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PREDICTION OF SINTER PLANT PRODUCTIVITY BY NEURAL NETWORK[1]

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Abstract
The prediction of productivity represents an important resource in order to anticipate losses, increasing the performance of the sinter machine. In this context, a neural network model which relates the main operating parameters and the sintering productivity was developed. The kind of neural network chosen was multi-layer perceptron. The best configuration was obtained with one hidden layer and nine neurons, and the correlation coefficient obtained between predicted and actual productivity was 0.77. Furthermore, the neural network showed better predictive ability than the multiple linear regression technique. The model was applied to Sinter Machine#3 at Usiminas - Ipatinga Plant.
Key words: Sinter plant; Neural network; Productivity.

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1 INTRODUCTION

In an industrial operation, measuring results is essential for the proper management and economic production process. In the sintering process case, productivity, fuel consumption, yield, physical and metallurgical properties of sinter are the major indices to be measured and controlled, when the goal is to improve the operating results.
Nowadays, there are numerous process variables controlled by the automation system, over there, the frequency of measurement is high. However, the influence of each variable in the process is not yet fully known and especially the interrelationships between them. This fact complicates the assertive role of the technicians, especially when sinter machine high productivity is the goal.
Thus, a model based in neural networks was developed in this study, linking the main operating parameters with the Sinter Machine#3 productivity at Usiminas - Ipatinga Plant. Also, results generated by artificial neural network were compared with the ones generated by multiple linear regression technique. This was realized to verifying what technique provides the best result. If the former technique will provide the best results, this one will be used. By the way, the use of this tool is new for the sinter plant at Usiminas.

1.1 Artificial Neural Network (ANN)

According to Braga[1] artificial neural network is a form of computing non based on rules or programs. The operating system is composed of simple processing units, called neurons. The aim of neurons is to calculate mathematical functions. These neurons are positioned in one or more layers and they are interconnected by a number of connections related to weights. These weights have the aim to balancer the input received by each neuron. The ANN tool is an option for the solution of problems like classification, categorization, approximation, prediction and optimization.
One type of structure is the Multi-layer Perceptron (MLP) and it is able to solve non-linearly separable problems. Networks like Perceptron and Adaline can only solve linearly separable problems, because they have just one layer. The patterns to be sorted should be sufficiently separated from each other, in other words, the separation should be such that it is possible to divide the patterns by a hyperplane, according to Figure 1. The difference between being linearly separable or not is the complexity of the solution.[2]

(a) (b)

Figure 1. Examples of relationship: (a) Linearly separable patterns and (b) Non-linearly separable patterns.

The MLP structure is comprised by one input layer called input signals, one or more hidden layers (hidden neurons) and one output layer. This kind of network structure is showed in Figure 2.

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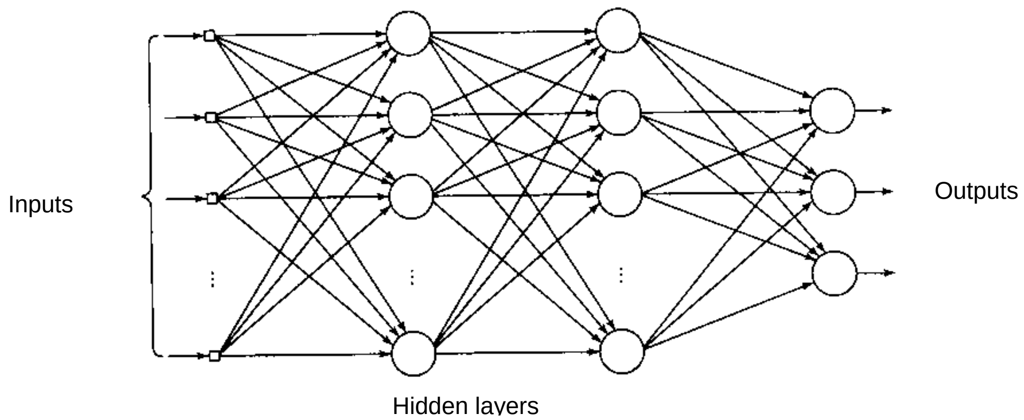

