JOM, Vol. 74, No. 2, 2022
https://doi.org/10.1007/s11837-021-05052-8

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN ENERGY STORAGE AND CONVERSION MATERIALS

Predictive Model of the Percentage of Copper in the Matte of the Teniente Converter Through an Artificial Neural Network

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The Teniente converter is the main fusion equipment of the Hernán Videla Lira Foundry, in which matte, slag and gases are produced. The matte produced in the smelting process of copper concentrates in the Teniente converter contains variable percentages of copper. The expected range of copper in the matte varies from 74% to 76%. It is important to obtain these percentages of copper in the matte, since the copper that is not obtained is lost in the slag. In this work, we propose a predictive model with an artificial neural network to predict the percentage of copper that will be obtained in the matte produced in the converter so that the prediction allows modifying the different variables involved in advance. The results obtained are promising and present a mean-squared error of 0.1004 and an adequacy index of 0.9 for 140 test data.

INTRODUCTION

The Hernán Videla Lira Foundry, which belongs to the National Mining Enterprise (ENAMI), is located in Paipote, approximately 8 km from the city of Copiapó, in the Atacama Region, Chile. The main objective of ENAMI is to promote the development of small- and medium-scale mining. Therefore, it has a wide variety of copper concentrates from small and medium-sized mining enterprises.[1]

The Hernán Videla Lira Foundry has witnessed fluctuations in the value of copper and the dollar, increases in the cost of supplies and energy, environmental regulations and water deficits. Therefore, the National Mining Enterprise considers the reduction of operating costs and increased production strategic objectives to obtain increased productivity.[2]

The Teniente converter is the main reactor in charge of the pyrometallurgical smelting process of copper sulfide concentrates from the Hernán Videla Lira Foundry. Matte, slag and gases are generated in the reactor. The matte produced in the reactor contains varying percentages of copper. When the matte is extracted from the Teniente converter, it is transported to the Peirce Smith converters, where the matte conversion process is carried out. In this stage, the matte is processed through chemical reactions to increase the copper purity of the material in process. As a result, blister copper is obtained, which has approximately 96% copper. Subsequently, the blister copper is taken to the pyrorefining equipment, where the remaining oxygen is extracted from the material in process. In this way, it is possible to further increase the purity of the copper. In pyrorefining, natural gas is injected with steam, which, together with the high temperatures, reduces the level of oxygen present in the blister copper, achieving a purity of 99.7% copper in the molten material. Finally, the product resulting from the smelting process is taken to the molding wheels, where copper plates of approximately 400 kg are produced, which are called copper anodes.[3]

The matte produced in the concentrate smelting process in the Teniente converter contains varying percentages of copper. The quality of the matte depends on the operational variables involved in the fusion process that takes place in the reactor. The desired percentage range of copper in the matte is between 74% and 76%.[4] It is of utmost importance for the company to obtain these percentages of copper in the matte, because the copper that is not obtained in the matte is mechanically dragged by the slag generated by the Teniente converter.[5]

(Received June 5, 2021; accepted November 16, 2021; published online January 14, 2022)

In Chile, the foundries that currently carry out the process of smelting copper concentrates using the Teniente converter are: Chuquicamata, Caletones, Potrerillos, Ventanas and Hernán Videla Lira, the latter located in the town of Paipote (see Fig. 1). At the global level in 2015, 11% of smelters used a Teniente or Noranda converter to perform the fusion of their concentrates.[6]

Currently, the Hernán Videla Lira Foundry does not have a predictive model for the percentage of copper in the matte produced in the Teniente converter operation. The correct operation of the Teniente converter depends on the adjustment of the operational variables in function for the circumstances of the operation. The factors that influence the operational decisions include the internal temperature of the reactor, need to melt circulating material, environmental conditions, injection rate of dry concentrate, percentage of magnetite generated in the slag, etc. Because the foundry does not have a predictive model for operation of the Teniente converter, the success of the operation depends on the expertise of the reactor operators and the chief of engineering.

