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Underground Mine Drilling Predictions using Artificial Neural Networks for Short Term Mine Planning

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ABSTRACT: Performance of jumbo operators directly affects productivity in current mining operations. Implementing tools to attack low productivity sources is the main focus of the mining industry due to the transition from "easy" deposits to remote, low grade and deeper deposits. Moreover, improving equipment productivities strongly impact by producing higher values of outputs with the same values of inputs. This paper presents a method to predict the performance of jumbo operators, seeking to link this predicted data into an efficient short mine planning. During 2018 several data related to jumbo operations was collected in order to create a manual control room to analyze real downtimes and their main sources. After data collection, typing, filtering, and adaptation were performed in order to prepare the database to train the Artificial Neural Network (ANN). Once the ANN was trained, an R2 of 0.9998 was obtained between the real value and the predicted value, finding that the proposed methodology is of great help when carrying out the mining planning in the short term within the mining operation.

Keywords: Artificial Neural Networks, Underground Mine, Prediction, Drilling

1 INTRODUCCIÓN

Performance of jumbo operators is a very crucial parameter within mining productivity. This performance is made considering several environmental and field aspects which impact directly in operator's results; hence, operators' performance in conjunction with operating conditions, mine planning and design impact energy efficiency of equipment which is consequently transformed in future productivities and final profits (Awuah-Offei, 2016). The aspects that influence the most in the performance of jumbo operators are geological and geotechnical characteristics of the labor, equipment constraints and daily variables in mining operations (Kahraman, 2006). Predicting the drilling performance of jumbos and the corresponded productivities is very significant within mine planning and cost estimation for the project. Performance given by jumbo operators should be constantly predicted by mine planners to analyze how far are those performances from the numbers that the plan needs and how that aspect impact productivities related to achieving mine schedule in order to create and apply corrective actions.

In the past decades, most mining and industrial companies have developed investigation in order to determine performances of equipment and productivities of a process by including the "operators' factor". According to Li (2018), high production targets and achievements are the results of operators with a strong viewpoint of daily demanding duties at work. He also mentions the importance of good and previously elaborated instruction to achieve high operators' performances. Whereas Lumley (2005) states that productivity within mine site hardly depends on the attitude of the operators and every good or bad performance is the result of how the operators feel at the job. She points out that good attitudes generate good productivity and low productivities are just the result of an unhappy worker that have not received proper conditions. Adopting a similar direction, Awuah-Offei (2016) and Dorey (2015) notes how operators' practices are directly related with skills and more important with training, stating that operators who receive proper instructions and guidance significantly impact in a good way the profitability of the project. Keeping that in mind, achieving benefits by measuring and improving operator's conditions, plans and practices in order to achieve higher performances are nowadays crucial to reach better productivities and finally more profits (Mohammadi, 2015).

Upcoming years represent several challenges to the mining industry due to the translation from deposits with relativity low costs of extraction, accessible and superficial locations to remote, low grade and deeper deposits which also represent higher demands of productivities to cover extra costs generated (Välivaara, 2016). Likewise, high productivities needed for the mining sector have not been a fact and instead of that, mining companies have had a constant decay of productivity in the last ten years and with the incentive of the fluctuation of commodity prices. Having low equipment efficiency in mechanized mining (e.g. availability, utilization, productivity, and quality) normally compromise the accomplishment of the operational plan, however, improving equipment productivities strongly impact by producing higher values of outputs with same input values (Fourie, 2016). Moreover, Maradia (2017) states that process optimization is key within a mechanized activity of drilling, by increasing productivity. That's why current mining engineers need to use every possible tool that allows them to improve KPIs within the projects.

For this reason, it is currently required within the mining operations to have a methodology that allows to predict the performance of the work that is being developed, in order to have a better control of the projected progress and this in turn is more adjusted to the reality of the operation. Traditionally, the most common method to be predicted is multiple linear regression which assumes that the variables that are being analyzed are not interrelated, which leads to having forecasts that are far from reality. This flaw is corrected by artificial neural networks, which in their internal algorithm can easily handle these interrelationships.

