NEURAL MODELING AS A TOOL TO SUPPORT BLAST FURNACE IRONMAKING

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Abstract: This paper describes the development of a hybrid model based on artificial neural network and its industrial application to the ironmaking at *Companhia Siderúrgica Nacional* (CSN -Volta Redonda/Brazil). The Iron Blast Furnace is highly complex process subject to oscillations in raw material characteristics. A precise model is essential to adjust © *2002* charging and blow conditions to match productivity, chemical quality and costs targets. A neural model was developed in order to estimate chemical and thermal parameters to feed a first principles model capable of evaluating alternative operation standards. As a consequence, operation efficiency is enhanced leading to higher productivity and lower costs. *Copyright © 2002 IFAC*

Keywords: modelling, neural network, ironmaking, iron blast furnace.

1. INTRODUCTION

The impulse from the domestic market and the abundance of quality raw materials have favored the development of the Brazilian steel industry, which is viewed as playing a fundamental part in the process of industrialization and development. CSN is one of the largest steelmaking groups in Latin America, with a production capacity of 5.8 million tons of raw steel per year.

The Iron Blast Furnace reduces iron ore, producing liquid iron (hot metal) which is converted to steel by exothermic oxidation of metaloids dissolved in the iron in the basic oxygen steelmaking process.

The Blast Furnace is a very complex processes in terms of chemistry, fluidodynamics and heat exchange. The composition of the burden material to be loaded and the blast to be blown determines productivity, quality and costs. Designing burden and blast requires a fairly accurate process model to define an appropriate operation standard from an almost infinite set. Particular characteristics, associated to both materials and equipment, are to be considered in the model requiring actual data to be analysed before applying first principle models.

Many simple models exist to analyse the blast furnace process based on heat, mass and chemistry balance and some are even ingenuous. However, chemical equilibrium mismatches and kinetics parameters need to be estimated based on materials and equipment characteristics in order to quantify performance indexes. Usually, to close that gap it is necessary to apply a comprehensive statistic model. Chemical composition analysis of every furnace stream need to be taken (raw material, blow, overhead gas and liquid metal), which introduces a dead time to the performance calculations.

One of the alternative and efficient tools, which enable one to obtain a numerical description of this kind of complex process, is the artificial neural network (ANN). Interactions and the dynamics among variables are readily captured from operating data base presentation to the network. From past operating conditions and calculated mismatch parameters, a network model allows performance indexes computation.

Neural networks are becoming an effective component of the steel manufacture automation system. There are various applications of neural networks in the steel industry. Schlang et al. (1997) describes the use of neural networks in the control of flat steel rolling mills and electric furnaces (Siemens AG). Cox et al. (2002) explore the use of neural networks to predict oxygen and coolant requirements during the end-blow period of the Port Talbot basic oxygen steelmaking - BOS - plant (Corus Group). However, the authors report that the application of the neural model 'in situ' was to be carried out just in future work. Ping et al. (2003) describe the implementation of an intelligent model for controlling BOS end-points at WISCO's No 2 steel shop. This static control model combines neural networks and first principles. Indeed for the iron Blast Furnace process there are few papers on neural networks. Radhakrishnan and Mohamed (2000) describe a successful application of a neural network for the identification and control of blast furnace hot metal quality.

A growing literature within the field of chemical processes describing the use of artificial neural networks has evolved for a diverse range of engineering applications such as fault detection, signal processing, process modelling and control (Himmelblau, 2000). According to the author, because neural networks are nets of basis functions, they can provide good empirical models of complex nonlinear process useful for a wide variety of purposes.

Considering the difficulties outlined above, obtaining accurate mismatch parameters for first principles models in iron and steelmaking has proved to be a very hard task. Usually two kinds of models are employed to blast furnace operation: those very simple using estimated mismatch parameters that are corrected as operation goes on and complex models with to many parameters to be of practical use.

The present work is concerned with developing a hybrid model - neural network and mass and heat balances – and its application to the ironmaking blast furnace at CSN (Brazil). The main goal is to obtain a tool to design burden and blast conditions in order to match the targets of productivity, chemical quality and costs of the liquid metal.