Being a highly complex multivariate process and strongly influenced by external variables, the percentage of copper obtained in the matte and that generated in the Teniente converter is not always as expected. Having a predictive model for the percentage of copper in the matte as a function of the operational variables of the Teniente converter would greatly facilitate decision making for the operators and chief engineers, helping to achieve the percentage of desired copper in matte.

Given the problem raised and considering the possible benefits, if the previously described process can be modeled, the following research question arises: Is it possible to predict the percentage of copper in the matte generated in the smelting process of the Teniente converter with the application of a machine learning algorithm, specifically with an artificial neural network?[7] To calculate the percentage of copper in the matte produced in the Teniente converter, it is necessary to quantify the impact of the operational variables that influence the process. For this, a model will be developed based on artificial neural networks using multilayer perceptron, which can simulate the smelting process, and predicting the percentage of copper in the matte generated in the Teniente converter. Neural networks have become vitally important recently because of their ability to learn and solve nonlinear problems that do not have a simple solution with traditional mathematical models.[8]

Fig. 1. Photograph of the Teniente converter, whose dimensions vary between 3.8 m and 5 m in diameter and between 14 m and 22 m in length, with a 2-inch-thick plate on its mantle and 3 inches in the mouth area.

RELATED WORKS

In this section, we present a description of the related works, where we mention the contributions to the state of the art of these works and describe the relationship with our research.

The research developed by[9] has been implemented in a model that simulates the cyanidation process of Aghdareh gold ore mineral with artificial neural networks and has been compared with a multivariate linear regression. The objective of the model was to predict the recovery of gold with respect to variables such as pH, percentage of solid, NaCN concentration, particle size and leaching time during the gold cyanidation process. An artificial neural network was used with an error backpropagation algorithm with five input neurons, nine neurons in the hidden layer and one neuron for the output signal. To compare the effectiveness of the model, a multivariate linear regression was used. The performance of the neural network was superior to that of multivariate linear regression, obtaining for the neural network a value for the coefficient of determination (R^2) equal to 0.9803 for the training data set and a value of R^2 of 0.8213 for the test data set. The multivariate linear regression obtained an R^2 of 0.5561 for the training data set and an R^2 of 0.6705 for the test data set. This work demonstrates the efficiency of simulating and predicting the dissolution rate of gold in the cyanidation process with respect to the variables that intervene in the process. Through trial and error, the optimal number of neurons for the input layer, hidden layer and output layer was determined. The results verified the efficacy of neural networks to model a complex process of non-linear and multivariate relationships.

In his work,[10] created a model that predicts the Fe/SiO_2 ratio in slag generated in a flash furnace, using an error backpropagation algorithm and artificial neural networks. The Fe/SiO_2 ratio is an important control parameter in the flash furnace smelting process. It is complex to model the relationship between Fe/SiO_2 in slag with traditional mathematics since the slag generation process in flash smelting is a complex nonlinear system. The developed network structure has 8 neurons in the input layer, 2 hidden layers with 15 and 12 neurons, respectively, and 1 neuron in the output layer. The eight input variables of the model include the volume of oxygen per ton of concentrate, degree of oxygen, flow rate, amount of copper, and concentration of sulfur, iron, silica and magnesium oxide. A genetic algorithm is used to avoid local minima in the training stage. The predictive model obtained can predict the Fe/SiO_2 ratio in the slag of the flash smelting process with great precision and good generalization performance.

In the research developed by,[11] a neural network with error backpropagation has been implemented to predict the melting temperature of Chinese coal instead of traditional techniques such as the phase diagram of ternary equilibrium and relationship regressions. The results indicate that there is a correlation between the melting temperature of the coal ash and its chemical composition. The performance of the neural network was superior to the traditional statistical models and presented the advantage of not having to establish the mathematical relationship between the different variables of the model. The difficulty of creating the neural network lies in selecting the number of hidden layers for the implementation of the network so that it can better simulate the phenomenon in question.

In the work developed by,[12] they compared the effectiveness of artificial neural networks with respect to a regression process to predict the probability of recovery and collision of quartz flotation under different operational conditions. The input parameters for flotation were dimensional numbers such as Froude, Reynolds and Weber, the particle size, air flow rate, bubble diameter and rate of ascent of the bubble. The linear regression method shows the relationship between the floating parameters and the probability of collision and recovery, obtaining a correlation coefficient of 0.54 and 0.87, respectively. The neural network obtained a correlation coefficient of 0.98 for both predictions.