Moreover, regression techniques are extensively employed in applications where the goal is to predict continuous values. Moreover, machine learning methods as artificial neural networks are proven to be powerful tools to solve both classification and regression tasks. An artificial neural network is a mathematical representation of computation based on the composition of the human brain. The model consists of many basic computing devices known as the neurons that are attached between them in a dense system, where highly complex computations are carried. The approach of learning with neural networks was first suggested in the mid-20th century. Learning with neural nets produces an effective paradigm and has recently been proven to accomplish advanced and innovative performance on several learning applications. In terms of mathematics, a neural network can be defined as a directed graph with nodes acting as the neurons and edges acting as the connections among themselves. At each node, a weighted sum of the outputs is taken as an input linked to its incoming edges. This paper is focused on feedforward networks also known as multilayer perceptron in which the principal and used graph does not include cycles Shalev-Shwartz et al (2014), McCulloch et al (1943), Widrow et al (1960), Rosenblatt (1962), Rumelhart et al (1986).

Artificial Neural Networks (ANN) has had various applications in the field of mining. Below, some of the cases where it has been applied are presented.

Panda & Tripathy (2014) predicted the performance of the vibrating table concentrator. The input parameters for the algorithm were the wash water flow rate, the table tilt angle and the feed rate of the mineral slurry, obtaining as the output parameters the mineral content (%) and recovery (%).

The application of ANN to study the performance of jigs was proposed by Panda et al (2012). For its implementation, the non-coking coal that is extracted in India is taken as the case study, which when it has a size smaller than 3 mm is not recovered. The particle size of the coal, the particle size of the bed material, the feed rate of the coal and the water flow were taken as input parameters, giving as the output parameters the percentage of ash in the coal and the recovery of the same.

Saimi-Irdemoosa et al (2015) performed the prediction of fuel consumption in the transport trucks of waste using ANN. For the formulation of the algorithm, the truck payload, load time, idle time while loading, travel time, empty travel time and empty idle time are taken as input parameters, obtaining as output parameter the amount of fuel consumed per cycle.

Monjezi et al (2011) proposed the implementation of ANN for fly-rock prediction and back-break, and Genetic Algorithm for optimization of blast pattern. 234 blast data were taken from the Soungun copper mine in Iran, establishing as input parameters the burden, spacing, drilling depth, stemming, explosive factor and specific drilling, obtaining as output parameters the fly-rock and back-break.

Hence, this paper aims to predict the performance of jumbo operators in one underground gold mine in Colombia with historical data, integrating an important tool to mine planners, an ANN model was performed.

2 METHODOLOGY

2.1 *Data Recollection*

During 2018, the daily data collection was implemented, measuring different operational variables within one underground gold mine. In Table 1, these variables are presented with their possible values and a brief description.

Shift supervisors and interns worked side by side to build a manual control room with real data which allowed proper measures of inputs within the mining cycles. In Figure 1, Data collection method is represented, showing the different steps until the final prediction report.

Type of variable	Name of variable	Possible values	Description
Independent variables	Guard	A, B, C	Every guard was in charge of 12 hours of operations per day during 20 days of the month
	Day	Monday, Tuesday, ⋮, Sunday	--
	Shift	Day, Night	6:00 am – 6:00pm/ 6:00pm- 6:00pm
	Equipment	JB-0001, JB-0002, JB-0003	JB-0001 and JB-0002 were jumbos with one hydraulic boom and JB-0003 was a jumbo with two hydraulic booms
	Labor	SR, AR, MB	Secondary Ramps (SR) and Much Bays (Muck Bays) are development tunnels with 4-meter width and 4.5-meters high. Attack Ramps (AR) are production tunnels with 3.5-meters width and 3.7-meters high
	Type of activity	Support	Activity performed by the operator.
		Development	Development drillings to blast and advance. Drillings for installing rock support
	Number of drillings	Numeric variable	Number of drillings in the tunnel face
	Length of drillings	Numeric variable	Length of the drillings related to the activity developed
	Operator	Operator 1, Operator 2, ⋮, Operator 15	--
Dependent variable	Drilled meters	Numeric variable	Drilled meters performed by one operator within one jumbo activity in one labor in one shift

Tabla 1: Descripción de variables

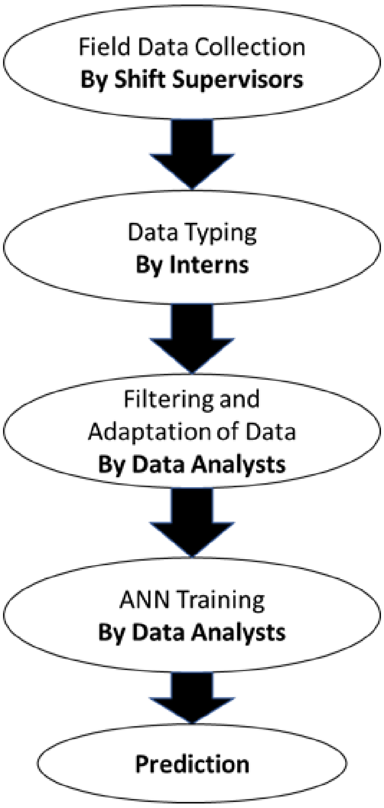

Figure 1. Information management process.

