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TESTING OF GRINDING MEDIA PERFORMANCES AT THE CONDITIONS OF Pb-Zn SMELTING SLAG WET MILLING AND PREDICTION OF BALLS CONSUMPTION BY ANN-BASED MODELS

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Abstract: *This paper describes a part of the experimental procedure for testing the performance of grinding media (steel balls) during the smelting slag milling, as well as the modeling procedure and model results that predict the consumption of balls under given experimental conditions. Firstly, the most suitable mineral raw material for testing the durability of the grinding media was defined. In laboratory conditions, it was determined that it is most expedient to use slag from the melting process of Pb-Zn concentrate for testing. The coarse moisture content was determined on the initial slag sample, while the particle size composition and Bond work index were determined on the crushed slag samples. In accordance with the characteristics of the raw material, the technical-technological parameters of the system for wet grinding of slag were defined, in which the balls durability test was performed. The obtained results showed that the consumption of grinding media is about 1 kg/t of slag. Six ANN models, developed on the basis of experimental results, showed good predictive abilities when it comes to stel balls consumption. As a result of modeling, high correlation coefficients were obtained, the value of which was about R = 0.99.*

Keywords: *grinding media consumption, Pb-Zn smelting slag, ANN model*

1. INTRODUCTION

Grinding is highly used procedure in Pb-Zn mineral processing for reducing particle size. Generally, grinding is the most expensive unit operation because of the high consumption of supplies [1]. It is estimated that approximately between 30% and 50% of overall mining operating costs is related to grinding [2, 3].

According to Díaz et al. (2018), the most important supplies in wet grinding are water, energy and steel, both for mill liners and grinding media. Discussing about cost management, they state that water cost can be minimized through improvements in solid-liquid separation and water recovery, energy cost is heavily dependent on the countries power supply system, and therefore special attention should be paid to the management of costs caused by the consumption of liners and grinding media [1].

Various dimensions grinding media are used in ball mills to achieve sufficient particle size reduction and mineral liberation for downstream separation processes. Particle breakage is attained by the collisions between the ore and the grinding media. During the interaction of ore and grinding media, a complex physical and chemical system is formed, causing changes in particle size, pulp chemistry, surface chemistry, and crystal structure of minerals [4].

It has been known that the total wear of grinding media in ball mills include mechanisms of impact, abrasion and corrosion, the latter being predominating in wet grinding, reaching between 10% and 50% of the overall steel grinding media consumption [1, 5]. Therefore, good grinding media should have high hardness, fracture toughness, wear resistance and corrosion resistance, but at the same time, it should have adequate ductility to minimize sudden ruptures and chipping [4].

Grinding media can be classified according to the materials used to manufacture them. The chemical composition and process conditions during the manufacturing of grinding media determine its microstructure, which directly affects the grinding media quality. Spherical balls are manufactured using cast iron, low-alloy and high-alloy carbon steels. Alloy steels are usually made by the addition of alloying elements like chromium, aluminium, manganese, and silica [4].

In this paper studies, balls made of iron alloys with vanadium and niobium, which have high wear resistance, were used.

According to Aldrich, the consumption of grinding media has been studied extensively in the mineral process industries, where steel balls and rods are mostly used to reduce rock fragments and ore particles to the fine sizes required for mineral liberation and further downstream processing. Apart from a better understanding of the phenomena involved in the wear of grinding media, many studies were also aimed at the development of models capable of predicting media consumption based on an understanding of the mechanisms involved in the process [3].

Part of the research presented in this paper also represents an attempt to develop models that predict the consumption of the grinding media, based on experimental results. The models are developed using artificial neural networks (ANN) technique.

ANNs are used for solving complex and nonlinear engineering problems. ANN is a widely used model in mineral processing applications with the ability to recognize patterns among parameters and predict the key performance parameters of the processes. A typical ANN comprises a large number of neurons or nodes, which are connected to each other. The neurons are grouped in layers and connected by weighted links and bias. The output of each neuron is transferred to the next layer as an input. Finally, the nonlinear basis function set is used to calculate the outputs of ANN. The model learning is modifying the weights and biases to minimize the error, taking into account the targets [6].