Related works describes methodologies for modeling processes related to metallurgy and chemistry. These works are mainly focused on the selection of input variables of the models with their corresponding output variables. The works emphasize neural structure, neuron transfer functions, network parameters and the training algorithm. In addition, they describe the training and testing process in detail. They specify the statistical tools for performance measurement, training data set, validation and test data set. Another important aspect is obtaining data and preprocessing it. In the process of selecting the number of neurons from the hidden layer of neural networks, there is common agreement to use trial and error. The most widely used neural network is the multilayer perceptron with error backpropagation. In the studies in each article, different results are obtained; however, neural networks are effective for modeling the processes in question, given their ability to model complex multivariate systems and generalize based on the training data set.

THEORICAL FRAMEWORK

This section provides the technical and theoretical foundations that support the work carried out after a detailed bibliographic review. Next, the description of the Teniente converter, copper concentrate fusion process, products of the fusion process and artificial neural networks are explained.

Teniente Converter and Fusion Process

The Teniente converter is the equipment in which copper sulfide concentrates are smelted, which allows them to go from solid to liquid. The reactor is a cylindrical metal furnace, installed horizontally, and it has refractory bricks inside. The dimensions of the Teniente converter vary between 3.8 m and 5 m in diameter and between 14 m and 22 m in length, arranged in a horizontal position. The Teniente converter, located in the Hernán Videla Lira Foundry, is 3.8 m in diameter and 14.9 m in length.[13] Figure 2 shows a detailed representation of the Teniente converter.

The Teniente converter is an innovation created in Chile in the 1970s; it is a pyrometallurgical reactor capable of melting and converting copper concentrate to matte in a single piece of equipment and without external energy input.[14] It has four dry concentrate injection tuyeres, with a humidity of 0.2%. These injection tuyeres have two perforators known as "*mapucos*," which clean the tuyeres to avoid obstruction of the dry concentrate by accumulation of material. The 43 blowing tuyeres supply the air enriched with 34% oxygen with a pressure of 2 atmospheres. Silica, circulating material and wet concentrate enter through the Garr-Gun.[15] In addition, it has a hood that captures the sulfur gases produced in the fusion process. The reactor achieves the fusion process thanks to the oxidation of the sulfur and iron contained in the copper concentrates. This is an exothermic reaction, so the concentrate melts autonomously and without requiring external energy for the process. Furthermore, the process is semi-continuous, since the matte and slag are obtained without stopping the melting process.[16] The temperature range of the

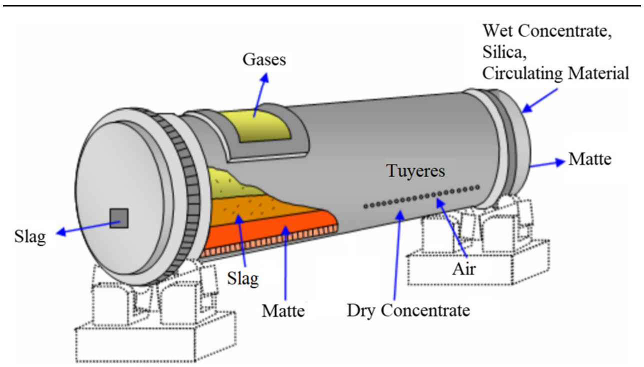

Fig. 2. Representation of the Teniente converter.

equipment varies between 1100°C and 1200°C. These temperatures allow the fusion process in order to achieve the conversion and separation of phases between the slag and matte because of their differences in densities. The slag and matte inside the Teniente converter are separated by the fayalitic slag material that makes up the interface.[17] The operational variables of the Teniente converter can be classified as solid and gaseous. In the solids we find the dry concentrate, silica, wet concentrate and circulating material. The inputs in gaseous state are the injection air and blowing air.[18]

Matte is the main product of the melting process. It has between 74% and 76% copper, 5% iron and 21% sulfur. Slag is mainly composed of a small percentage of copper, fayalite, silicon oxide and magnetite. The gases produced by the Teniente converter are sulfur dioxide. The gases from the fusion process are continuously extracted into the mouth of the equipment through a hood at a temperature of approximately 1260°C. These gases are cooled, processed and sent to the acid plants[19] (see Fig. 2).