2.2 *Artificial Neural Network (ANN)*

An ANN is a structured information processing methodology inspired by the behavior of biological neural networks, in order to obtain a prediction about any element that is desired. ANN base their work on the following assumptions (Abraham, 2005).

a) The information that initiates the training of the neural network is structured as a simple element or "neuron".

b) The information is transmitted from neuron to neuron through links that connect to these.

c) Each link inside the neural network has a weight associated with it that indicates the importance of the signal it is transmitting, and usually, the signal that is passed through this link is multiplied by its weight.

d) For each neuron, an activation function is applied for the input signal it receives, which combined with the weight of the link produces the output signal.

In Figure 2, the architecture of a generally ANN is shown.

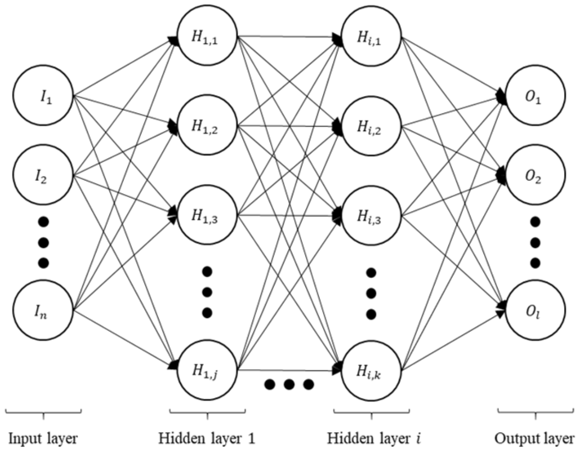

Figure 2. A general scheme of an ANN.

As seen in the previous figure, an artificial neural network consists of an input layer, an output layer, and multiple hidden layers; and inside each layer, there may be a different number of neurons that compose it. The number of hidden layers, as well as the number of neurons inside each of these, is what makes up the architecture of the neural network, the number of neurons in the input layer corresponds to the number of independent variables with which it is desired to predict and the number of neurons in the output layer is equal to the number of dependent variables on which you want to make the prediction.

The input and output variables can be of two types: numerical or categorical.

In the case of numerical variables, the values of these must be normalized in order to eliminate the dimensions of the same and avoid having problems by orders of magnitude that may occur, for example, handling data in millions of dollars as well as data on temperature. To normalize the values, in the Equation 1 the procedure is performed:

$$\dot{X} = \frac{X - \mu}{\sigma} \quad (\mathbf{1})$$

In equation 1, the following nomenclature is presented:

$X^{\cdot}$ = Normalized value.
X = Measured value.
μ = Mean of variable
σ = Standard deviation of variable.

On the other hand, if you work with categorical variables, they cannot be entered into the neural network in its format, for which it is necessary to create indicator variables (IV). For example, the color registration used for a certain activity was carried out and the possible answers that can be had are blue, red or white; to be able to enter this information into the neural network, 3 indicator variables must be created (1 for each possible response), thus:

$$IV_1 = \begin{cases} 1 \; if \; the \; color \; is \; blue \\ 0 \; in \; other \; cases \end{cases}$$

$$IV_2 = \begin{cases} 1 \; if \; the \; color \; is \; red \\ 0 \; in \; other \; cases \end{cases}$$

$$IV_3 = \begin{cases} 1 \; if \; the \; color \; is \; white \\ 0 \; in \; other \; cases \end{cases}$$

Once the input and output data have been properly transformed, the training of the network is carried out. For this, initial weights are assigned for each link between neurons (feed for the forward process), then these weights are modified according to the error in the prediction of the output layer (back propagation process). Because the operation of these processes is not the objective of the article will not be deepened in them, however for those people who wish to know more about the internal functioning of an artificial neural network can be addressed to Abraham (2005).

