SIMULATION OF PRODUCTIVITY PARAMETERS APPLIED TO ELABORATION OF MINING PLANS

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ABSTRACT

One of the main functions of a monthly mining plan is to define the ROM mass, waste volume and the location of mining polygons. Mining plans applied to open-pit mining method need to adopt hourly productivity parameters for haulage and loading operations. The most common source to provide this data is consulting a historical database. However, the adoption of historical data as a parameter may not accurately represent the productivity capacity of fleet dedicated to implementing the plan. The switching between rainy and dry periods implies adjustments in the operation, which causes oscillations in productivity of haulage and loading operations. This study aims to simulate the main operational parameters through multivariate equations that explain the production cycle of these operations. To obtain the equations were applied techniques and multiple regression based on a database obtained via operational management system of a mine. The simulation model is supported by high correlations among variables. Thus, the simulated indicators reached values very close to the real ones. This adherence and high correlations validate the model. Therefore, the application of this tool ensures high feasibility of monthly mining plans.

KEYWORDS

Monthly mining plan, productivity capacity, simulation

INTRODUCTION

Simulation techniques applied to mining projects are widely used in industry because support operational decisions. On account of the possibility to reach reduced costs and risks, these tools have been developed over the last decades and can be applied to mine planning (Nader et. al, 2012). In most operations that use the open-pit mining method, the mining plan leads the drilling, blasting, loading and haulage. Thus, the mining plan shall set targets compatible with the system capacity. Bozorgebrahimi et al. (2003), claim to be necessary to select a group of key variables able to build a model that explains a particular process. One of the main responses obtained from a simulation model is the performance estimation of a certain process.

Monthly mining plans must provide the locations of mining faces, quality and material quantities. As this mining plan will be implemented by a given fleet of equipment, it is necessary to establish a feasible performance target. The conventional method of establishing productivity targets is a background query. However, these reports can inform only the productivities performed in previous months and do not consider the variability of cycle times, average haulage distance and other operational variables. This practice can threaten the viability of the mining plan because adopts a performance obtained in a different operating condition of the current. Thus, the use of background reports can lead to situations in which the targets are too bold or too simple to be accomplished.

Considering the monthly mining plan as the most important technical guidance for mining operations, it is necessary that the targets are achievable. Rodovalho and Cabral (2014) performed estimations of hourly productivity that consider a database built during one month. The current study aims to generate equations able to estimate the productivity parameters of loading operations and mining haulage of a mine with high adhesion in relation to productivity performed. In this regard, a group of variables that have strong influence on the operations productivity will be evaluated. The studies adopt a database built during four months and were carried in a large open-pit mine in the state of Minas Gerais, Brazil. Using techniques of multiple linear regressions, equations were generated for each load equipment and haulage fleet in operation. A fleet management system was used to record the behavior of the operating variables and build the database. The main contribution of this study is to develop more realistic mining plans. It is also important to discuss the results of a simulation that uses larger database. In addition, the simulation model can be an excellent management tool because it allows the mapping of deviations or process failures (Rodovalho et. al., 2016).

METODOLOGY

The development and implementation of simulation models may require high costs. Even with high proficiency in software applied to the simulation, a meaningful collection of data is needed. This way, the model must generate output data capable of supporting an adequate analysis of the process. This action depends on the identification of variables that influence the process. The method used to obtain the equations that explain the processes studied and compose the simulation model is the multivariate linear regression. The use of this tool in the development of monthly mining plans represents a novelty able to increase the quality of short-term plans (Rodovalho and Cabral, 2014).

Data Collection

Data collection occurred in a large open-pit mine in Minas Gerais, Brazil. In this same mine also was the execution of a mining plan prepared according to the methodology described in the present study. The database meant to evaluate the behavior of the main variables, related to the mining process, includes the previous four months before the plan. Both parameters behavior analysis and equations generation were executed by using this database. The studied period corresponds to the dry season in the region. Rodovalho and Cabral (2014) studied the same season but considered one month to perform the multivariate analysis. In addition, the authors considered the previous three months to perform the parameters behavior analysis. The present study uses the same database to generate the equations through multivariate linear regression and perform the parameters behavior analysis. Furthermore, a comparative analysis will be performed to evaluate the impact of database size.

