ARTIFICIAL NEURAL NETWORK USED IN THE MATERIAL AND MASS BALANCE IN THE REDUCTION ZONE DURING HCFMN II

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Abstract

Simple material and mass balance were efficiently drawn in high carbon ferromanganese production processes based on simple calculations. However the prediction on different products in different reactive zones using a mathematical model using artificial intelligence nueral network has not been well conducted. The current project has investigated means to use AI to predict products. The establishement of a mathematical model to predict each product in each zone is not a trivial exercise. To ease the prediction of every product quantitatively, MATLAB was used as an efficient tool to generate the mathematical programming model for each product. Theoretical assumptions were used to generate the mathematical programming model which was developed per reactive zone.

Keywords: Metallurgy, HCFeMn, Artificial Neural Network, prediction

1. INTRODUCTION

The Artificial Neural Network predicts the furure based on the past data that have been learnt. In the last three decades, the most golden and worthwhile technology broadly used in a number of applications in diverse areas is the Artficial Neural Network [1]. Modelling and prediction using Artificial Neural Network has generated strong and reliable models in the tourism industry [2-4] while the prediction using Artificial Neural Network in finances has [5, 6]. For neural netwaork amongst the first-order learning method the resilient backpropagation (Rprop) algorithm proposed by many researchers stands out [7]. It has proven fast convergence, good stability and reliable results are generated [7-10]. A study on the speeding up backpropagation algorithm was proposed [11]. To increase the rate of convergence, heuristics were suggested [12] while the complexity of the derandomized evolution strategy was reduced using different methods [13-15]. In the pyrometallurgy research area, the Artificial Neural Network has started to be at the centre of prediction. In this work, the Lavenberg-Marquardt backpropagation algorith (trainml) has adopted to generate a model.

2. METHODOLOGY

The setting of variables that are connected and the configuration of the network are the pillars of the performance of an artificial neural network model in the current work. Levenberg-Marquardt backpropagation algorithm (trainlm) was used. The conjugate gradient backpropagation (transcg) was utilised when the memory was narrow and the software assigned initial parameters randomly. The best artificial neural network was obtained through a “trial and error” approach of setting and re-setting the number of hidden layers, learning functions and number of neurons. **Figure 1** below shows the structure of the neural network.

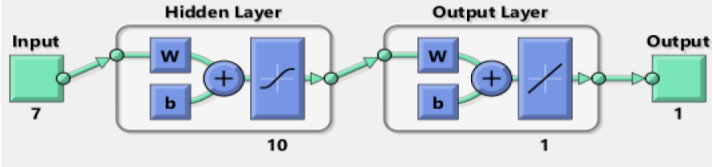

Figure 1 Structure of the neural network [16]

Considering that x data have been collected, the establishment of the model was conducted by considering an average of z samples of the experimental data were used for the training step. The remaining data samples were halved. The first half of the samples was utilized to test the artificial neural network prediction performance and the second half was used for the validation of the artificial neural network model. The regression value (R^2) remained the factor determining whether the artificial neural network used was learnt well and could be able to establish the relationship between the inputs and outputs for different parameters and to predict the outputs accurately. The deviations lower than 3% were considered to confirm the strength of the model. In this work the deviations were examined to assess the reliability of the model. The input data were derived from the products descending from the prereduction zone and gases from the lower zone. A mass of 1 ton was assumed to have been produced to assess the model.

3. RESULTS AND DISCUSSION

3.1 MnO prediction

Figure 2 below shows the targeted versus predicted values and the deviations. From **Figure 2** provides the comparison between the targeted and the predicted values of MnO. It transpires that the deviations values are below 3% as per the criteria with only one discrepancy of 21%. This qualifies the mathematical programming model to be strong and reliable since the calculated regression value was 0.9989 which is an indication that the algorithm is valid. The prediction of MnO in zone 2 is therefore efficient.