1. METHODS

2.1 Process Description

Companhia Siderúrgica Nacional's steelworks entails three blast furnaces, two of them in operation and one out of service. Blast Furnace 2 produces nearly 4,000 tons of hot metal per day whereas Blast Furnace 3 produces between 9,500 and 11,000 tons per day. Iron ore sinter, pellets and lumpy hematite constitute the ferrous burden. As reducing agents, metallurgical coke and pulverised coal are used, being the latter injected through the tuyeres. Sometimes dolomite or quartzite are used as fluxes to control slag composition. The blast composition (air, oxygen and steam) and the rate of coal injection are the main and most sensitive parameters of control. Operation aims at production rate, hot metal chemical composition and temperature and ultimately, low cost. Because the plant is self-sufficient in coke, a small proportion of it is imported bringing significant characteristic variations to the mixture.

The core of the process is a counter-flow reactor where a series of chemical and thermal exchanges are performed in several ent internal zones (Figure 1).

As the ferrous burden descends it is first dried, then reduced by the up-coming process gas containing CO and H_2 . This zone, called upper granulated zone, or preparation zone or even indirect reduction zone, ideally produces wustite (Fe_yO) to be reduced to metallic Fe in the inferior zones. The index y, in this case, approaches 0.95. In real terms, however, the wustite will have an excess of oxygen which is quantified in terms of kg-mol of O / kg-mol of Fe. This parameter is necessary to establish a proper mass and thermal balance of the process and will be designated by ω (Rist and Maysson, 1967). The thermal balance also needs a parameter to represent real conditions. This is the heatloss that will be represented by λ.

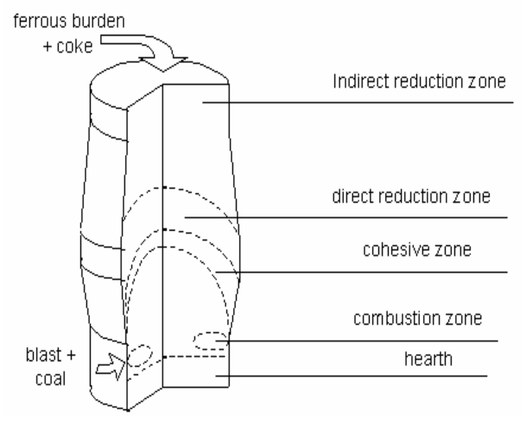


Fig. 1. The Iron Blast Furnace internal zones.

The main heat source is the combustion of coal and coke that produces mixture of CO, CO_2, H_2, H_2O and N_2. CO is regenerated in the direct reduction zone and below by the Boudouard reaction (Eq. 2) . H_2 also plays an important role and the C-H-O will be in equilibrium in most sub-processes.

The basic chemical reactions involved are:

$$CO + 1/2\,O_2 \rightarrow CO_2 \quad (1)$$
$$CO_2 + C \rightarrow 2CO \quad (2)$$
$$H_2O + CO \rightarrow H2 + CO_2 \quad (3)$$
$$3Fe_2O_3 + CO \rightarrow 2Fe_3O_4 + CO_2 \quad (4)$$
$$yFe_3O4 + CO \rightarrow 3Fe_yO + (4y - 3)/2\,CO_2 \quad (5)$$
$$Fe_yO + CO \rightarrow yFe + CO_2 \quad (6)$$
$$SiO_2 + C \rightarrow SiO_{(gas)} + CO \quad (7)$$
$$SiO_{(gas)} + C \rightarrow \underline{Si} + CO \quad (8)$$

Silicon is partially reduced from silica into gaseous silica monoxide and incorporated to the liquid by further reduction. This process is rather complex and the metal silicon content is very hard to estimate.

The other impurities in the metal, manganese and phosphorous, do not represent a difficult estimation task depending more on the raw materials composition than on the process conditions.