To collect data in real time was used a fleet management system. This system also organizes the reports and stratifies the database for each of the variables studied. Also it is possible to stratify the information in shifts, days, weeks and months. For the haulage fleet the following variables were evaluated: cycle time (CT), operational delay (OD), queuing time (QT), loading time (LT), maneuvering time (MT), payload (P), average haulage distance (AHD), operational moment (M) and the ratio of haulage distance when the truck is loaded and empty (RFD). Regarding the load equipment the following variables were evaluated: cycle time, operational delays, AHD, downtime (DT) and operational moment.

Variable Selection

Each of the cited variables in the previous section must be analyzed in a statistical tool that classifies as correlation with the response variable. In this study the response variable is the hourly productivity and statistical tool is represented by the stepwise forward and backward regression method. This method performs some rounds of correlation evaluating between each predictor variable and the response variable. In each round it is possible that variables are included or excluded. The selection ends when it identifies a group of predictor variables that hold the greatest correlation with the response variable. This study includes this type of analysis for eight shovel hydraulic excavators, four large mechanical loaders and three haulage fleet.

Table 1 shows the matrix correlation of excavator number one which has been applied the stepwise regression analysis. The report informs the group of variables that have more influence in hourly productivity of the excavator 1. The signs before the coefficients indicate direct or reverse proportionality in relation to the response variable.

Table 1 – Stepwise regression for excavator 1.

Response	Hourly productivity				
Step	1	2	3	4	5
Constant	1892	1704	1761	1837	1999
Variables	**Coefficients**				
AHD	-278	-604	-561	-549	-423.4
M		0.2274	0.2411	0.2574	0.2301
OD			-311	-309	-314.2
DT				-1732	-791
LT					-1981.7
R^2_{adj} (%)	11.12	84.51	90.49	91.57	92.5

Productivity Equations

After the variable selection step, for each transport fleet and loading equipment, will be possible to build equations using multiple linear regression. The hourly productivity equations are obtained by applying the stepwise regression method. Charnet (2008) states that the adjusted coefficient of determination (R^2_{adj}), measures the quality of the regression and the capability of the equation to explain a particular process. Table 2 shows each equation generated for loading operations with their respective adjusted coefficient of determination. Table 3 lists the equations for the haulage fleets. Blank fields in tables 2 and 3 indicate that the variable has been dropped or does not have significant influence in a given process. Analysis of tables two and tree show that the adjusted determination coefficients are satisfactory. This information indicates that the equations have high possibility to explain the studied process.

Table 2 – Loading Machines equations for hourly productivity estimations

Loading Machines	Coefficients of equations							
	Constant	AHD	M	DT	OD	CT	LT	R^2_{adj} (%)
Excavator 1	1999.2	-423.4	0.2301	-791	-314.2		-1981.7	92.5
Excavator 2	2399.8	-350.7	0.1799	-4592.6	-332.96		-5721	93.9
Excavator 3	1981.1	-406.4	0.2386	-2271.2	-362.3	54.2	-4502.5	90.2
Excavator 4	1739.5	-331.2	0.1885	-1656.4	-306.8	180	-1092.5	92.3
Excavator 5	1394	-399.5	0.2597	1896.3	-331.4	12.3	3260.2	96.8
Excavator 6	1041.9	-249.1	0.2457	144.2	-209.9		-93.4	92

Excavator 7	1255.9	-271	0.2267	260.2	-258.4		-276	90
Excavator 8	1497.5	-85.9		-8287.2		889		88.6
Loader 1	1553.9	-385.4	0.2305	-497.5	-297.2			91.9
Loader 2	2302.4	-88.2	0.02	-10411.1	-251.59	395.68	-13190.6	94.5
Loader 3	2074.8	24.6	-0.0238	-13437.5	-285.7	-55.6	-13436.4	92.7
Loader 4	2649.1	-23.6	-0.0083	-12746.9	-261.6		-18302.9	91

