

# Modeling the Temperature of the Evacuation Chamber with Artificial Neural Networks

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## Abstract

This investigation approaches the artificial neural networks applied to the ore drying process in carbonate-ammonia leaching. To carry out this research, the main variables that characterize the process were identified. Besides, it was collected the data that comprise a whole month of facility's operation. Furthermore, it was developed a regression analysis backwards, step by step, which allowed to determine that the linear correlation coefficient did not reach values higher than 0,62. In addition, it was pinpointed a two layered feed - forward back propagation neural network to model the temperature. Thins one reached the correlation coefficient values of 0,97 during its training and 0,95 in validation, as well as 0,87 in its generalization.

**Keywords:** Artificial Neuronal Network; Regression; Feed-Forward Backpropagation; Mineral Drying

## Introduction

In a global context, nowadays, modern control systems play a fundamental role when developing solutions to issues or problems presented in domestic and industrial applications. The main contributions of modern control systems at industrial level contribute to technological innovation, profitability and maintainability of the controlled processes. Within the advanced control strategies under investigation to automate complex processes are: adaptive control, predictive control based on models, robust control, and intelligent control, among others. Intelligent control relies on several techniques such as: fuzzy logic, evolutionary algorithms, and artificial neural networks. Artificial neural networks can be used effectively and accurately for modeling systems with complex dynamics, especially for nonlinear processes that vary over time. The growing interest in neural networks is due to its great versatility and the continuous advance in network training algorithms and hardware [1-4]. The nickel producing companies have continuous processes of great complexity that require automation to achieve a greater efficiency in their productions. In the process of ore preparation, it is important to maintain a temperature control at the outlet of the dryer evacuation chamber, in order to obtain the mineral drying with an established humidity level of 4 to 5,5 %. It must also be ensured that the temperature at the outlet of the electrofilters is above the dew point temperature; to prevent the deterioration of electrofilters, which

leads to high economic losses, from accelerating considerably. The inefficiencies in the control of the outlet temperature of the dryer evacuation chamber in the ore preparation process are taken as a research problem and as an objective to obtain an artificial neural model for the outlet temperature on the basis of the main input variables, using Matlab as a calculation tool.

## Materials and Methods

### Description of the Mineral Drying Process

The drying of the ore is carried out in elongated cylinders formed by a combustion chamber where the hot gases that dry the ore are produced, and by the cylinder where the ore will receive the drying process. These drums (Figure 1) have in their interior lifting elements that are responsible for allowing the transfer of heat between the hot gas and the mineral, in addition the dryer drum has a motor system coupled to the body of this which allows it to rotate on its axis. The dryer drum externally rests on two wheels that has two pairs of roller. Internally the dryer is formed near the combustion chamber by guides or baffles welded to the body of the drum that are the ones that direct the mineral towards the outside of the cylindrical part of the drum [5]. The mineral dryer is a complex physical-mathematical modeling object with a large number of input and output parameters which are in a complex interdependence (Figure 2).