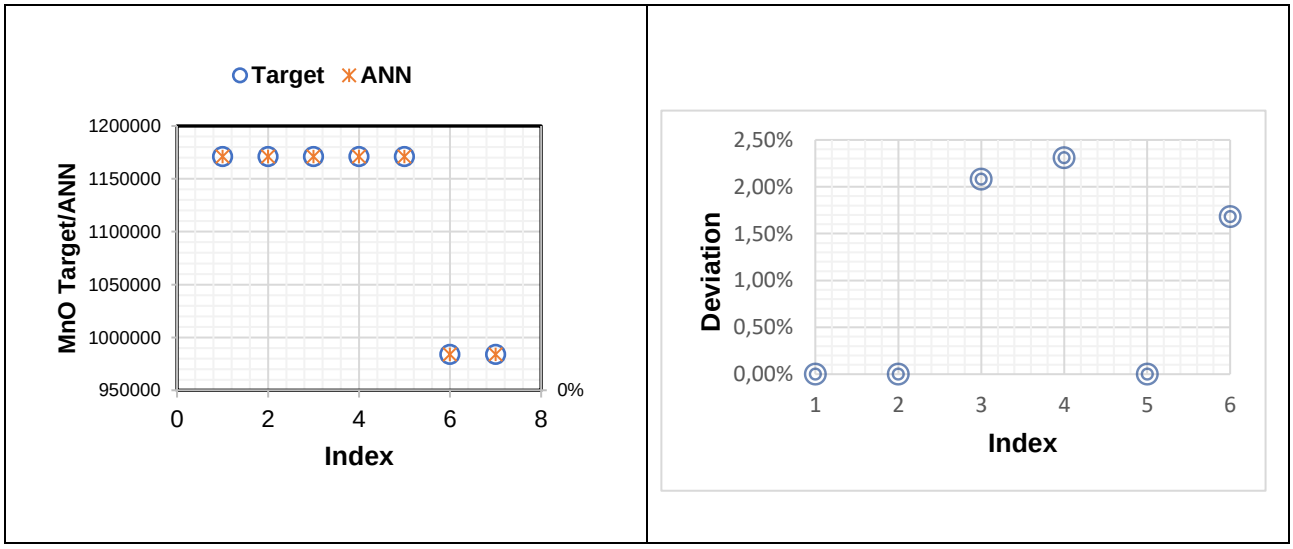

Figure 2 Artificial neural network (ANN) prediction Vs Target and Deviation of MnO

2.2.1 Fe prediction

Figure 3 presents the targeted, the ANN predicted values and the deviation for Fe. It can be noted the closeness between the targeted and predicted values. Also, the calculated deviations indicate that the discrepancies between the target and output values remain below 3%. This makes the model strong and reliable to predict Fe.

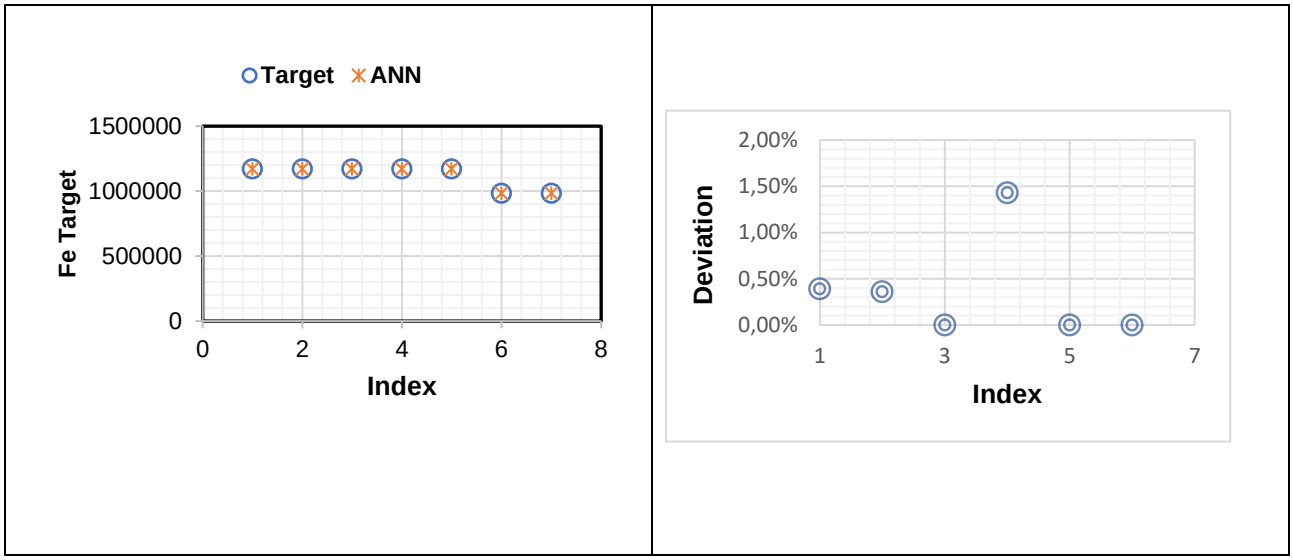

Figure 3 Artificial neural network (ANN) prediction Vs Target and Deviation of Fe