2. MATERIALS AND METHODS

2.1 Characterization of slag

Ball durability tests were performed on a sample of Pb-Zn slag from the "Smelter – Probištip Veles" landfill, North Macedonia. The initial sample of slag, size –50.00+0.00 mm, was homogenized and samples were taken out for determination of coarse moisture. The homogenized sample was then crushed in two stages to the size of –3.36+0.00 mm. After crushing, the slag sample was homogenized again and a sample was taken from it using the chess board method to determine the Bond work index. The remaining part of the slag sample, size –3.36+0.00 mm, was used to test the durability of the balls during wet grinding, that is, it was the starting point for determining the consumption of the grinding media.

Coarse moisture content was determined on three initial samples of Pb-Zn slag, size –50.00+0.00 mm. All three samples were dried at room temperature for 24 hours. The obtained result represents the arithmetic mean of the measured values for each of the three samples. The measurements showed that in the initial samples of Pb-Zn slag, the coarse moisture content was 0.0924%.

The particle size composition of the crushed sample of Pb-Zn slag with a size of – 3.36+0.00 mm was determined by sieving on a Tyler series of sieves, using a standard procedure. All oversizes, together with the undersize of the last sieve, were individually measured, and the results are shown in Figure 1.

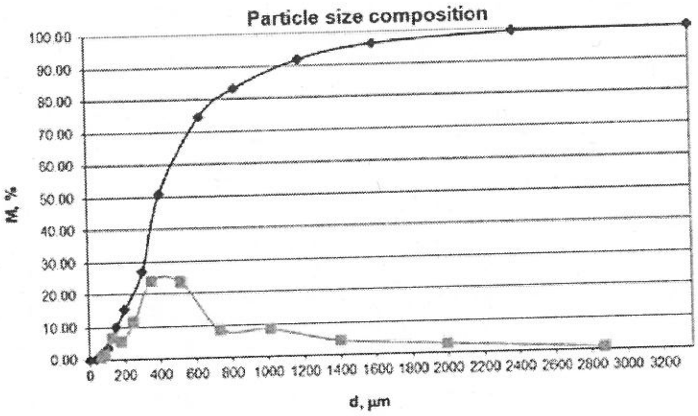

***Figure 1.** Particle size composition of Pb-Zn smelting slag "Smelter – Probištip Veles": blue – undersize curve; pink – incremental curve*

It can be seen from Figure 1 that d_{80} of the crushed sample is 730 µm, while d_{50} is 380 µm. This sample was the starting sample for determining the ball mill Bond work index of the slag. The procedure was carried out according to the standard Bond methodology, and the obtained value was Wi = 28.34 kWh/t. Given that slag has a high Wi value, it can be concluded that it is a suitable material for testing the consumption and strength of balls in more difficult grinding conditions than is usual for natural metallic mineral raw materials [7 – 9].

2.2 Grinding media properties

Three identical batches of grinding balls (of the same dimensions and of the same alloy composition) cast in the Foundry Laboratory TMF – Belgrade were used as grinding media whose durability was tested under wet grinding conditions. The entire batch of tested balls was cast in accordance with the defined parameters of the existing grinding media in the pilot plant ball mill of the Center for mineral processing, ITNMS. In other words, each batch of cast balls was identical to the existing balls that make up the batch in the pilot plant mill, in terms of their number and dimensions. The balls for these tests were obtained by alloying iron with vanadium and niobium. The basic characteristics of one batch are given in Table 1.

***Table 1.** Properties of grinding media*

Total number of balls	Range of ball sizes, mm	Grinding media mass, kg	Grinding media surface, m^2	Grinding media volume, dm^3	Ball desity, g/cm^3
301	64 – 16.6	87.5	1.56	11.9	7.38

2.3 Experimental conditions

The durability of the balls (their consumption) was tested under the same working conditions and on the same amount of raw material, so the test results are comparable. Namely, in the Center for mineral processing, ITNMS, there is a continuous pilot plant for ore flotation. Within this facility, there is a ball mill with an electromagnetic feeder and a spiral classifier that works in a closed cycle with the mill. These devices (feeder and spiral classifier) enable continuous feeding of the mill.

Durability testing of grinding media (their consumption) was performed in the described grinding system under the following experimental conditions:

- continuous wet grinding of slag in the pilot plant mill "Denver", with diameter D = 30 cm, length
- L = 65 cm, volume V = 42.41 dm^3.
- solid phase content in the mill: 70%
- volume share of the mill occupied by grinding media: 47%
- bulk mass of grinding media: 4.4 t/m^3

- size of input raw material $F_{80} = 730$ μm
- size of the finally ground product $P_{80} = 104$ μm

Tests were performed through three continuous experiments under the same conditions. The consumption of grinding media is determined by measuring their mass before and after grinding.