Figure 2. MLP network structure.[3]

In MLP network, one hidden layer is sufficient to approximate a continuous function and two hidden layers can approximate any mathematical function.[4]
The number of neurons is defined empirically. Wong[5] used the following formulations: (2n), (n/2), (2n+1), where 'n' represents the number of inputs, to determine the number of neurons.
The algorithm used at ANN is a well-defined set of rules for a learning phase. Two types will be discussed: Levenberg-Marquardt and Scale Conjugated Gradient that are based on optimization models. The former uses learn rate variable and it is based on the determination of second derivatives of the squared error in relation the weights. This algorithm is considered the fastest method for training feedforward backpropagation networks. The latter algorithm is based on informations from the second derivative of the cost function.[6]

1.2 Neural Network Applied to Sintering

Artificial neural network may become an indispensable tool for prediction of certain processes characteristics. Since the network is well trained and the results are satisfactory, the possibility of technical and economic gains is high.
Caporali et al.[7] used a neural network trained through a reverse propagation algorithm to understand the relationship between macro and micro-structural characteristics of mixtures of ores and sintering performance. For this purpose, data was collected from a pilot sintering. The used variables were described on table 1.

Table 1. Selected variables

Inputs	Outputs
amount of goethite	productivity (t/m^2.dia)
crystal size average	coke-rate (kg/t sínter)
particles over 1 mm	tumbler index
particles from 0.149 mm to 1 mm	RDI.
silica content in the iron ore mixture	
alumina content in the iron ore mixture	

The process variables such as bed height, depression, binary basicity, return rates and burnt lime in the mixture were kept constant.
Caporali et al.[7] concluded that the crystals average size and the amount of goethite in the mixture strongly influenced the output variables.

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Laitinen and Saxén[8] used operational data to predict the productivity, softening and melting index, fuel rate, LTB (Low Temperature Breakdown) and tumbler index. The input variables were: binary basicity, particle size range (0.5 mm to 1 mm of sinter feed), ratio hematite/magnetite and moisture of the mixture. The particle size range and the ratio of hematite/magnetite at the sinter feed were determined by the composition of the blending stack. The fuel rate prediction was inconclusive, however, were obtained evidence that the increase in particle size fraction lead to an increase in fuel rate. Similar behavior was observed with LTB. For the prediction of productivity, the particle size fraction 0.5 mm to 1 mm of the sinter feed was found to be inversely proportional to productivity. To predict the tumbler index, the basicity was found to be the determining factor.
In this case, the ANN showed that the productivity had an inverse correlation with the fraction between 0.5 mm and 1 mm. This situation was expected, since the higher sinter feed particle size in this range, decreases the permeability of the bed in the sintering, with consequent reduction in productivity.
In another study, Laitinen and Saxén [9] developed a model to predict the same indexes, but adding the return rate. He used a historical equivalent of five years production. The following input variables are: basicity; ratio of hematite and magnetite; fraction of particles in the range 0.5 mm to 1 mm, moisture of the total mixture, ignition temperature, mass flow of mixture fed into the strand, strand speed and permeability of the mixture in the strand.
The best result of the network was the productivity which was able to describe 87% of the variation of the this variable, the worst result was tumbler index with 65%, fuel rate was 82%, the rate of return 83% and LTB with 76%.
Kinnunen and Laitinen[10] used industrial data from sintering process of three years to build an RDI and productivity prediction model. The variables used to predict the productivity were as follows:

- total heat;
- ignition heat/m^2;
- percentage of coke breeze;
- percentage of 0.2 mm to 0.7 mm in the mixture;
- percentage of burnt lime;
- average grain size of the mixture;
- hearth layer height;
- fuel rate;
- binary basicity;
- percentage of slag converter;
- titanium content, MgO, potassium and Fe_T in the sinter; and,
- outside air temperature.