Artificial Neural Networks

Artificial neural networks can be defined as computational mathematical models inspired by the functioning of biological neural systems.[20] They are made of adaptive information processing units called neurons that are interconnected with each other. The most widely used neural network is the multilayer perceptron.[21]

The multilayer perceptron is made of a set of neurons that are distributed in the different layers of the neural network. In the first layer are the input neurons, and the last layer corresponds to the output neurons. The neurons located between the input and output layers are located in the hidden layer. Each layer has a certain number of neurons with their respective transfer functions. The neurons of one layer are connected to the neurons of the next layer, such that the signals sent by the neurons of layer $n-1$ are the input signals of layer n. The parameters of the neural network are expressed mathematically as vectors and matrices. The neural network must be trained to adjust its synaptic weights, reducing the error of the output. This process consists of providing a set of training data to the network so that the error of the output signal is minimized. See more details in Ref. 22.

Performance Indicators

To measure the performance of the neural model, two performance indicators are used: the square root of the mean squared error (RMSE) and the adequacy index (IA). The range of these performance indicators varies between 0 and 1. Values close to 0 indicate a good predictive performance for the mean square error, RMSE, while values close to 1 indicate a good estimate for the adequacy index, IA.[23]

The mean square error (RMSE) measures the average of the squared errors, i.e., the difference between the estimator and what is estimated. It is expressed mathematically as shown in Eq. 1.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n} o_i^2}} \tag{1}$$

where o_i is the desired value for i and p_i is the prediction value of neural network i.

The adequacy index (IA) determines the similarity between the graph of the prediction values with respect to the graph of the expected values. It is expressed mathematically as shown in Eq. 2.

$$\mathrm{IA} = 1 - \frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(|o_i - o_m| + |p_i - o_m|)^2} \tag{2}$$

where o_i is the desired value for i, p_i is the prediction value of neural network i, and o_m is the mean value of the desired predictions.

PROPOSED METHOD

This section describes the work methodology used to carry out the research. The work methodology can be divided into four stages: (1) data extraction, (2) data preprocessing, (3) neural model design and (4) model test. Each of the stages of the work methodology is described below.

Data Extraction

Data were collected over a period of 1 year, where a total of 700 operating cycles of the Teniente converter were obtained. Data were extracted from the foundry's *PlantPax* Distributed Control System (DCS) database and daily operational report. The data of the daily operational report are extracted manually because of the impossibility of being exported, while the data collected from the DCS are obtained by exporting them to an Excel sheet. From the daily operational report, information is obtained on (1) the output variable (percentage of copper in the matte during the bleeding phase of the Teniente converter operation), (2) the operational variables of the copper residence time between each operating cycle and (3) the percentage copper of the matte from the previous operating cycle. Information regarding the injection of dry concentrate, silica, circulating material, wet concentrate and blowing oxygen is extracted from the distributed control system.

It is important to note that the larger the data set is, the greater the variety of possible scenarios to predict and the greater the certainty in the prediction. In addition, if the data set is large enough, it will prevent the risk of obtaining biased results. Therefore, the size of the data set could affect the performance of the neural network. With a larger data set, the performance of the neural network tends to improve, allowing the phenomenon in question to be better modeled.

Data Preprocessing

Data preprocessing consists of eliminating periods of operation where production is negatively altered as a result of environmental restrictions. Data for periods when there are blowing, injection and belt feeding problems in the Garr-Gun are also deleted. Information on periods in which there were operational problems due to equipment and instrumentation failures is discarded. Finally, the information on the operating periods in which the information on the selected operational variables was not complete is suppressed.

The database for the training, validation and testing of the neural network was registered in an Excel sheet together with the refined data. For solid material input variables, we carried out the transformation from units to kg/10 min. For input variables in the gaseous state, we carried out the transformation of units to $m^3/10$ min. In this way, we used the operational variables in the same time frame.