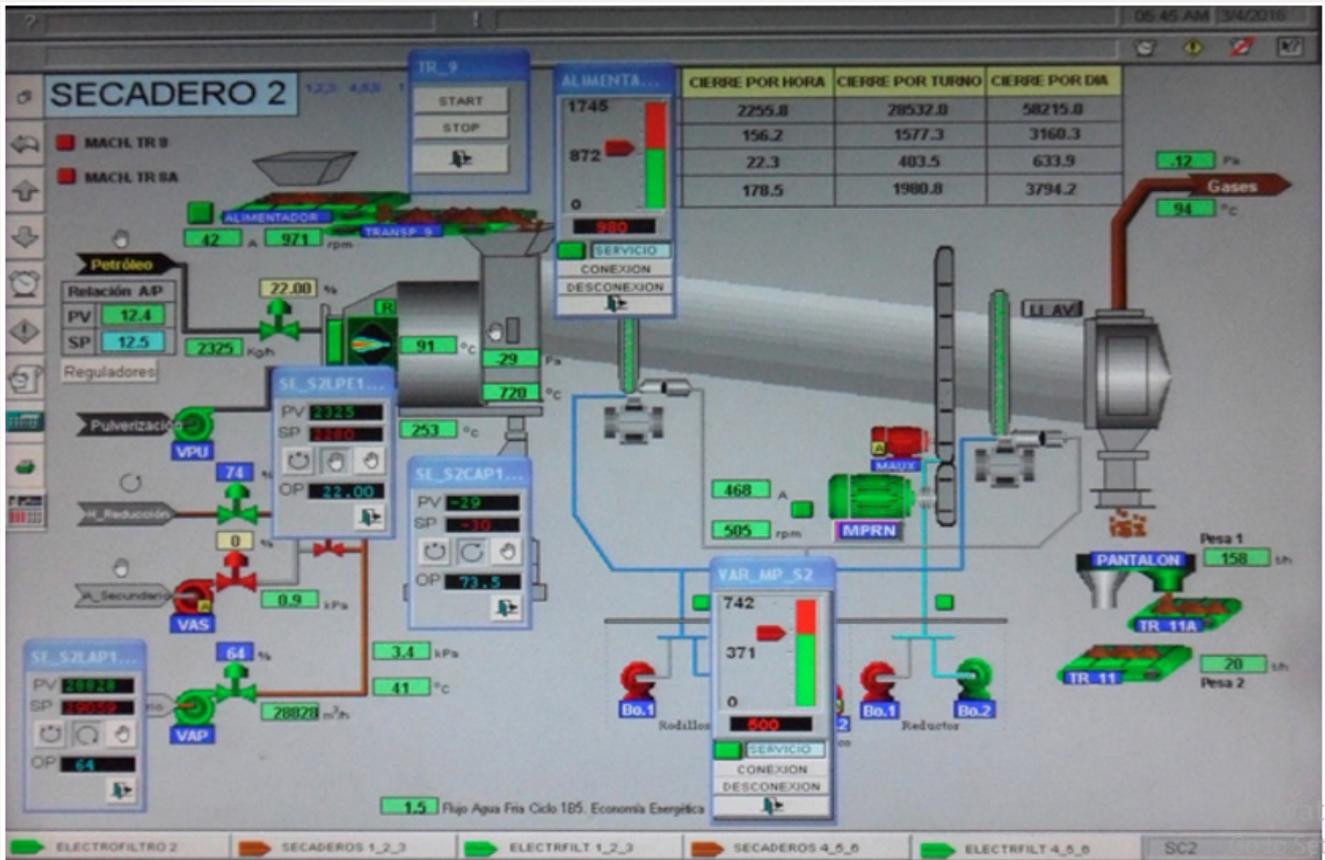


Figure 1: Schematic diagram of the dryer.

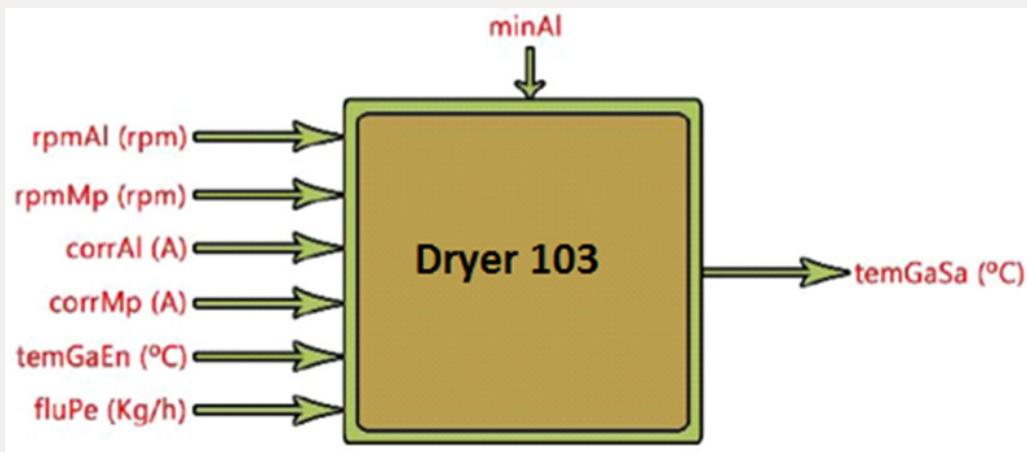


Figure 2: Structural diagram of the mineral drying process.

**The Input Parameters in the Process are:**

- a) rpmAl - Feed motor speed [rpm].
- b) rpmMp - Speed of the main motor [rpm].
- c) corrAl - Feed motor power [A].
- d) corrMp - Power of the main motor [A].
- e) temGaEn -Temperature in incoming gases [°C] (coming from the Reduction Furnaces Plant).