2.2 Artificial Neural Network (ANN)

Theory. ANN are mathematical models constituted by several neurons, arranged in different layers (input, hidden and output), interconnected though a complex network. The multi-layer feedforward, that is the most popular of the much architectures currently available, was used. According to Equation (9), a neuron is responsible for the summation of all signals from previous layer's neurons, $y_{i,j}$ (amplified or weakened by weight values, $w_{i,j,k}$) and a value called bias, $b_{i,j}$. i represents the order of the layer whereas j and k indicate the order of the neuron in the layer. An activation function, f - such as hyperbolic tangent, sigmoid or linear function – is used for the activation of the neuron output, $y_{i,k}$.

$$y_{i,k} = f(\Sigma\ (w_{i,j,k}\, y_{i-1,j}) + b_{i,k}) \quad (9)$$

The data processing within the ANN structure is executed collectively and simultaneously through the dense network of neurons and their connections. Those characteristics were crucial for the this technique to be chose and not other multivariate regression ones which tend to give too much weigh to extreme values of the input variables.

Training the ANN. Once the network weights and biases have been initialized, the network is ready for training. The training process requires a set of examples of proper process behavior - network inputs and target outputs. During training the weights and biases of the network are iteratively adjusted to minimize the network objective function. The basic training algorithm is the backpropagation algorithm, in which the weights are moved in the direction of the negative gradient (Demuth and Baele, 2002).

The first method for improving generalization is called regularization. This involves modifying the objective function, which is normally chosen to be the sum of squares of the network errors on the training set. It is possible to improve generalization if we modify the objective function by adding a term that consists of the mean of the sum of squares of the network weights and biases:

$$F = \beta .\ SSE + \alpha SSW \quad (10)$$

where *SSE* is the sum of squared errors, *SSW* is the sum of squares of the network weights, and β and α are objective function parameters (Demuth and Baele, 2002).

According to Foresse and Hagan (1997), using this objective function will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to overfit. One feature of this algorithm is that it provides a measure of how many network parameters, (weights and biases) are being effectively used by the network. This effective number of parameters will be called p. P is the total number of parameters in the network.

Neural network training can be made more efficiently if certain preprocessing steps are performed on the network inputs and targets. Then, before training the network the training data was normalized in the range [0.1, 0.9], as follows:

$$y_{0,j} = 0.8\ ((x_j - xmin_j) / (xmax_j - xmin_j)) + 0.1 \quad (11)$$

where $y_{0,i}$ is the normalized value for the variable x_j, and $xmin_j$ and $xmax_j$ are the minimum and maximum of each variable x_j.

Modeling and data set. A neural model was developed in the present work to predict: the equilibrium mismatch parameter for the oxygen mass balance (ω), the thermal loss parameter for the heat balance (λ), the gas flow resistance parameter (ρ), the hot metal Silicon content (*[Si]*) and the sulfur partition coefficient between slag and metal (Ks). Feeding those parameters to a simple mass and heat balance, a precise operation pattern is defined to guide operators and technical staff for immediate and strategic decision making.

Table 1 shows the final variables selection and their meaning. Coke drum (*x15*) and reactivity (*x16*) indexes quantify physical strength and chemical activity, respectively, and are important both to gas flow and chemistry in the process.

Three years of Blast Furnace 3 operation were observed. Records were condensed into 23 input variables. Sets corresponding to days with missing or inconsistent data were filtered out . Records include those acquired by the furnace digital automation system, works and mines laboratories. Finally a 28 x 820 data bank was gathered, randomized and fed into a MATLAB® program. The final data-base was then split into two sets, one for training and the other for generalization tests (15% of the data). It was carefully checked the range of each variable since it should be similar to both sets.

In the search for the architecture that could yield the best possible prediction model accuracy, a study was performed to establish the number of nodes in the network hidden layer.

Table 1. Input (x) and output (y) variables used for the neural modeling.