Subsequently, we normalized the input data of the neural network to facilitate training. The normalization of the input data allows the synaptic weights of the neural network to be consistent to avoid disproportions in the initial weights of the neural network. The data normalization method consists of interpolating the data of each input variable between 0 and 1 with respect to the range of the variable in question.[24] To normalize the data, we used Eq. 3.

$$p_n = \frac{p_i - p_{\min}}{p_{\max} - p_{\min}} \tag{3}$$

where p_n is the normalized value of the n element of the input vector, p_i is the value of the i element to normalize from the input vector, $p_{\min}$ is the minimum value of the input vector of the data set, and $p_{\max}$ is the maximum value of the input vector of the data set.

Neural Model Design

The neural network is created with the database generated with the information from the previous stage ("Data Preprocessing" section). The creation of a neural network is based on a certain architecture, with random initial synaptic weights. To create a neural model that represents the conversion process, it is necessary to train this model. Training is the learning process in which the neural network adjusts the weights of the neurons to minimize the error of the output with respect to the training data set. The training data set must be representative in terms of dispersion for the network to be able to internalize the different scenarios of the test data set.[25]

Network training consists of continuous iterations of the developed algorithm until the desired model is obtained. For this stage, a set of 420 training data and 140 validation data was used. Because neural networks are very sensitive to overfitting, we used two strategies to avoid this problem:

- *Stopped Training* We divided our data set into three groups; training, validation and testing. We proceed to stop training when the error of the validation set increased continuously for a number of epochs.
- *Regularization* We restricted the size of the weights, adding to the cost function (which is minimized), a penalty term proportional to the weights squared Euclidean norm.

Model Test

When the network has completed the training stage, it must be determined whether the neural network has generalized the phenomenon or not. In case the network succeeds in simulating successfully, the training process is stopped. If the neural network does not simulate properly, it is necessary to repeat the learning process.

The tests of the predictive model are performed by simulating the input variables of the test data set and comparing them with the value estimated by the network for the percentage of copper in the matte and its real value. The statistical analysis of the results is carried out using the mean square error (RMSE) and the adequacy index (IA). A set of 140 test data was used for this stage.

RESULTS

In this section, we show the results obtained from the research carried out. The design of the obtained neural network is shown as well as the performance of the neural network for the training, validation and test data set.

Neural Network

The neural network that we propose has seven input variables: (1) dry concentrate injection, (2) silica, (3) wet concentrate, (4) circulating material, (5) blowing oxygen, (6) percentage of copper in the matte from the previous bleed and (7) residence time of matte between bleeds. The neural network has one hidden layer, which has seven artificial neurons. The output variable is an artificial neuron that represents the percentage of copper in the matte produced during operation of the Teniente converter. The transfer function for all neurons in the network is the logarithmic sigmoid. The training algorithm used was the Levenberg-Marquardt. See details of the algorithm in Ref. 26. The training data set was 420 cases; the validation data set was 140 cases, as was the test data set. Figure 3 shows our proposed neural network.

The hyperparameters were empirically defined for the Levenberg-Marquardt error backpropagation training algorithm. In this case, the learning rate was 0.003. To avoid overfitting, we use two methods: (1) the stopped training method, which consists of stopping the training when the error of the validation set increases continuously, and (2) incorporating regularization to the cost function, which penalizes the weights, as training progresses. The problem with regularization is that it is difficult to determine the optimum value for the performance ratio parameter. If we make this parameter too large, we may get overfitting. If the ratio is too small, the network will not adequately fit the training data. In our case, we used a regularization parameter of 0.0001 (this being a classic value for prediction tasks). The architecture of our artificial neural network is simple, but performs very well. We use a three-layer model, which was also empirically defined: seven neurons in the input layer, since we have seven variables, seven neurons in the hidden layer and one neuron in the output layer.