3 CASE STUDY

For the case study, a special case of artificial neural networks called General Regression Neural Network (GRNN) was used, giving the architecture shown in Figure 3. On the other hand, the explanation of each one of the variables that are part of the ANN was made in Table 1, presented previously in section 2.1.

In the architecture used there are 9 neurons in the input layer corresponding to the number of independent variables recorded, in the first hidden layer there are 452 neurons, in the second hidden layer there are 2 neurons and finally in the output layer is has 1 neuron. This type of architecture is used because the GRNN method specifies it (Specht, 1991).

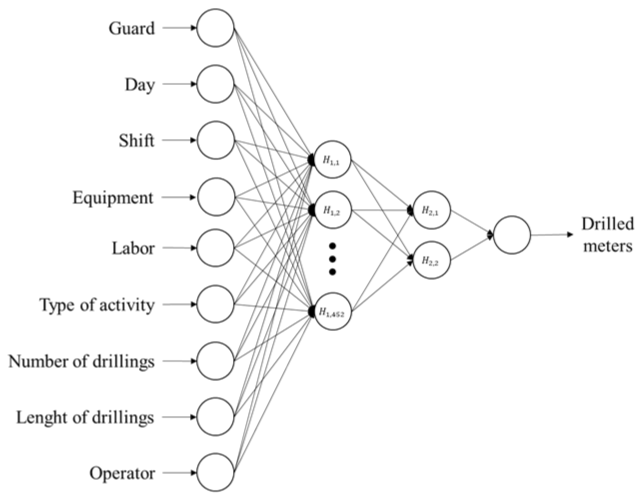

Figure 3. The architecture of the ANN trained

To measure the convergence of the ANN was used the cost function known as the root mean square error (RMSE), which is calculated as follows in the Equation 2:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (2)$$

Where P_i,O_(i,) and n represent the prediction of the output variable, the actual value of the output variable and the amount of data trained in the artificial neural network respectively.

Once the optimal neural network is found, additional error measurements as the mean absolute error (MAE) and mean absolute percentage error (MAPE) were obtained and are shown in table 2. Both MAE and MAPE reflect how far the predictions made with the neural net model are from the input targets.

RMSE	1.213
MAE	0.486
MAPE	1.186%

Table 2. Precision measurements

In order to graphically observe the accuracy of the predictions, Figure 4 shows the relation between the actual measurements (targets) and the predictions, where is possible to visualize the high correlation (0.999) obtained with the machine learning model. Moreover, this model is proven to be trustworthy and accurate for performing future predictions while gathering more data.

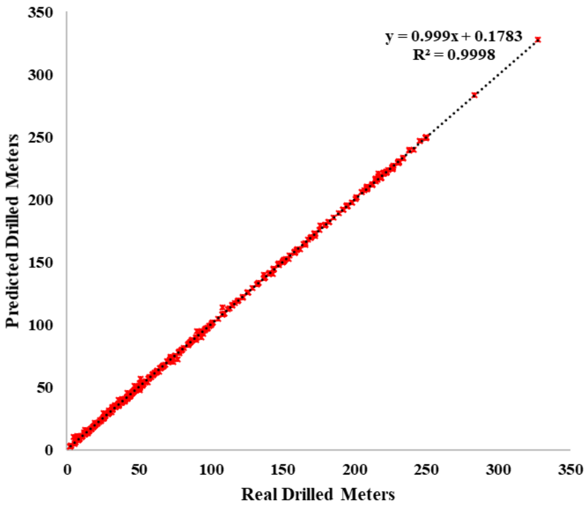

Figure 4. The relation between real values vs predicted values.

4 CONCLUSIONS AND FUTURE WORKS

Measuring jumbo activities within mining operations allows one to determine the sources of downtimes affecting mining daily operations, productivity and final profits. Likewise, implementing a complete and real database is not only helpful for specific research but also for daily, monthly and yearly analyzes with the porpoise of determining problems and give solutions.

The proposed approach allows mine planners to shorten the gap between planned and operational performance by using historical data. Moreover, by predicting key drilling factors, mine planners are more informed to present accurate plans with a reduction of the deviation with respect to the reality, and consequently more likely to be achieved. Performance predictions can be applied to a wide range of activities within the preparation of short-term mine plans. In cases where the mine planners assume a continuous state as is the case of the type of rock or the geology of the tunnel, the proposed model can be useful to determine what are the real performances to be achieved regarding the different types of rocks or geologies that can be found during the development of the tunnels.