2.4 Artificial neural networks characteristics

For the purposes of developing the ANN process models, 3 input and 1 output variable are chosen during the selection of the appropriate influential parameters. These input and output variables are shown in Table 2. Their values are based on experimental data, obtained from the procedure described in previous sections.

Table 2. *Input (independent) and output (dependent) parameters*

Variable type	Variable	Label in the model	Unit of measurement
Input	Grinding media mass	MGM	kg
Input	Grinding media surface	SGM	cm^2
Input	Grinding media volume	VGM	cm^3
Output	Grinding media consumption per 1 t of slag	CGM	g/t

In order to gain a better insight into the range and characteristics of the input and output variables, Table 3 presents some of the statistical indicators of the associated data sets.

Table 3. *Statistical indicators of the input and output variables*

Statistical indicator	MGM	SGM	VGM	CGM
MIN	6.449	1379.460	879.560	80.480
MAX	20.077	3470.340	2718.430	246.741
AVERAGE	12.524	2231.717	1701.276	141.290
MEDIAN	10.900	2009.930	1479.700	132.032
STDEV	4.415	748.869	599.711	49.632

At the first step, four different models based on the principle of feed-forward backpropagation neural networks were trained. The ANN models consist of one input layer with three elements (MGM, SGM, VGM), one hidden layer including desired number of nodes, and the output layer where the CGM value is calculated. The logsigmoid and purelin functions are implemented as the activation functions in the hidden layer and the output layer. The optimum NN structure is selected using the "trial and error" method by adjusting the number of neurons in the hidden layer (10, 20, 50 and 100) in order to achieve the best model by minimizing the errors. The widely applied Levenberg Marquardt (LM) algorithm is used for the model training.

At the second step, the most suitable architecture of the network was selected and after that it was trained with the other two backpropagation algorithms: Bayesian Regularization and Scaled Conjugate Gradient. The basic characteristics of all six artificial neural networks are shown in Table 4.

Table 4. *ANN based models characteristics*

Label	Number of neurons in the hidden layer	Training algorithm	MSE of validation/training	Key epoch
ANN1	10	Levenberg Marquardt	5983.55	15
ANN2	20	Levenberg Marquardt	32.77	5
ANN3	50	Levenberg Marquardt	41.92	44
ANN4	100	Levenberg Marquardt	11.56	3
ANN5	20	Bayesian Regularization	68.94	86
ANN6	20	Scaled Conjugate Gradient	16.81	8

The criteria for choosing the most favorable network architecture were the number of neurons in the hidden layer and the Mean Square Error (MSE) of validation (best validation performance). The number of neurons in the hidden layer is very important. In addition to complicating the network architecture, too many neurons in the hidden layers may result in overfitting. Overfitting can be spotted when the error on training data decreases to a small value, but the error on the test/validation data increases to a large value. Some reasons for overfitting are: small size of training dataset (such as in this case), very noisy dataset and complex ANN architecture [6].

Mathematically, MSE can be defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X - Y)^2 \qquad (1)$$

Where X is the measured value, Y is the predicted value, and n is the number of samples.

Figure 2 shows the best validation/training performance for all 6 models.