	Blast variables
$x1$	kg-mol of N2 in blast / ton of metal
$x2$	kg-mol de H2O in blast / ton of metal
	Burden variables
$x3$	kg of slag / ton of metal
$x4$	Primary slag B4
$x5$	Hearth slag B4
$x6$	blast temperature (^oC)
$x7$	kg of small-coke / ton of metal
$x8$	kg of injected coal / ton of metal
$x9$	kg of lumpy hematite / ton of metal
$x10$	kg of pellets / ton of metal
$x11$	kg of quartzite / ton of metal
$x12$	external coke / total coke
$x13$	pulverized coal ash content
$x14$	pulverized coal oxygen content
$x15$	average coke Drum Index
$x16$	average coke Reactivity Index
$x17$	coke mean size (mm)
$x18$	hematite < 6,35 mm fraction
$x19$	hematite > 38 mm fraction
$x20$	hematite Decrepitation Index
$x21$	kg of stock sinter / ton of metal
	Equipment and environmental variables
$x22$	rain fall index (mm)
$x23$	tapping hole campaign index (1 or 0)
	Output variables
$y1$	wustite stoichiometric index (ω)
$y2$	gas flow resistance (ρ)
$y3$	metal silicon content (*[Si]*)
$y4$	heat losses in MJ / ton of metal (λ)
$y5$	sulfur in slag / sulfur in metal (*Ks*)

The predicted parameters are combined with other variables in a deterministic model to estimate the overall process pattern. The parameter θ represents the ratio between metal and gas produced. ϕ represents the unity gas flow calculated from the predicted gas resistance, ρ, and the pressure imposed by the equipment, blower and reactor. The overall performance index, π, is the final product of the model, meaning the amount of metal produced in a unity time for each cross section area unit and results form the product ϕ x θ. Figure 2 shows a cause and effect diagram for the hybrid model. The four final variables: *[Si]* , *[S]*, μ and π are efficient process performance indexes. The first two indicate metal silicon and sulfur content, respectively. The parameter μ, as defined by Rist (Rist and Misson, 1967) quantifies the specific consumption of reducing agents (C + H_2) and ultimate the metal cost. The index π quantifies the amount of metal per unity area, therefore, the overall process productivity.

2.3 Experimental Industrial Application

The operation process using the model as supporting toll at Blast Furnace 3 is shown on Figure 3. The application will be extended to Blast Furnace 2 after the experimental application to Blast Furnace 3.

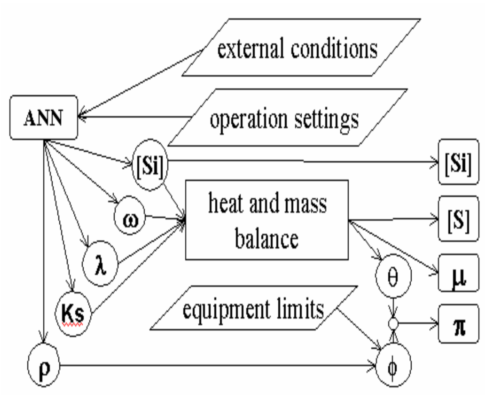


Fig 2. Data flow diagram for the hybrid model.

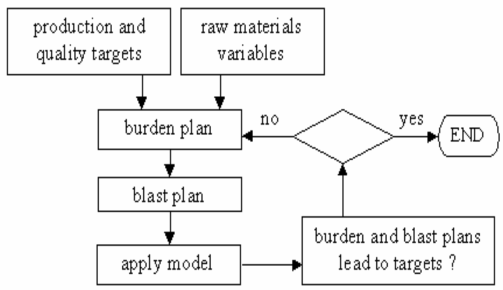


Fig 3. Industrial application procedure flow diagram.

3. RESULTS

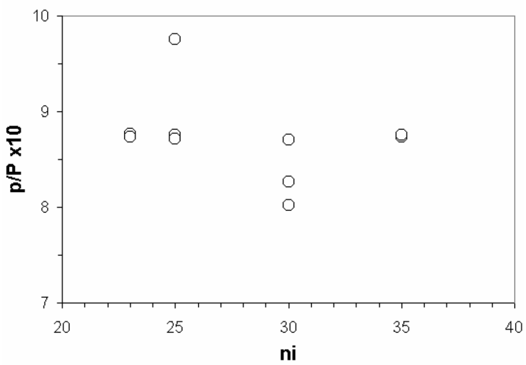


Fig 4. Relationship between effective parameter ratio (*p/P*) and the number of neurons in the hidden layer (n_l).

Figure 4 shows how the ratio between initial number (*P*) of network parameters - weights and bias – and the number of effective parameters after training (*p*) behaves with the increase in the number of neurons in the hidden layer (n_l).

