metallurgy and Petroleum (CIM) and Ghana Institution of Engineers (GhIE).