- f) fluPe - Oil flow at the burner inlet [kg/h].

**The Output Parameter is:**

- a) temGaSa - Outlet gas temperature [°C].

In addition to the input and output parameters, it is important to highlight a specific disturbance of this process that influences it, which is: minAl - Mineral fed to the dryer. It is known that there are other parameters that are involved in the drying process of the ore and that in turn influence the temperature of the exhaust gases

in the evacuation chamber (granulometry in the entrance mineral, humidity of the entrance mineral, exact amount of mineral fed to the dryer), but due to the process itself, they are not registered. Due to the automation existing in the process, the values of the process parameters are sensed by the instrument corresponding to each of them and the signal is sent to the computer located in the process control office. The data obtained along 1 month of operation, were recorded every 240s and processed with the Stat graphics Plus V 5.1 software.

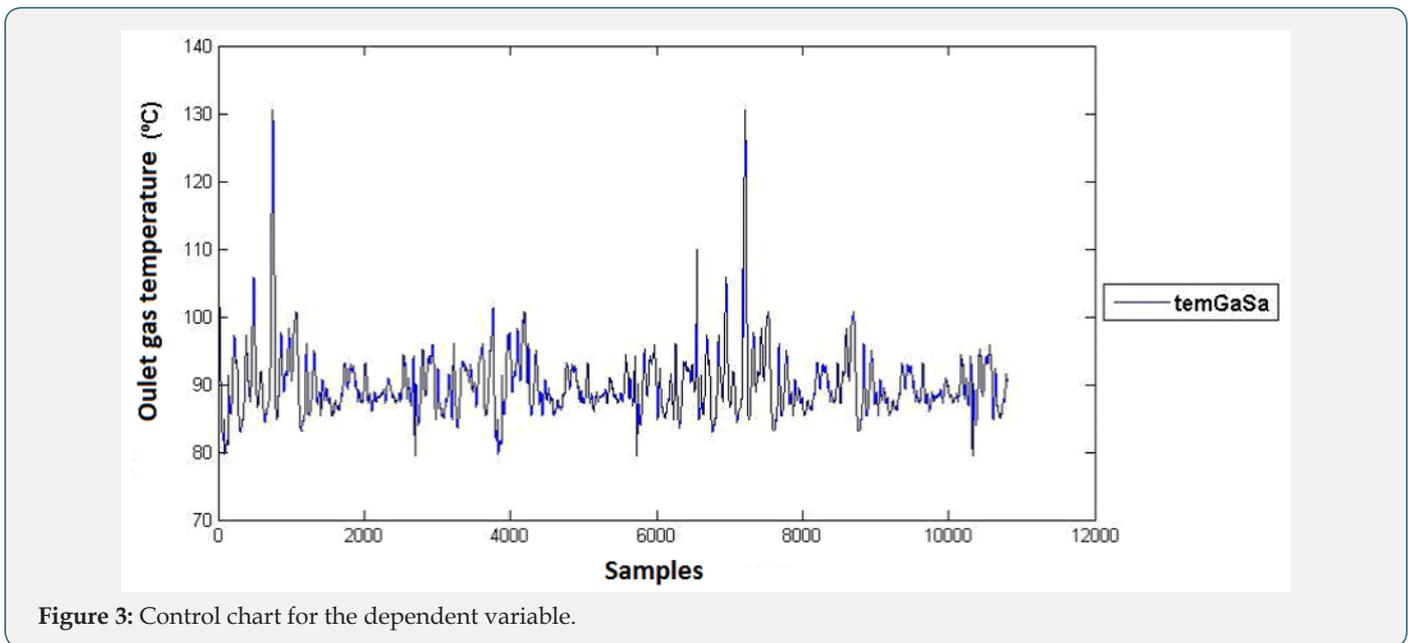
**Artificial Neural Networks**

The determination of the type of artificial neural network, the number of layers and the number of neurons in each layer that best characterize the process of ore drying process was carried out through a trial and error process that plays with the number of neurons and the maximum permissible error. Through Matlab’s Toolbox (nntstart), the performance of artificial neural models was evaluated by using the mean square error and the correlation coefficient between the real values and those obtained by the network [6]. The objective was to provide the network with an

adequate number of neurons in the hidden layer to learn about the characteristics of the possible relationships between the sample data. Through the trial and error process, it was identified the feed-forward back propagation structure that provided better results. The proposed network consists of two layers: a hidden layer and an output layer. The output layer will only have one unit, which will indicate the value of the outlet gas temperature associated with each input vector presented to the network. The hidden layer will have a variable number of neurons.