2.23 MgO prediction

The targeted, predicted and deviations for MgO in the reduction zone are depicted in **Figure 4** below. The difference between the predicted outputs and the targeted values is considerably narrow. Besides, the calculated deviations indicate that three remarkable discrepancies between the target and output values were noted ranging between 39.8% and 20.72%. The discrepancies are not impacting the robustness of the model since it is amongst thousands of values generated.

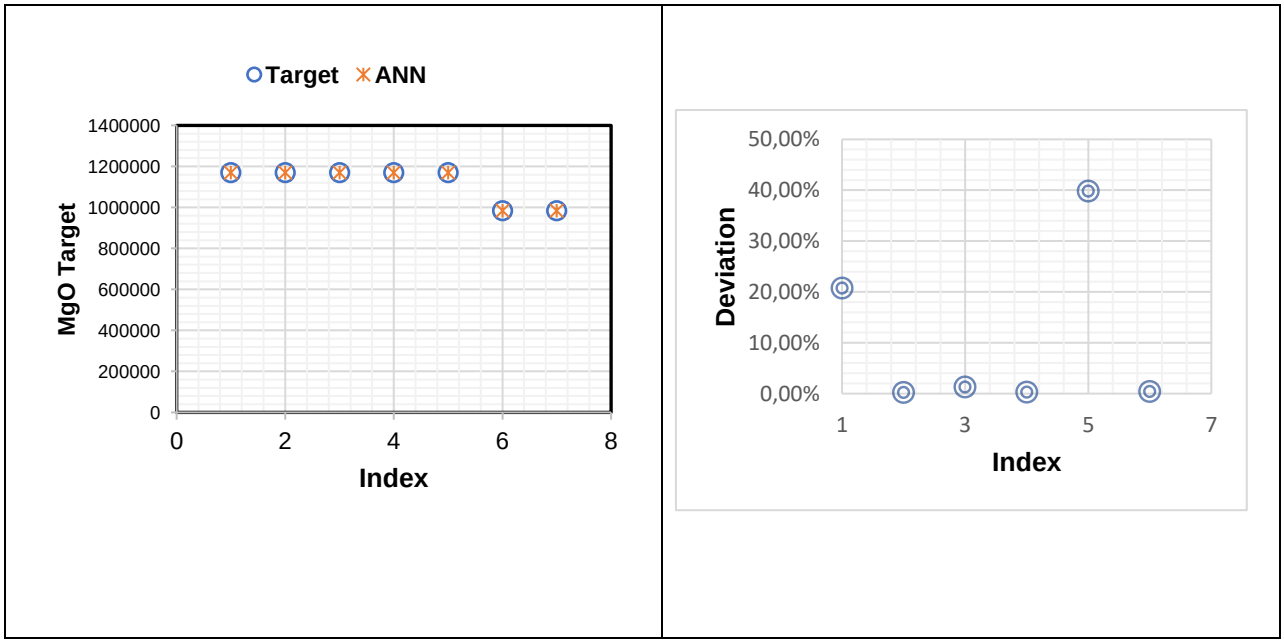

Figure 4 Artificial neural network (ANN) prediction Vs Target and Deviation of MgO

2.2.4 CaO prediction

Figure 5 shows the correlation between the target, the ANN values and the deviation for CaO in the reduction zone. The regression value generated from the model was 0.99973 and only one deviation of 7.18% was recorded whereas the rest of values remained below 3%. The model is therefore strong and can be used to predict CaO in the reduction zone.