Table 3 – Haulage fleet equations for hourly productivity estimations

Coefficients	Haulage fleet		
	Fleet A	Fleet B	Fleet C
Constant	253.9	346.6	398.7
M	0.2938	0.2944	0.2654
OD	-4.47	-2.8	-4.89
CT	-189.2	74.36	18.95
QT	-388.3	-60.63	141.5
MT	790.8	216.2	11.2
LT	-161.3	212.2	
P	0.8027	-0.1875	-0.1523
AHD	-80.352	-103.8	-102.7
RFD	-9.7	21.384	5.22
R^2 adj (%)	96.1	95.2	93.4

CASE STUDY

The equations presented in the previous section were applied to the development of a mining monthly plan in a large mine. All stages of this study were conducted in an iron open-pit mine. The operations occur in shifts of six hours for 24 hours a day with no production stoppage during the year.

The ore production demands and waste removal are defined in the first stage of mining plan development. These demands include the ore feeding to the crusher, waste removal and other flows of budget. The performance indicators provided in the budget are used for setting the volume for each mining face. This information is used to draw the haulage profiles and calculate the AHD. Therefore, the volumes obtained for each mining face are preliminary.

In the studied mine there are twelve active loading points. Each mining face can be composed by ore and waste. The ore volume can supply the crusher or strategic stock piles. The waste is disposed in one of the actives waste piles. The mass calculation of each mining face uses the indicator OEE (Overall Equipment Effectiveness). This indicator is provided in annual budgets and is calculated by multiplying mechanical availability, operational usage and hourly productivity of the fleet. However, before the development of the mining plan these masses will be adjusted according to the results obtained in the simulation. The AHD is generated by the distance between each mining face to the active destinations. This distance is weighted by the mass of each flow. Table 4 presents all the parameters to replace in the equations described in Table 2. Table 5 shows all the parameters that should be replaced in the equations described in Table 3.

Table 4 – Operational parameters for loading equipments

Loading Machines	Operational parameters						
	AHD (km)	M (t. km/h)	DT (h)	OD (h)	CT (h)	LT (h)	HP (t/h)
Excavator 1	4.85	10010.2	0.0376	0.556		0.053	1934.8
Excavator 2	4.2	9944.2	0.0384	0.447		0.042	2150.9
Excavator 3	2.81	7068.7	0.0279	0.594	0.018	0.043	2053.5
Excavator 4	4.34	9842.1	0.0291	0.556	0.028	0.051	1886.2
Excavator 5	2.99	6388.4	0.0282	0.6405	0.029	0.053	1871.9
Excavator 6	3.92	5234.6	0.0475	0.5616		0.073	1231.7
Excavator 7	4.03	7581.8	0.0384	0.8056		0.062	1666.6
Excavator 8	4.09		0.0396		0.329		1110.2
Loader 1	2.79	5162.2	0.0392	0.5243			1493.2
Loader 2	2.15	2725.7	0.038	0.7854	0.1881	0.041	1093.8
Loader 3	1.98	2506.4	0.0285	0.7548	0.1683	0.042	887.3
Loader 4	1.98	2681.9	0.0381	0.5202		0.040	1190.7

Table 5 – Operational parameters for haulage fleet

Operational parameters	Haulage fleet		
	Fleet A	Fleet B	Fleet C
M (t.km/h)	828.86	1148.46	1401.35
OD (h)	9.48	8.2	10.29
CT (h)	0.181	0.237	0.311
QT (h)	0.0224	0.0249	0.0298
MT (h)	0.01995	0.01908	
LT (h)	0.03588	0.04004	0.041
P (t)	141.93	176.65	234.31
AHD (km)	2.21	2.85	3.43