According to Foresse and Hagan (1997) the decreasing effective parameters ratio (p/P) indicate that the number of neurons is excessive. Another criterion leads to the same conclusion, as illustrated by Figure 5. It is clear that the larger number of hidden layer neurons does not contribute to a smaller mean quadratic error for the generalization set although the mean error for the training set decreased. In conclusion, the best network architecture was found to be 23x23x5.

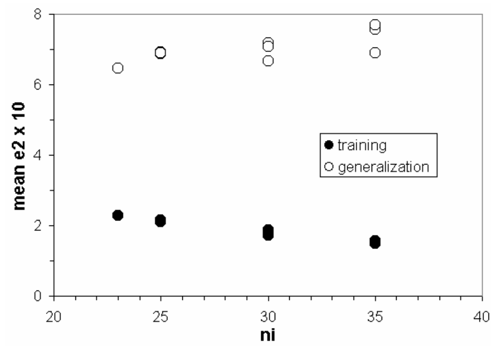


Fig 5. Relationship between mean quadratic errors (*mean* e^2) and the number of neurons in the hidden layer (n_l).

In this study and for the chosen architecture, the neuron activation function used in the hidden layer was a sigmoid one while a linear function was chosen for the output layer neurons.

Table 2 shows the mean square error for each of the 5 output variables expressed in terms of respective standard deviations. As expected, smaller mean quadratic errors are obtained for training sets. Mean errors for generalization sets were considered acceptable.

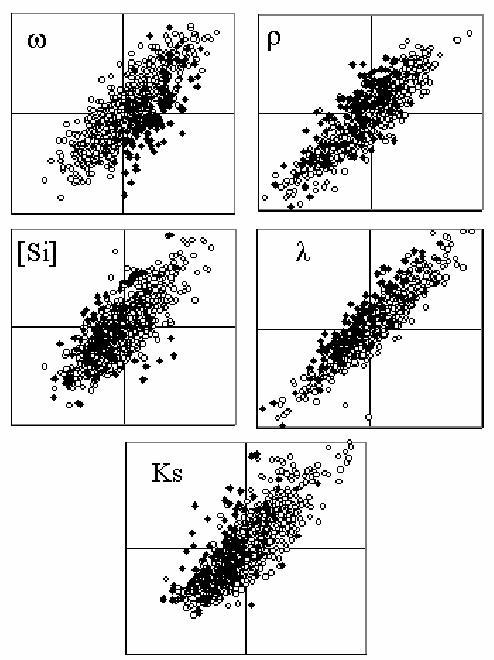
Table 2 – Square mean errors for the output variables in terms of respective standard deviations

	training	generalization
ω	0.503	0.722
ρ	0.400	0.651
[Si]	0.560	0.822
λ	0.354	0.496
Ks	0.531	0.729

Figure 6 shows how estimated standardized values (horizontal axis) match actual ones. It could be also noted from Figure 6 the tendency of experimental seen and unseen points to follow the diagonal line, indicating the accuracy of the network approach. The estimation of low values of ω and high vales of *Ks* was deficient for a few cases.

It should be pointed out that ϕ, θ and, consequently, π will depend not only on the values estimated by the network but also on other process variables. Therefore there is no point in estimating them at this moment.

Fig 6. Dispersion plots of the network output



variables (predicted values x actual values) for both training (O) and generalization (♦) sets. Axes cross at the mean value.

3.2 Experimental Industrial Application

Following the steps previously described (Figure 3), the experimental industrial application was carried out during a twenty-day period. During the first twenty days of September 2005, the Blast Furnace number 3 operation was guided by the model. According to Figure 2, four variables were taken to access the prediction capacity of the model: coke-rate *(CR)*, metal silicon content *[Si]* , sulfur metal content *[S]* and Ergun fuidodynmic resistance index *(K)*. Figures 7 shows the results of the industrial observations while in Table 3 results can be numerically compared.

Table 3 – Statistical analysis of indexes observed during the test period without and with model

	error mean	error sd	set sd	population sd
CR (kg/t)?	2.8	2.7	4,6	36.9
[Si] x10^4	0.8	2.9	4,4	13.5
[S] x 10^5	1.5	3.8	4,4	7.9
K	19.0	11.42	8,9	24.0

It can be observed from table 3 that the error standard deviation was smaller than the relative standard for the experimental set and much smaller than the standard deviation observed in actual operation. For the fluidodynamic resistance it can be pointed out that the test period did not present sufficient variation for the adequate assessment of the model on this aspect.