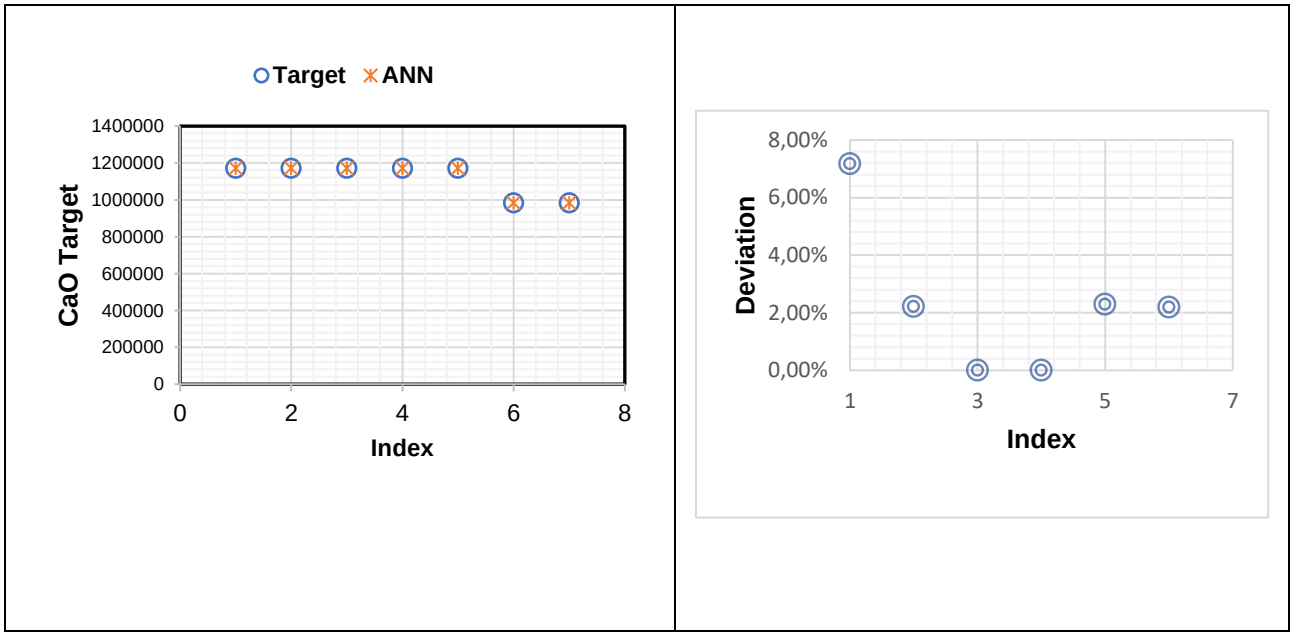

Figure 5 Artificial neural network (ANN) prediction Vs Target and Deviation of CaO

2.2.5 SiO_2 prediction

Figure 6 shows the correlation between the targeted SiO_2 values, the predicted and the deviations to assess the model. A regression calculated value of .99975 was recorded. It showed that the targeted values are very close to the predicted values with 12.56% as the highest deviation value. The model is therefore valid and can be used to predict SiO_2 in the reduction zone. From the regression value, the closeness between targeted and predicted values, the deviation values it is concluded that the mathematical programming model is valid.