RFD	0.837	0.892	0.891
HP (t/h)	350.9	380	346.6

The equation (1) is related to excavator 1. This equation represents the way that the values should be replaced. It must consider the results obtained in the rounds of multiple linear regression analysis. The result is provided in t/h and represents the hourly productivity planned for excavator 1 during the month. The same process should be repeated for the other equipments.

$$HP = 1999.2 - 423.4*AHD + 0.2301*M - 791*DT - 314.2*OD - 1981.7*LT \qquad (1)$$

The results of hourly productivity estimation for all equipments allow calculation of the mass for each mine face. This process ensures that the mass of each mine face is compatible with the actual capacity of the equipments during that month. Therefore, it is possible to design the mining monthly pushbacks compatible with the handling capacity of each mine.

DISCUSSION OF THE RESULTS

After implementing the plan is possible to evaluate the degree of deviation between the estimated hourly productivity and actual productivity achieved in the month. Furthermore, it is possible to evaluate the deviation for each load equipment or haulage fleet. Table 6 shows the estimated hourly productivity, the actual values and the deviation between both values. Analyzing this table, there is low variation for loading and haulage operations. However, some loading equipments have high variation. The excavators 5, 7 had many mechanical and operational failures. Each failure occurred between short periods of time and caused instability in the production process. Depending on these specific failures, there was high deviation for these machines. On the other hand, the loader 3 achieved productivity higher than estimated because this equipment supported the feeding of crusher. The result was assigned to operation in closer load points. Regarding other loading equipment and haulage fleets, the deviation was satisfactory. The analysis performed by Rodovalho and Cabral (2014) showed variations of up to 26%. In this study the maximum variation was less than 15%. This result is attributed to the use of larger databases. A larger volume of data makes the simulation more accurate and reliable.

Table 6 – Hourly productivity results and deviations related to the estimative

	Estimate (t/h)	Real (t/h)	Deviation (%)
Excavator 1	1934.8	1952.9	0.9%
Excavator 2	2150.9	2124.6	-1.2%
Excavator 3	2053.5	1996	-2.9%
Excavator 4	1886.2	1861.9	-3.8%

Excavator 5	1871.9	1686.7	-11%
Excavator 6	1231.6	1258.7	2.1%
Excavator 7	1666.6	1521.8	-9.5%
Excavator 8	1110.2	1119.6	0.8%
Loader 1	1493.2	1478.5	-1%
Loader 2	1093.8	1195.6	8.5%
Loader 3	887.3	1036.8	14.4%
Loader 4	1190.7	1182.1	-0.7%
Loading Machines (Total)	**1717.8**	**1768.3**	**2.9%**
Haulage fleet A	350.9	349.2	-1%
Haulage fleet B	380.1	366.1	-4%
Haulage fleet C	346.6	357.3	3%
Haulage fleet (Total)	**362.2**	**360**	**-1%**

CONCLUSION

This work established aim at generating productivity equations for loading operations and haulage with reduced variation. Methodology application for loading and haulage fleets achieved the objectives. Evidence of compliance is low deviation between estimated and actual. This result can be assigned to the database. The use of a larger database provides greater accuracy and reliability to the simulation results. However, the simulation model showed high deviations for excavator 5 and 7 for the loader 3. These negative deviations are justified by mechanical and operational failures unplanned. This type of event is considered an outlier to the simulation model and it shows the complexity of translating an industrial process in mathematical equations. However, the model can be considered as a tool to become a mining plan more realistic and suitable with production capacity of a mine. Management decisions can also influence the results. The allocation of the loader 3 in stocks near the crusher was not planned and justified the increase of productivity.

The techniques and statistical tools used are affordable. There is availability of various packages that are able to perform these analyzes or generate similar equations. Many packages can be used for free. Thus, future work can be developed by adapting the methodology of this study. Research can move forward from application to other mine settings or develop analysis covering quarterly, annual and multi-year horizons.

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