The variables binary basicity; room temperature (-10°C to 20°C); hearth layer height; alumina content, percentage of 0.2 mm to 0.7 mm in the mixture; fuel rate, and titanium content, were the main variables in predicting of productivity.

2 MATERIALS AND METHODS

The method used is shown by a flowchart in Figure 3. A system of data acquisition process, a statistical software capable of performing multiple linear regression and selection forward and backward and a software with the function neural network were used to implement the steps.

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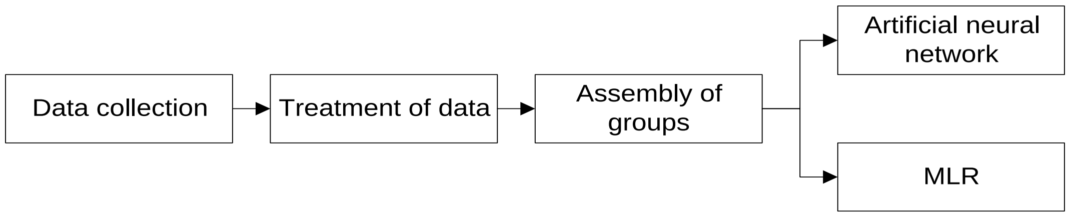

Figure 3. Flowchart of the method.

2.1 Data Collection

At this stage the brainstorm technique was used with the experts in the sintering plant from Usiminas to define all variables and controller of process that could influence the productivity of the Sinter Machine#3 - Ipatinga Plant.

2.2 Treatment of Data

In this step, the outliers were removed from the dataset one by one without any statistical technique, for this the technical expertise was used to define the values that were incompatible with the process.

2.3 Assembly of Groups

Some groups of variables were created aiming seek the best prediction result. The definition was performed using multiple linear regression, variable selection by backward and forward and choosing based on technical know-how of experts from Usiminas staff.

2.4 Multiple Linear Regression (MLR)

In this step the statistical technique of multiple linear regression was applied for all groups. Multiple linear regression was performed using a statistical software. The results of productivity generated by the equation were compared with the real values of productivity obtained from sinter industrial machine. This was made by the means comparison of the correlation coefficient (R^2).

2.5 Artificial Neural Network (ANN) Modeling

In parallel with the multiple linear regression step, the neural network was realized. Therewith it was possible to verify the effectiveness of the neural network with respect to multiple linear regression.
The construction of the neural network has been performed with the MLP type, It was varying the following parameters of the neural network structure: (i) number of neurons in the hidden layer: (n/2) to (2n+1) where 'n' is the number of input variables; (ii) number of hidden layers (1 and 2) and (iii) the training algorithms (Scale Conjugated Gradient - SCG and Levenberg-Marquardt - LM). The transfer function used was sigmoidal. The inputs and output were normalized, in order to be between -1 and +1. This normalization was performed using the equation 1, suggested by Wong.(5)

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$$X_n = 2 \cdot \left(\frac{X_R - VLI}{VLS - VLI} \right) - 1 \qquad (1)$$

Where:

- X_n the normalized value $-1 < X_n < 1$ from X_R;
- X_R the real value of the input or output;
- VLI the lower limit of X_R;
- VLS the upper limit of X_R.

The neural network assembling was consisted by two phases: training and validation. For this, the data was divided so that 60% for training and 40% for validation.

The data were randomly divided to prevent any possible addict. The following parameters of stopping were: target error (0.0001), number of epochs (1000) or the Early Stopping criterion. The training phase was finished when one of these parameters has been reached.

The results of productivity generated by the validation step were compared with the real values of sinter machine productivity, using the technique paired analysis of differences between real and predicted values. The normality of distribution was evaluated by measuring skewness and kurtosis. For cases of normal distribution, the hypothesis tests: t-test and sign test were used to construct the confidence interval of standard deviation, but for the cases where the null hypothesis were rejected, the average error was used, according to equation 2.

$$\text{Average error} = \left| \frac{\sum (\text{real value} - \text{predicted value})}{x} \right| \qquad (2)$$

X is the number of paired samples.