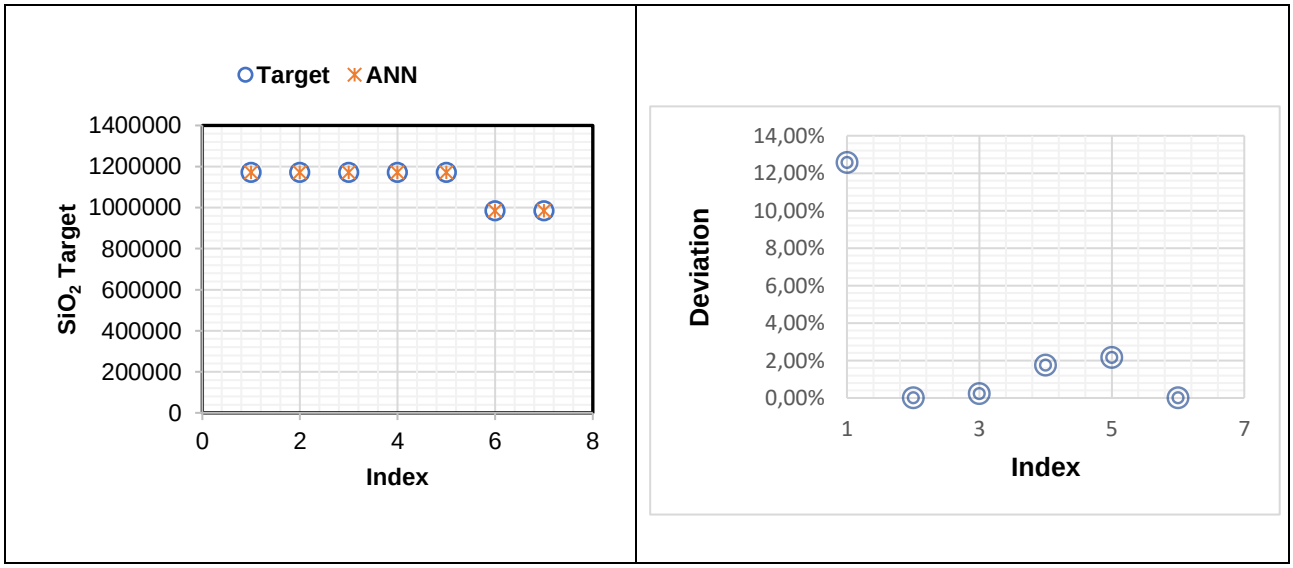

Figure 6 Artificial neural network (ANN) prediction Vs Target and Deviation of SiO_2

3.2 Al_2O_3prediction

Figure 7 below draws the predicted outputs match closely the target values. The calculated deviations remained below 4 %.

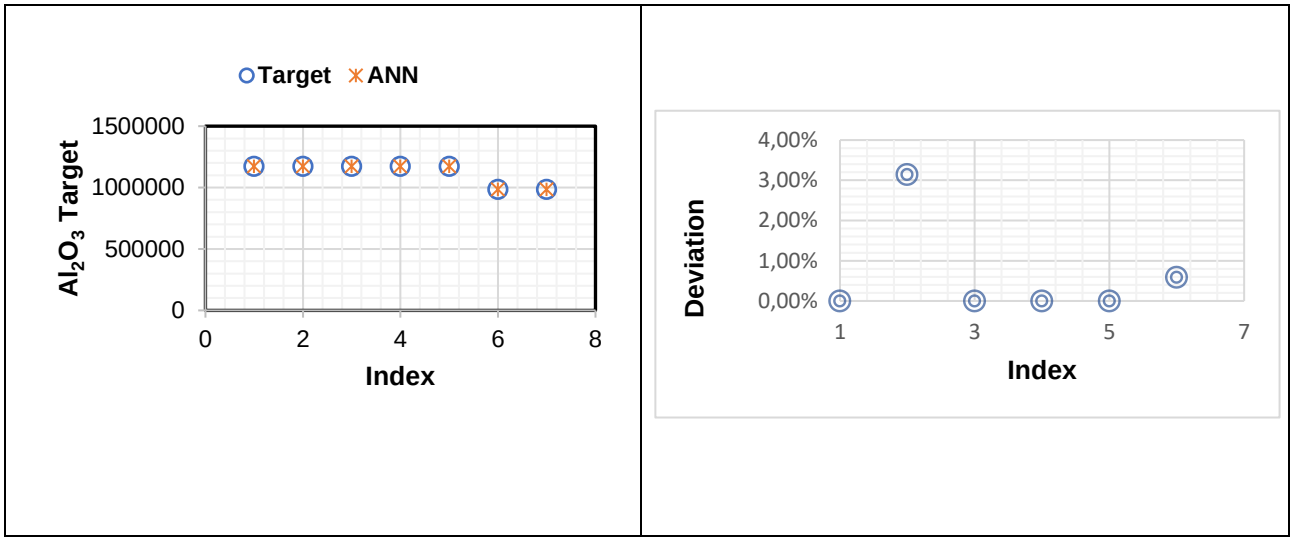

Figure 7 Artificial neural network (ANN) prediction Vs Target and Deviation of Al_2O_3

4. CONCLUSION

The grading of the furnace has led in the model to establish of a reliable mass and energy balance. An empirical model led to generate data that were used in the establishment of the mathematical programming of the model. Due to a non-linear correlation, MATLAB was used as tool. The correlation for global models has been applied successfully to furnace with nondeterministic input variables. The models consist of computational intelligence techniques and one algorithm. With the available dataset, training was performed using the neural network fitting tool, the best iteration was considered using the R^2, deviation values obtained to facilitate the prediction of mass balance or energy balance. Results have proven that the mathematical programming model was valid and could be used to predict different products in the reduction zone during high carbon ferromanganese using Artificial Neural Network.