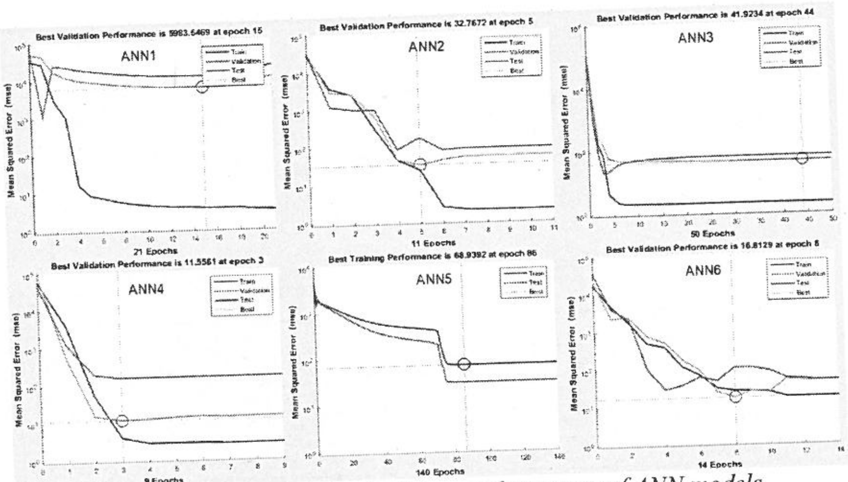

Figure 2. Best validation/training performances of ANN models

As can be seen from the Figure 2, ANN1 model shows overfitting. ANN3 model has the higher MSE of validation than ANN2 model. On the other hand, although ANN4 model showed somewhat better properties than ANN2 model, it was taken into account that ANN2 model has a simpler architecture, therefore this architecture (20 neurons in the hidden layer) was adopted for further research. By comparing the performance of models with the same architecture and different training algorithms, it can be seen that the best performance is achieved by the Scaled Conjugate Gradient backpropagation algorithm.

3. RESULTS AND DISCUSSION

3.1 Results of the experimental testing

The results of the experimental procedure are shown in Table 5.

Table 5. Experimental testing results of the grinding media consumption

/	I batch	II batch	III batch
Average consumption of balls, kg/t of slag	1.01	1.01	0.95
Average consumption of balls per balls specific surface, g/cm²/t of slag	0.065	0.065	0.061

As can be concluded from the results in Table 5, all three batches of balls have a very similar average consumption per ton of ground raw material. This consumption is relatively low and ranges around 1 kg/t of Pb-Zn smelting slag.

3.2 Results of the modeling

The results of ANN models predictive properties are expressed through the one of the most important criteria – correlation coefficient (R). The correlation coefficient is a statistical measure of the strength of a linear relationship between two variables (in this case real and predicted values of output). Figure 3 shows the R values for all six models.

The obtained results show that ANN models have very good predictive properties when it comes to predicting grinding media consumption under wet slag grinding conditions. The highest correlation coefficients between actual and predicted values were obtained in the case of ANN3 and ANN4 models, with R = 0.996 and R = 0.994, respectively. ANN2 and ANN6 models also showed very good predictive capabilities, both with the correlation coefficient of R = 0.993.

The ANN5 model has a slightly lower correlation coefficient compared to the previously mentioned models and the same is R = 0.988. This means that in the considered case there is no significant difference in the predictive characteristics of the models in relation to the applied training algorithm. The only model that did not show good predictive properties is the ANN1 model with a correlation coefficient of R = 0.664. The assumption is that the number of neurons in the hidden layer is insufficient, and that's the reason why overfitting is occurred.