**Results and Discussion**

Figure 3 shows the behavior of the exhaust gas temperature in the evacuation chamber, between its minimum and maximum values of 79,59 and 130,51°C, respectively, for the month of work. Once the database was analyzed, the sample functions that evaluate the measures of central tendency and dispersion of the sample were determined through a descriptive statistical analysis (Table 1). The mathematical model that best represents the relationship between the variables analyzed. Table 2 shows the regression analysis for the output pulp density, where a 0,7 correlation coefficient is observed.



**Table 1:** Summary of the sample’s descriptive statistical analysis for one month.

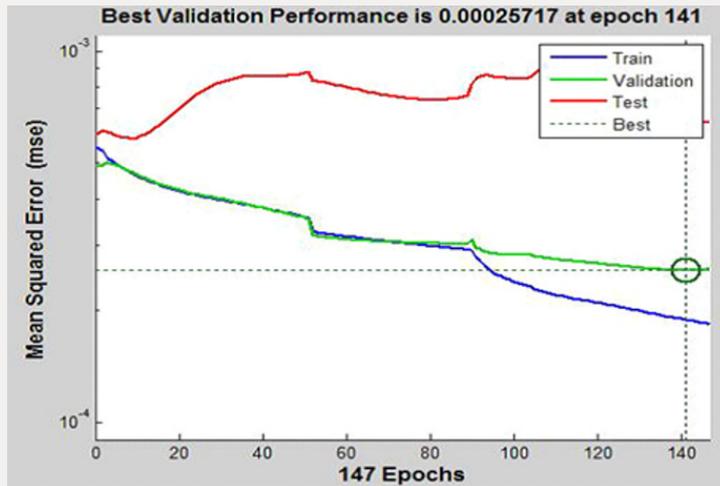
Statistics	Temperature(°C)		Flow(Kg/h)	Power (A)		Speed (rpm)	
	temGaSa	temGaEn	fluPe	corrAl	corrMp	rpmAL	rpmMp
Average	89,9	108,8	2175,2	11,27	428,08	855,20	459,22
Desv.Est.	5,3	99,96	75,62	1,80	9,55	54,52	24,01
Curtosis	17,2	-1,58	205,19	2,61	4,46	89,39	55,26
Asymmetry coefficient	3,05	0,52	-8,38	0,49	-0,63	-6,11	-2,83
Minimum	79,6	26,21	8,99	0,25	366,95	-10,99	100,54
Maximum	130,5	263,02	2301,44	18,29	458,47	997,45	549,48
Confidence interval (99%)	0,17	3,29	2,49	0,05	0,31	1,79	0,79