3 RESULTS AND DISCUSSION

3.1 Assembly of Groups

Data from 24 variables and/or controllers of a historic from 2010 were used. They were collected every 4 hours, comprising a database of 1,868 lines. The total number of data was 44,832. The selected variables and their minimum and maximum values are presented in Table 2.

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Table 2. Selected variables

Inputs	Minimum	Maximum
Slag volume (%)	17.66	24.88
Moisture (%)	3.5	7.5
Carbon Rate (kg/t.sinter)	34.6	68.7
Burnt lime (%)	1.0	4.5
BTP	22	24
Charge density (t/m^3)	1.57	2.16
Temperature of the box 23 (ºC)	110	428
Return hot sinter (%)	6	26
% > 4.76 mm of CB* and ATR*	0.4	16.2
% < 0.25 mm of CB* and ATR*	8.2	47.5
Return cold sinter (%)	2	18
Basicity binary (CaO/SiO_2)**	1.52	2.98
Temperature of ignition furnace (ºC)	828	1223
FeO sinter (%)	2.27	9.49
Ignition Intensity (Nm^3/m^2)	1.7	5.3
Roll feeder speed (RPM)	200	1064
Temperature of exhaust gas (ºC)	75	172
Suction (KPa)	-8.62	-17.65
Tumbler Index (%)	56.74	66.96
Hearth layer (kg/t.sinter)	55	220
Hopper Level (%)	29	82
Shatter Index (%)	86	94
Strand speed (m/min)	1.34	3.06
Bed height (m)	0.53	0.55
Output	**Minimum**	**Maximum**
Productivity (t/m^2.day)	32.08	45.08

*CB = Coke breeze; ATR = Anthracite; **CaO/SiO_2

Each variable is explained below:

- Slag volume; SV = (% CaO + % MgO + % SiO_2 + % FeO - % Al_2O_3);
- Moisture percentage of the total mixture;
- Carbon rate is the specific consumption;
- Burnt lime is its proportion in the mixing part;
- Temperature of the box 23 (penultimate wind box sinter machine);
- Charge density is the amount of mixture per volume of pallet of the sinter machine;
- Return hot sinter is the hot sinter screened;
- % > 4.76 mm of CB and ATR is the concentration of fine particles of coke breeze and anthracite greater than 4.76 mm;
- % < 0.25 mm of CB and ATR is the concentration of fine particles of coke breeze and anthracite smaller than 0.25 mm;
- Return cold sinter is the proportion of sinter less than 5 mm, generated in the sieving of blast furnaces in the mixture of partial;
- Binary basicity is the ratio of CaO e SiO_2;
- Temperature of ignition furnace of sinter machine;
- FeO in sinter is the percentage of this compound;
- Ignition Intensity is the consumption of gas passing area of the machine, that means, the gas consumption for 4 hours divided by the belt speed multiplying by the length of the ignition;
- Roll feeder speed is the speed of the motor feed roller;

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- Temperature of exhaust gas is the temperature measured at the entrance of primary electrostatic precipitator;
- Suction is the negative pressure exercised by gases passing through the mixture;
- Tumbler index is the index of physical resistance;
- Hearth layer is the sinter between 10 mm to 20 mm and it is used as a protection of grate bars;
- Hopper level is the level of the total mixture in the bin;
- Shatter index is another index of physical resistance;
- Strand speed of sinter machine;
- BTP is the end point of burning, indicating in which case the sinter machine is the highest temperature desired thermal profile and,
- Bed height is the height of the mixture in sinter machine.