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REFERENCES

[1] KRENKER, A.; BEŠTER, J. and KOS, A. (2011). Introduction to the Artificial Neural Networks, Artificial Neural Networks - Methodological Advances and Biomedical Applications, Prof. Kenji Suzuki (Ed.), ISBN: 978- 953-307-243-2, InTech, Available from: http://www.intechopen.com/books/artificial-neural-networksmethodological-advances-and-biomedical-applications/introduction-to-the-artificial-neural-networksAUTHOR'S SURNAME, Author's first name. *Title.* City: Publisher, Year of publication.

[2] FERNANDES, P. O.; TEIXEIRA, J. P. A New Approach to Modelling and Forecasting Monthly Overnights in the Northern Region of Portugal. Proceedings of the 15th International Finance Conference (CD-ROM). Université de Cergy. Hammamet, Medina, Tunísia. 2007.

[3] FERNANDES, P. O. Modelling, Prediction and Behaviour Analysis of Tourism Demand in the North of Portugal. Ph.D. Thesis in Applied Economy and Regional Analysis. 2005. 159 p.

[4] TSAUR, S; CHIU, Y.; HUANG, C. Determinants of Guest Loyalty to International Tourist Hotels-a Neural Network Approach. Tourism Management, No 23, 2002, p. 397-1505

[5] YAO, J.; LI, Y.; TAN, C. Option Price Forecasting Using Neural Networks. Omega, The International Journal of Management Science, No 28, 2000, p. 1555–1566.

[6] CHIANG, W.C.; URBAN, T.L.; BALDRIDGE, G.W. A Neural Network Approach to Mutual Fund Net Asset Value Forecasting. Omega, The International Journal of Management Science, Vol 215, No 2, 1996, p. 205–215.

[7] CHRISTIAN, I and MICHAEL, H. Proceedings of the Second International Symposium on Neural Computation, NC'2000, pp. 115–121, ICSC Academic Press, 2000.

[8] H¨USKEN, M.; GOERICK, C. and VOGEL, C. Fast adaptation of the solution of differential equations to changing constraints. In Proceedings of the Second International Symposium on Neural Computation, NC'2000. ICSC Academic Press, 2000.

[9] RIEDMILLER, M. Advanced supervised learning in multi-layer perceptrons – from backpropagation to adaptive learning algorithms. Computer Standards and Interfaces, 16:265–278, 1994.

[10] RIEDMILLER, M. and BRAUN, H. A direct adaptive method for faster backpropagation learning: The RPROP algorithm. In Proceedings of the IEEE International Conference on Neural Networks, pages 586–591. IEEE Press, 1993.

[11] JOOST, M. and SCHIFFMANN, W. Speeding up backpropagation algorithms by using cross–entropy combined with pattern normalization. International Journal of Uncertainity, Fuzziness and Knowledge-based Systems (IJUFKS), 6(2):117–126, 1998.

[12] JACOBS, R.A. Increased rates of convergence through learning rate adaptation. Neural Networks, 1(4):295–307, 1988.

[13] HANSEN, N and OSTERMEIER, A. Convergence properties of evolution strategies with the derandomized covariance matrix adaptation: The (μ/μ, λ)- CMA-ES. In EUFIT'97, 5th European Congress on Intelligent Techniques and Soft Computing, pages 650–654, Aachen, 1997. Verlag Mainz, Wissenschaftsverlag.

[14] N. Hansen, A. Ostermeier, and A. Gawelczyk. On the adaptation of arbitrary normal mutation distributions in evolution strategies: The generating set adaptation. In L. J. Eshelman, editor, Proceedings of the Sixth International Conference on Genetic Algorithms, pages 57–64, Pittsburgh, 1995.

[15] SILVA, M. and ALMEIDA, L.B. Speeding up backpropagation. In R. Eckmiller, editor, Advanced Neural Computers, pages 151–158. North-Holland, 1990.

[16] WA KALENGA, M. Challenges During Ores Sintering Process And Possible Impact of The use of Artificial Intelligence. *22nd International Multidisciplinary Scientific GeoConference SGEM 2022*, Vienna, Austria, pp. 191-196.