Next, we describe the input variables of the neural network structure created:

- *Dry concentrate injection* is the concentration process of the copper sulfide minerals. It is rich in copper, sulfur and iron. To reduce the percentage of humidity, the concentrate goes through the drying process, obtaining the dry concentrate. The injection of dry concentrate into the Teniente converter is pneumatic, through the injection tuyeres. The sulfur in the concentrate reacts with oxygen and the high temperatures inside the Teniente converter; the oxidation that occurs is an exothermic reaction. In this way, the Teniente converter obtains the energy necessary for the melting process.
- *Silica* is the quartz mineral added to the melting process using the Garr-Gun. The role of silica is to generate fayalitic slag in the melting process, thanks to its rich silicon content. Silica is necessary to generate the interface between the matte and slag. In addition, it helps reduce the generation of magnetite in the slag.
- *Wet concentrate* is the concentrate rich in sulfides without the drying process and with a high percentage of humidity that is added through the Garr-Gun. The objective of the wet concentrate is to lower the temperature of the Teniente converter without having to reduce the injection rate of the dry concentrate.
- *Circulating material* is the foundry material that solidifies in the slag and matte transport pots. The circulating material is crushed to be reprocessed in the Teniente converter and added through the Garr-Gun. Like the wet concentrate, it helps to control the temperature of the Teniente converter.
- *Blowing oxygen* blowing air is the mixture that results from ambient air and 95% enriched air from the oxygen plant. It enters to the Teniente converter through the blow tuyeres. It has an approximate enrichment of 35% oxygen, decisively influencing the melting process.
- *Percentage of copper in the matte of the previous bleed* corresponds to the percentage of copper in the matte obtained in the previous bleed. This has the objective of entering the remaining of copper in the Teniente converter in the model.
- *Residence Time of matte* corresponds to the time from when the previous bleeding stage begins until the start of bleeding, to determine the percentage of copper in the matte that is generated during operation of the Teniente converter.

Neural network model performance

Next, we present the results obtained in the development of the investigation for the training, validation and test data set. In addition, the performance indicators for ten neural networks are presented, which were obtained by training ten neural networks, applying cross-validation (see Fig. 4).

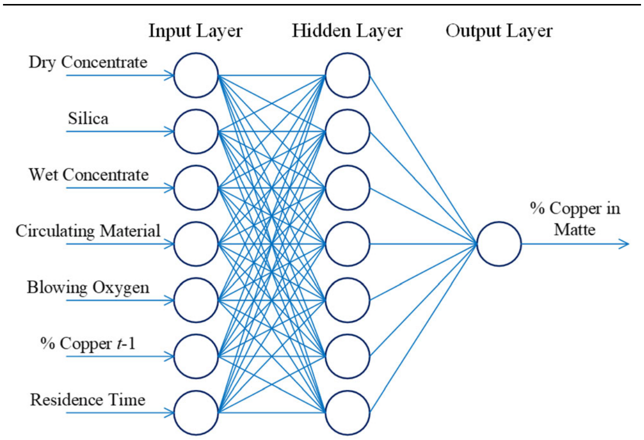

Fig. 3. Neural network structure.

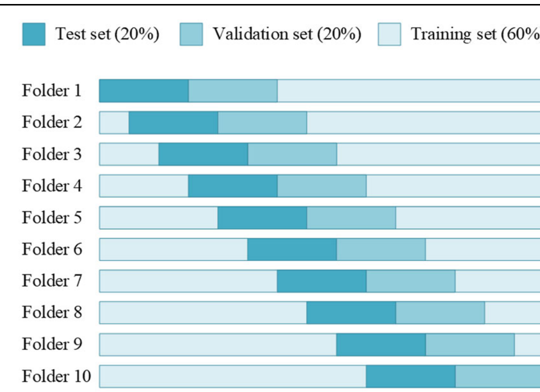

Fig. 4. Cross-validation method.

To perform the cross-validation, 10 folders were created, which were obtained by randomly selecting 420 data for training, 140 for validation and 140 for testing from the initial data set of 700 operating cycles of the Teniente converter. With the ten resulting folders, each of the ten resulting artificial neural networks was trained, validated and tested. Of the ten neural networks obtained, neural network number 2 was selected as the one with the best performance since it had the lowest mean square error and the best adequacy index for the training data set.