The chosen groups are shown in Table 3. Group 1 is composed of variables chosen by the staff of Sinter Ipatinga Plant - Usiminas. Group 2 is composed of variables selected by MLR, forward and backward techniques in all variables. Group 3 is the result of the use of MLR, forward and backward selection in all variables, without the strand speed. Group 4 is formed by Group 3 plus shatter index and FeO in place of the variable volume of slag and ignition intensity. And finally, the Group 5 is comprised by group 4 without FeO plus strand speed, temperature of the box 23, and slag volume. The changes done at groups 4 e 5 were due to verify the influence those variables on results.
It is possible to note from the table 3 that the following variables: temperature of the box 23; % > 4.76 mm of CB and ATR; % < 0.25 mm of CB and ATR; FeO in the sinter; temperature of exhaust gas; tumbler index; hopper level, and shatter index were not selected by the technique forward and backward. These kind of variables (except the level of the hopper), perhaps, would be more related to the yield of the sinter, since they are indicators of the thermal condition of the process. Another explanation is that the data did not vary enough to influence the sintering machine productivity, thus the technique selection of forward and backward withdrew from the groups.

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Table 3. Description of groups formed

	Groups				
	1	2	3	4	5
Slag volume (%)	X	X	X		X
Moisture (%)	X	X	X	X	X
Carbon Rate (kg/t.sinter)	X	X	X	X	X
Burnt lime (%)	X	X	X	X	X
BTP	X	X	X	X	X
Charge density (t/m^3)		X	X	X	X
Temperature of the box 23 (ºC)					X
Return hot sinter (%)	X	X	X	X	X
% > 4.76 mm of CB* and ATR					
% < 0.25 mm of CB* and ATR*					
Return cold sinter (%)			X	X	X
Basicity binary (CaO/SiO_2)**			X	X	X
Temperature of ignition furnace (ºC)		X	X	X	X
FeO sinter (%)				X	
Ignition Intensity (Nm^3/m^2)		X	X		
Roll feeder speed (RPM)		X	X	X	X
Temperature of exhaust gas (ºC)					
Suction (KPa)	X	X	X	X	X
Tumbler Index (%)					
Hearth layer (kg/t.sinter)		X	X	X	X
Hopper Level (%)					
Shatter Index (%)	X			X	X
Strand speed (m/min)		X			X
Bed height (m)		X	X	X	X

3.2 Results with Multiple Linear Regression (MLR)

At Figure 4 it is showed the correlation coefficients and average errors obtained by multiple regression. The average error was calculated according to equation 1. Group 1 showed the lowest correlation, meaning that the sintering process is governed by the interaction of several variables, not only the variables in that group. Furthermore, observing the Group 2, it can be noted that the level of correlation improved significantly, mainly due to addition of the variable strand speed.
The change of variables had little effect on the Group 4, compared to Group 3, as correlation coefficient showed in Figure 4 (d). The Group 2 and Group 5 showed good correlation with productivity.