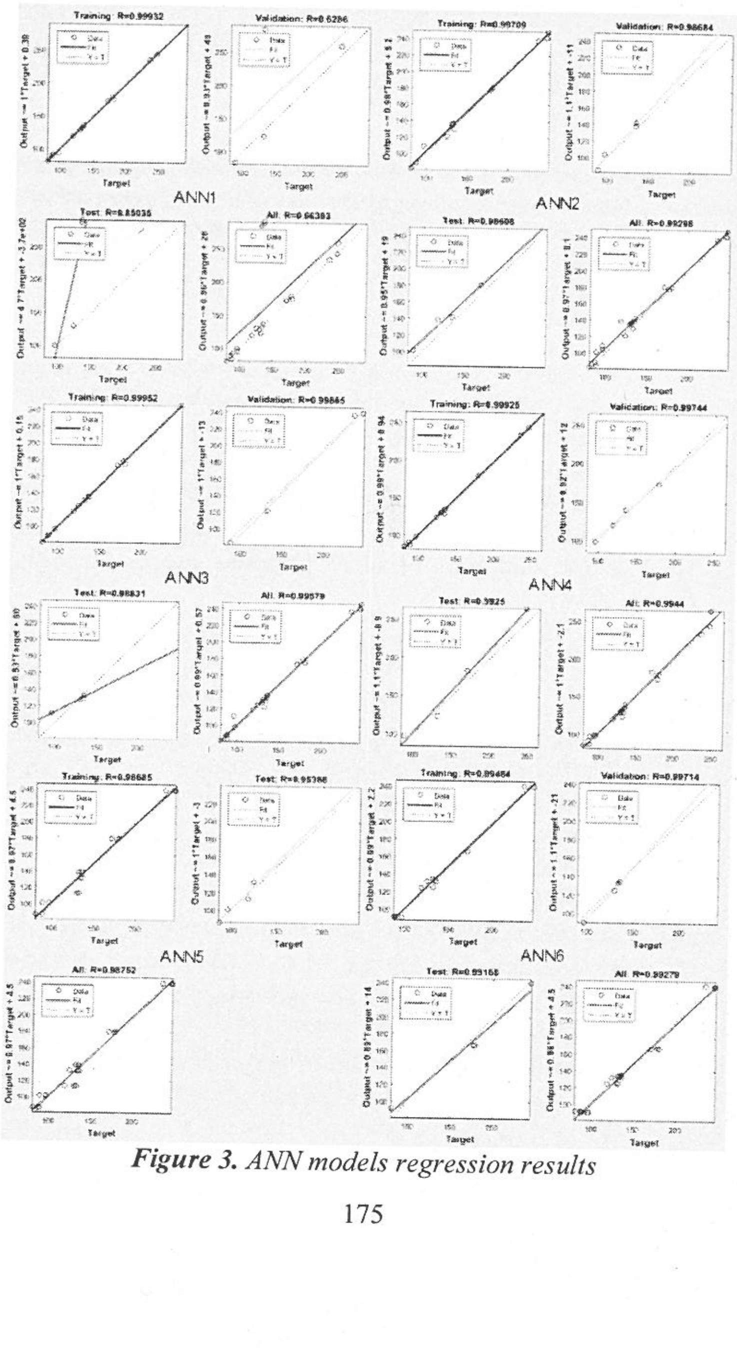

Figure 3. ANN models regression results

4. CONCLUSION

On a sample of Pb-Zn slag from the "Smelter – Probištip Veles" landfill, North Macedonia, durability tests of grinding media were performed. The balls for these tests were obtained by alloying iron with vanadium and niobium. The experimental procedure was carried out under conditions of wet grinding of slag, in a pilot plant mill for continuous grinding, with a working volume of approximately 42.5 dm^3. Based on the obtained experimental results, six ANN-based models were developed. By considering the achieved results of pilot plant tests and modeling, the following can be concluded:

- Consumption of grinding media is relatively low, about 1 kg/t per ton of ground material (slag).
- ANN models have good predictive properties when it comes to ball consumption in wet slag grinding conditions.
- Most of the obtained correlation coefficients between actual and predicted values of grinding media consumption are high and above 0.99.
- The minimum number of neurons in the hidden layer should be 20, due to the appearance of overfitting in ANNs with a small number of them.
- Increasing the number of neurons in the hidden layer above 20 does not significantly affect the modeling outcome.
- There is no significant difference in the modeling results when applying different backpropagation training algorithms – Levenberg Marquardt, Bayesian Regularization and Scaled Conjugate Gradient.

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REFERENCES

1. Díaz, E., Voisin, L., Kracht, W., Montenegro, V. (2018). Using advanced mineral characterisation techniques to estimate grinding media consumption at laboratory scale. Minerals Engineering 121, pp. 180–188.
2. Moema, J., Papo, M., Slabbert, G., Zimba, J. (2009). Grinding media quality assurance for the comminution of gold ores. In: Proceeding of the World Gold Conference, pp. 27–33.
3. Aldrich, C. (2013). Consumption of steel grinding media in mills – a review. Minerals Engineering 49, pp. 77–91.
4. Matsanga, N., Nheta, W., Chimwani, N. (2023). Grinding Media in Ball Mills-A Review. Preprints (www.preprints.org), Posted: 24 April 2023, doi:10.20944/preprints202304.0811.v1.
5. Azizi, A., Shafaei, S.Z., Noaparast, M., Karamoozian, M. (2015). An investigation of the corrosive wear of steel balls in grinding of sulphide ores. International Journal of Mining and Geo-Engineering, Vol.49, No.1, pp.83–91.
6. Jovanović, I., Nakhaei, F., Kržanović, D, Conić, V., Urošević, D. (2022). Comparison of fuzzy and neural network computing techniques for performance prediction of an industrial copper flotation circuit. Minerals 2022, 12(12), 1493.
7. Ćalić, N. (1990). Teorijski osnovi pripreme mineralnih sirovina, Rudarsko-geološki fakultet Beograd, Serbia, 496 p. (In Serbian).
8. Ahmadi, R., Hashemzadehfini, M., Parian, M.A. (2013) Rapid determination of Bond rod-mill work index by modeling the grinding kinetics. Advanced Powder Technology, Vol. 24, Iss. 1, pp. 441-445.
9. Bilal, D. (2017). Geometallurgical estimation of comminution indices for porphyry copper deposit applying mineralogical approach. MSc thesis, Luleå University of Technology, Sweden, 89 p.