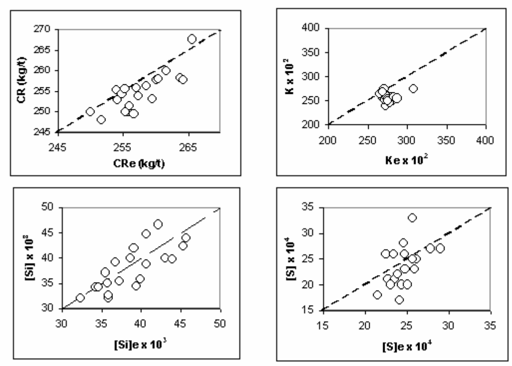


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Fig 7 – Results of experimental industrial tests.

Because operational corrective actions were still too timid, fuel-rate corrections were allowed some hot metal temperature variations which contaminated sulfur control. This can be observed in Figure 8. In future, better heat control, with more confident use of the model, will also improve chemical quality, because chemical equilibrium is strongly connected to temperature.

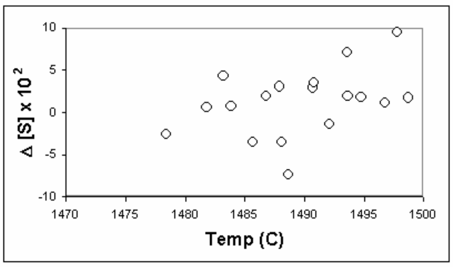

Figure 8 – Influence of hot metal temperature on the prediction error for hot metal sulfur

4. CONCLUSIONS

The main contribution of the present work is the development of a neural model which can increase prediction accuracy and operation performance while reducing costs for the blast furnace process at *Companhia Siderúrgica Nacional* (CSN-Volta Redonda/ RJ/ Brazil). Obtaining liquid iron in stable conditions is a very hard task, because the Blast Furnace is a complex process, conjugating several sub-processes. Some of them are continuous, some transient, occurring in the same reactor and still subject to oscillations in raw material composition.

The developed hybrid model, based on mass and heat balance associated to an artificial neural network, aims at supporting both operational and strategic decision making.
A 23x23x5 feedforward network proved to be an efficient architecture, using sigmoid and linear activation functions for the hidden and output neurons, respectively.

Except for fluidodynamic resistance, in other words, permeability, the period in which the model was used to guide industrial furnace operation proved to be predictable and consistent. For assessment of the permeability prediction a longer period will be necessary to allow for significant variation of that parameter.

The analysis of alternative raw materials or practice standards can be held also with the support of the model as long as the variables are kept inside the operating range studied.

It could be concluded that the neural model is a relevant tool to support an iron Blast Furnace operation since some corrections and retraining are carefully carried out by expert human operators in a systematic way. These procedures are crucial for adopting the neural model as a standard operating practice.

REFERENCES

Demuth, H., Beale, M., 2002. *Neural Network Toolbox User's Guide for Use with MATLAB®* The Mathworks Inc., Version 4, Reading:

Hagan, M., Chapter 5: *Backpropagation.*

Foresee, F.D., Hagan, M.T., 1997. Gauss-Newton approximation to Bayesian Learning. Proc. IJCNN, 1930-1935.

Himmelblau, D.M., 2000. Applications of artificial networks in chemical engineering. *Korean J. Chem. Eng.* **17** (4), 373-392.

Ping, H., Liu, L., Lihong, Y., Zhigang, H., Rong, D., Jingbo, X., Wei, C., Yisheng, T., Chenghuan, Y., Fengxi, L., 2003. Combining intelligent and mathematical models for BOS control at WISCO. *Steel Times International* **27** (8), 31-32.

Radhakrishnan, V.R. , Mohamed A.R.,2000. Neural networks for the identification and control of blast furnace hot metal quality. *Journal of Process Control* **10**, 509-524.

Rist, A.; Meysson, N. 1967. *Journal of Metals*, April, **50**..