The training data set was made up of 60% of the measurements made, i.e., 420 independent cases, from which the measurement of the seven input variables of the model was obtained for each operating cycle of the Teniente converter. Table I shows the performance obtained for the training of the ten artificial neural networks with their respective performance indicators.

The average obtained for the mean square error was 0.1218, and the average adequacy index was 0.8670. Neural network number 2 obtained the lowest mean square error, which was 0.1042. In addition, it obtained the highest adequacy index, which was 0.8817 for the training data set.

Figure 5a shows the graph corresponding to the training result for neural network number 2. On the Y axis of Fig. 5a, the percentage of copper in the matte can be seen. The X axis corresponds to 420 operating cycles of the Teniente converter.

The validation data set is made up of 20% of the measurements, i.e., from 140 independent cases, from which the measurement of the 7 input variables of the model was obtained for each operating cycle of the Teniente converter. Table II shows the performance obtained for the validation of the ten artificial neural networks with their respective performance indicators.

The average obtained for the mean square error was 0.1252, and the average adequacy index was 0.8696. Neural network number 2 obtained a mean square error of 0.1073 and an adequacy index of 0.8707.

Table I. Performance for training set

Neural network	RMSE	IA
1	0.1066	0.8620
2	0.1042	0.8817
3	0.1288	0.8656
4	0.1299	0.8608
5	0.1220	0.8707
6	0.1243	0.8630
7	0.1237	0.8690
8	0.1267	0.8609
9	0.1243	0.8700
10	0.1272	0.8663
Average	0.1218	0.8670

Figure 5b shows the graph corresponding to the validation result for neural network number 2. On the Y axis of Fig. 5b, the percentage of copper in the matte can be seen. The X axis corresponds to 140 operating cycles of the Teniente converter.

The test data set was made up of 20% of the measurements, i.e., from 140 independent cases, from which the measurement of the 7 input variables of the model was obtained for each operating cycle of the Teniente converter. Table III shows the performance obtained for the test of the ten artificial neural networks with their respective performance indicators.

The average obtained for the mean square error was 0.1117, and the average adequacy index was 0.9044. Neural network number 2 obtained a mean square error of 0.1004 and an adequacy index of 0.9.

Figure 5c shows the graph corresponding to the test result for neural network number 2. On the Y axis of Fig. 5c, the percentage of copper in the matte can be seen. The X axis corresponds to 140 operating cycles of the Teniente converter.

CONCLUSION

The neural model created for the prediction of the percentage of copper in the matte of the operation of the Teniente converter allows predicting the test data set of neural network number 2 with a mean square error (RMSE) of 0.1004. Therefore, a model can be created to predict the percentage of copper in the target metal from the operation of the Teniente converter using artificial neural networks. The adequacy index (IA) of 0.9 obtained with neural network number 2 in the test data set reaffirms the capacity of neural networks for the simulation of complex and non-linear processes such as modeling the percentage of copper generated during operation of the Teniente converter.

The data extracted from the PlantPax distributed control system (DCS) allowed adequately obtaining the data for the training, validation and testing of the neural networks. These data could not be obtained continuously since the operation of the Teniente converter is affected by operational and environmental factors that interrupt the continuous operation of the equipment.

Although the operational temperature variable is excluded because of the nonexistence of an instrumental record of this variable, the seven variables chosen for the model were able to satisfactorily predict the percentage of copper generated in the matte. The results obtained with the performance indicators for the 140 data of the test data set indicate that the neural network managed to learn satisfactorily based on the training data set to predict the obtaining of copper in the matte of the equipment operation with the test data set.

To carry out the cross-validation, 10 folders were created, which were obtained by randomly selecting 420 data for training, 140 for validation and 140 for