On the other hand, having trained the ANN it is possible to identify what will be the combination of operational variables that maximize the number of meters drilled, this in order to assign this combination to those tasks where exceptional performance is required due to its importance to the inside the operation, for example the opening of an access gallery to a block of ore.

In the future, it is planned to include these predictions made within the real mining planning of operation and to measure the percentage of deviation that one has with reality, in order to compare it with the one obtained through traditional mining planning where this type of tool is not included.

4.1 SUPPLEMENTARY DATA

The dataset use in this article can be found online at https://github.com/jcdelcunal/ANN-MINING. The software that is used in this research is NeuralTools, from Palisade Corporation.

5 REFERENCIAS

Abraham, A. (2005). Artificial neural networks. In Handbook of Meauring System Design (pp. 901-908). John Wiley & Sons. doi:10.1002/0471497398

Awuah-Offei, K. (2016). Energy efficiency in mining: a review with emphasis on the role of operators in loading and hauling operations. Journal of Cleaner Production, 1-9.

Dorey, F. a. (2015). Quantifying the benefits of simulator training for dragline operators. Mining Technology, 97-106.

Fourie, H. (2016). Improvement in the overall efficiency of mining equipment: a case study. The Journal of The Southern African Institute of Mining and Metallurgy, 275-281.

Li, D. (2018). Effects of Information Content in Work Instructions for Operator Performance. Procedia Manufacturing, 628-635.

Lumley, G. (2005). Reducing the Variability in Dragline Operator Performance. Coal Operator´s Performance (pp. 97-106). Wollogon: in Aziz, N.

M. Mohammadi, P. R. (2015). Performance Measurement of Mining Equipment. International Journal of Emerging Technology and Advanced Engineering, 240-248.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous acactivity. Reprinted in Anderson and Rosenfeld (1998): Bulletin of Mathematical Biophysics.

Monjezi, M., Amini Khoshalan, H., & Yazdian Varjani, A. (2011). Optimization of Open pit Blast Parameters using Genetic Algorithm. International Journal of Rock Mechanics and Mining Sciences, 864-869. doi:10.1016/j.ijrmms.2011.04.005

Panda, L., & Tripathy, S. K. (2014). Performance prediction of gravity concentrator by using artificial neural network-a case study. International Journal of Mining Science and Technology., 24, 461-465. doi:10.1016/j.ijmst.2014.05.007

Panda, L., Sahoo, A. K., Tripathy, A., Biswal, A. K., & Sahu, A. K. (2012). Application of artificial neural network to study the performance of jig for beneficiation of non-coking coal. Fuel, 97, 151-156. doi:10.1016/j.fuel.2012.02.018

Productivity in Mining: now comes the hard part. (2017). Retrieved from https://www.ey.com/Publication/vwLUAssets/EY-productivity-in-mining-now-comes-the-hard-part/$FILE/EY-productivity-in-mining-now-comes-the-hard-part.pdf

Rosenblatt, F. (1962). Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanismn. Spartan.

Rumelhart, D. E., & J. L. McClelland, a. t. (1986). Parallel Distributed Processing: Explorations in the Microstructure of Cognition. MIT Press: Volume 1: Foundations.

S. Kahraman, M. I. (2006). Performance prediction of a jumbo drill in Pozanti–Ankara Motorway Tunnel (Turkey). Tunnelling and Underground Space Technology, 265.

Saimi-Irdemoosa, E., & Dindarloo, S. R. (2015). Prediction of fuel consumption of mining dump trucks: A neural networks approach. Applied Energy, 151, 77-84. doi:10.1016/j.apenergy.2015.04.064

Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding machine learning: from theory to algorithms. Cambridge University Press.

Specht, D. (1991). A General Regression Neural Network. IEEE Transactions on neural networks, 2(6), 568-576. doi:10.1109/72.97934

U. Maradia, A. B. (2017). EDM Drilling optimisation using stochastic techniques. 11th CIRP Conference on Intelligent Computation in Manufacturing Engineering (pp. 350-3550). Gulf of Naples, Italy: Procedia CIRP.

Välivaara, J. (2016). Automated Drilling Features for Improving Productivity and Reducing Costs in Underground Development. SEVENTH INTERNATIONAL CONFERENCE & EXHIBITION ON MASS MINING , (pp. 223-229). Sydney.

Widrow, B., & Hoff, M. E. (1960). Adaptive switching circuits. In IRE WESCON Convention. Record, Volume 4, pp. 96–104.