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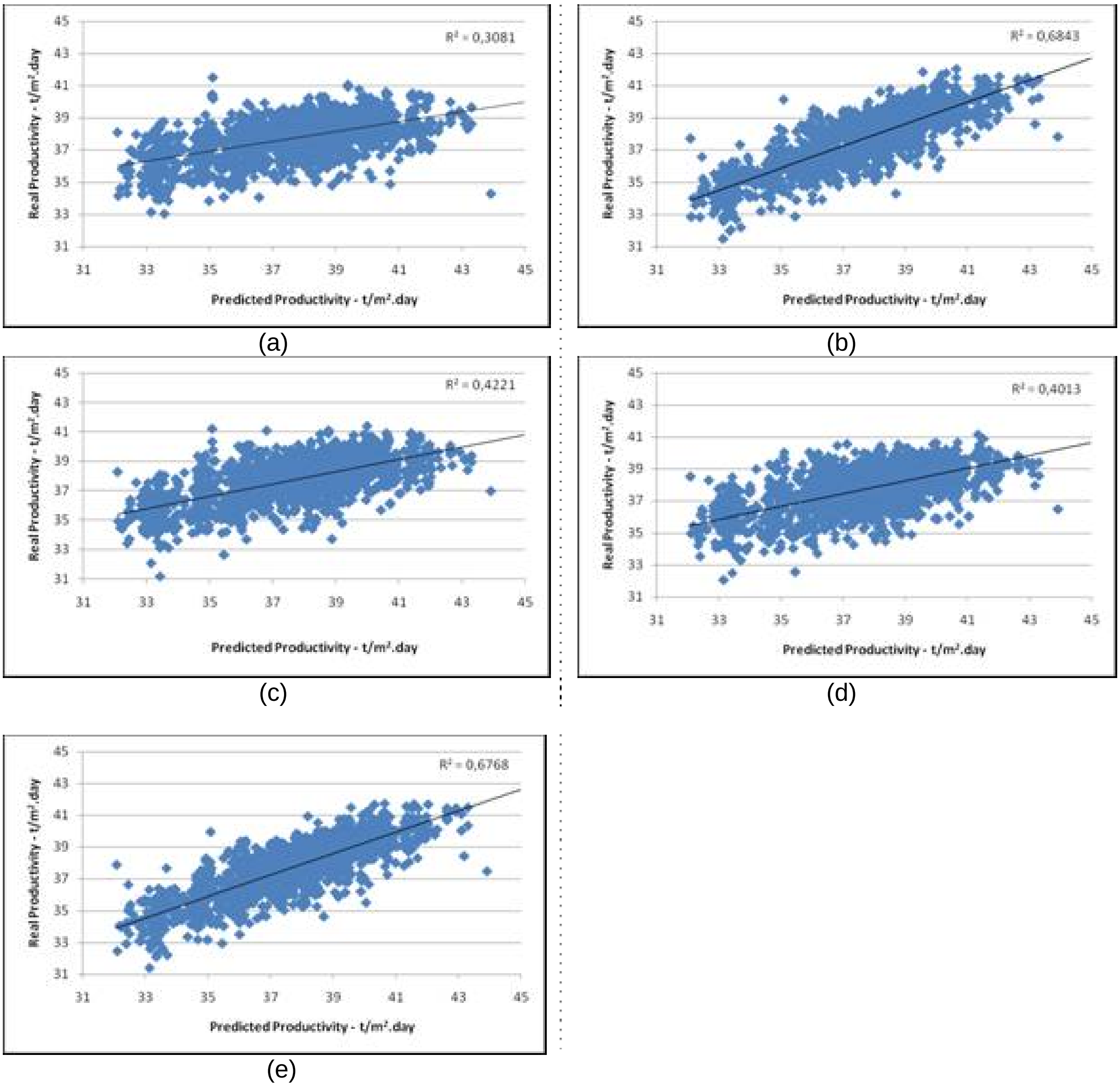

Figure 4. Relationship between predicted and real productivity Groups 1 to 5: (a) Group 1, mean error: 1.49 t/m^2.day; (b) Group 2, mean error: 0.93 t/m^2.day; (c) Group 3, mean error: 1.42 t/m^2.day; (d) Group 4, mean error: 1.39 t/m^2.day; (e) Group 5, mean error: 0.94 t/m^2.day.

3.3 Results with Artificial Neural Network

The results of the correlation obtained with the comparison between productivity predicted by the neural network and real productivity of groups are shown in table 4. The Group 5 showed the best result using the neural network with one hidden layer, 9 hidden neurons and algorithm type Levenberg-Marquardt (LM).

It can be inferred from the table 4 that the algorithm and the number of hidden layers have a weak influence on the predictive ability of artificial neural network, nevertheless these variations must be tested and other possibilities not contemplated in this study to evaluate the best configuration of ANN.