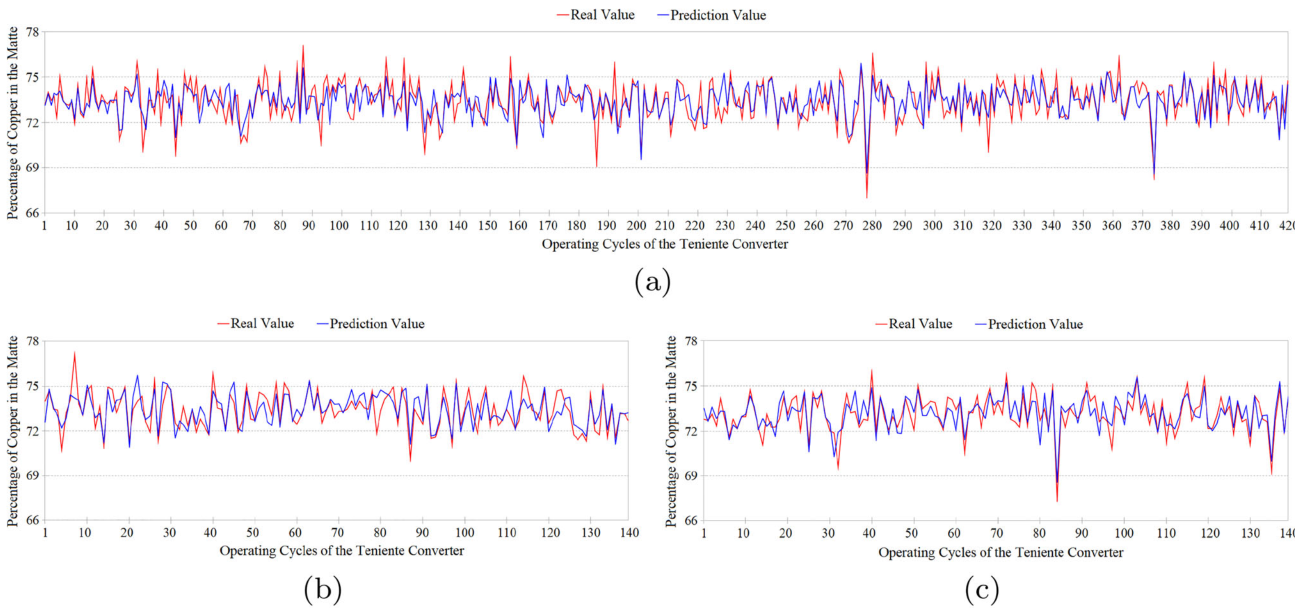

Fig. 5. Performance comparison between real value and prediction value for neural network 2: (a) comparison for training set, (b) comparison for validation set and (c) comparison for test set.

Table II. Performance for validation set

Neural network	RMSE	IA
1	0.1087	0.8701
2	0.1073	0.8707
3	0.1182	0.8827
4	0.1352	0.8666
5	0.1264	0.8779
6	0.1374	0.8677
7	0.1385	0.8664
8	0.1247	0.8636
9	0.1390	0.8653
10	0.1177	0.8652
Average	0.1252	0.8696

Table III. Performance for test set

Neural network	RMSE	IA
1	0.0973	0.9117
2	0.1004	0.9000
3	0.1148	0.9022
4	0.1037	0.9050
5	0.1227	0.9045
6	0.1173	0.9007
7	0.1138	0.9019
8	0.1144	0.9123
9	0.1087	0.9021
10	0.1237	0.9033
Average	0.1117	0.9044

the test of the initial data set of 700 operating cycles of the Teniente converter. With the ten resulting folders, each of the ten resulting artificial neural networks was trained, validated and tested. Of the ten neural networks obtained, neural network number 2 was selected as the one with the best performance since it presented the lowest mean square error and the best adequacy index for the training data set.

The ten neural networks obtained by cross-validation showed similar values for the performance measurement indicators, so the ten networks obtained showed similar efficiency in predicting the percentage of copper in the matte in the fusion process of the Teniente converter.

The results obtained are promising. However, as future work we propose that the created neural model be contrasted with controlled field tests to fully validate it. In addition, we propose using LIME (Local Interpretable Model-agnostic Explanations) to obtain a global intuition of the model and to replicate its behavior in the vicinity of the instance that is predicted.

ACKNOWLEDGEMENTS

We are deeply grateful to Dr. Karina Carvajal Cuello (RIP) for defining the guidelines of this research, to the Postgraduate Direction of the University of Atacama and to the Hernán Videla Lira Foundry of the National Mining Enterprise (ENAMI) for their support for conducting this research.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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