**Table 2:** Regression analysis summary.

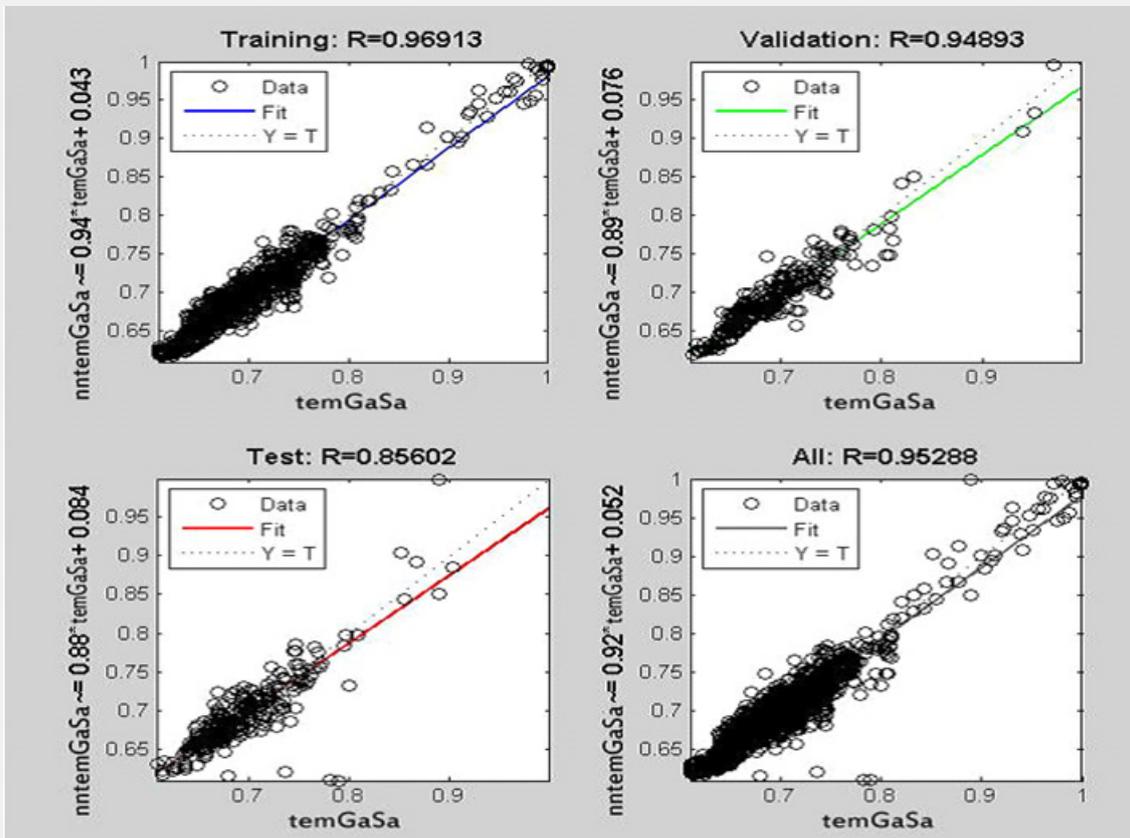
Correlation coefficient R	0,6217
Adjusted R <sup>2</sup>	0,6219
Average absolute error	41,892
Samples	10 800

Figure 4 shows the training behavior of the network for the learning process, observing the training, validation and test curves,

which converge to the iterations for an error of 0,00026. Figure 5 shows the behavior of the correlation coefficients for the training, validation, testing and adjustment of the artificial neuron network (it is assumed as an artificial neuronal model for the outlet gas temperature in the ore drying process “nntemGaSa” and the real temperature “temGaSa”). Figure 6 shows the generalization of the network with 1767 data not presented during training, where a 0,87 correlation coefficient is observed.



**Figure 4:** Behavior of training and validation of the neural network.



**Figure 5:** Correlation coefficients of the neural network.

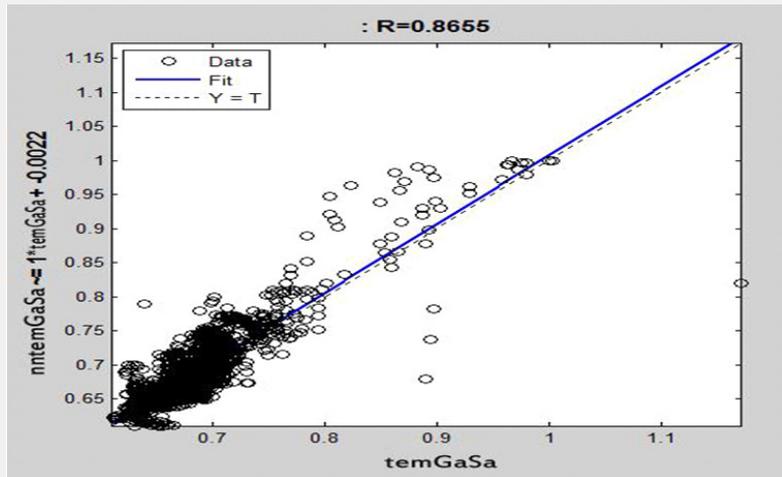


Figure 6: Network Generalization.

**Conclusion**

The capacity of the feed-forward back propagation network for the simulation of pulp sedimentation processes in the industry was demonstrated. The structure that best characterizes the behavior of the temperature in the exhaust gases of the evacuation chamber is characterized by two layers with 50 neurons in the hidden layer and one in the output layer, with the Levenberg Marquart learning method (trainlm), and the log-sigmoidal (logsig) and sigmoidal hyperbolic tangent (tansig).

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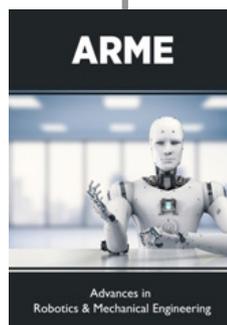
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