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Table 4. Results using artificial neural networks

		neural network			hypothesis test p-value		evaluation of the normality		
algorithm		hidden layers	number of neurons	R^2 (predicted vs. real)	t-test	sign-test	skewness	kurtosis	mean error
Group 1	L.M.	1	-	-	-	-	-	-	-
		2	-	-	-	-	-	-	-
	S.C.G.	1	18	32.80	0.85	0.79	1.44	4.87	1.41
		2	-	-	-	-	-	-	-
Group 2	L.M.	1	8	73.70	0.34	0.87	7.19	17.25	0.82
		2	8	76.34	0.33	0.71	2.53	13.59	0.81
	S.C.G.	1	8	75.00	0.51	0.88	3.54	10.01	0.82
		2	8	76.07	0.36	0.50	2.11	6.37	0.82
Group 3	L.M.	1	8	48.59	0.27	0.32	-2.05	11.98	1.15
		2	8	53.53	0.90	0.96	0.63	7.98	1.10
	S.C.G.	1	16	49.59	0.74	0.41	-2.22	4.97	1.19
		2	21	46.94	0.64	0.75	-0.04	2.96	1.22
Group 4	L.M.	1	10	48.75	0.51	0.40	0.76	3.66	1.22
		2	8	48.76	0.51	0.43	-0.76	3.66	1.22
	S.C.G.	1	8	43.07	0.83	0.40	-0.10	3.64	1.26
		2	8	44.02	0.27	0.50	0.05	2.32	1.30
Group 5	L.M.	**1**	**9**	**77.47**	**0.77**	**0.79**	**2.78**	**4.11**	**0.80**
		2	9	72.26	0.55	0.38	3.54	8.10	0.84
	S.C.G.	1	9	72.80	0.75	0.23	2.52	7.83	0.86
		2	9	73.82	0.48	0.69	4.27	8.39	0.82

The RNA of Group 5 was chosen for industrial application. It is known that such variables as: % over than 1 mm and less than 0.104 mm of iron ore and of the stack blended, flow and % O_2 influences the productivity, however due to problems during acquisition of data it was not possible to add them in database. If they were in the group, probably the results would be better. Laitinen[9] obtained better result than this work due to the kind of variables chosen.
It's important to say that the group 2 showed good results, however industrial variables as shatter index and return cold sinter was not present in this group, so the group 5 was chosen.
In table 5 it can be seen by the distribution of frequency of the error range between predicted and real productivity that 71.08 % of the errors were below 1 t/m^2.day.

Table 5. Distribution of the frequency ranges of the errors

error range (t/m^2.day)		relative frequency (%)	cumulative relative frequency (%)
0.00	0.25	24.05	24.05
0.25	0.50	18.92	42.97
0.50	0.75	13.78	56.76
0.75	**1.00**	**14.32**	**71.08**
1.00	1.25	8.92	80.00
1.25	1.50	5.14	85.14
1.50	1.75	4.05	89.19
1.75	2.00	4.05	93.24
2.00	2.25	2.16	95.41
> 2.25		4.59	100.00

3.4 Comparison of Multiple Linear Regression and Artificial Neural Network

The results of multiple regression and neural network are compared in table 6. It can be noted that the artificial neural network performed better than the model by multiple regression, in agreement with results obtained by Oliveira and Modenesi.[11] The

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artificial neural network, as well as the brain, has the ability to learn through error made between predicted and real, being better than the multiple regression to predict outcomes, but in this paper the artificial neural network works like a "black box" so it is not possible, know the real influence of each variable in the output.

Table 6. Comparison between results of multiple regression and neural network

group	multiple linear regression		neural network	
	R^2	mean error (t/m^2.dia)	R^2	mean error (t/m^2.dia)
1	0.3081	1.49	0.3280	1.41
2	0.6843	0.93	0.7634	0.81
3	0.4221	1.42	0.5353	1.10
4	0.4013	1.39	0.4876	1.22
5	0.6768	0.94	0.7747	0.80

4 CONCLUSION

The artificial neural network was used as a tool for predicting the productivity of the Usiminas Sinter Machine#3 (Ipatinga Plant) from variables and controlling of the sintering process.
The configuration of the artificial neural network that led to the best result was: Levenberg-Marquardt, with one hidden layer, 9 neurons. This network achieved 77.47% of the correlation with the real productivity. The differences between the average error was 0.80 t/m^2.day and 71.08% of these errors were less than 1 t/m^2.day.
The results indicated that neural network can provide better correlations than the multiple linear regression.

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