Revista de metalurgia

Neural predictor of the end point in a converter(•)

R. Valentini*, V. Colla* and M. Vannucci**

Abstract The paper presents a system based on neural networks which is capable of predicting the so-called End Point of a converter by exploiting the measurements of the oxygen content and of the temperature in order to predict the final carbon content.
Due to several disadvantages of current LD algebraic model and the usage of modern process in steel plant, a new model based on neural network and knowledge base is designed. The new model allowed to obtain excellent simulation result and satisfied online testing report.

Keywords LD Converter. Model. Neural Network.

Predictor neuronal del end-point de un convertidor

Resumen La memoria presenta un sistema basado en redes neuronales capaz de predecir el llamado *End Point* de un convertidor, que utiliza la medida del contenido de oxígeno y de la temperatura para predecir el contenido de carbono final. A causa de las diversas desventajas del modelo algebraico normal LD, se han diseñado algunos modelos innovadores realizados mediante técnicas de *soft-computing*. El nuevo modelo permite obtener excelentes resultados en simulación y también en las pruebas on line.

Palabras clave Convertidor LD. Modelo. Red neuronal.

1. INTRODUCTION

In the past years, a lot of effort has been devoted to improvement of the productivity in many steel plants. These efforts were concentrated on all parts of the steel plant: BOF, secondary metallurgy and continuous casting. On side of BOF, the sublance device that measures carbon content and temperature rapidly before the late period of blowing is still the most important tool for BOF process control.

Use of sublance proved to be an important step in control of BOF steel making processes. Sublance is basically used to take sample at the end of blow usually 3-4 minutes before end of blow for analysis of sample and also measures temperature of the bath. Since the introduction of sublance, the accuracy of end point prediction (hit rate) at most of steel plants has gradually increased from approximately 60 % to 90 %.

Many dynamic models based sublance information have been developed to predict the necessary oxygen and coolants about 2 to 3 minutes before end of blowing[1 and 2]. This paper presents some new simple models for estimation of the carbon content at the end—point in LD converters.

All the estimators have been extracted from experimental data, as over 400 heats data records have been gathered from online database and exploited in order to optimize the developed models. In particular the waste gas analysis data has been employed for prediction of carbon at the end point.

Development project has been running for two years which is aimed at creating of an intelligent prediction system for the LD converter steelmaking process.

There is a number of measuring methods and control systems for reaching the aimed final temperature and carbon content of the bath by the end of oxygen blowing which use sophisticated measuring methods and robust equipment. The application is restricted by local technical circumstances and economical considerations.

(•) Trabajo recibido el día 31 de mayo de 2003 y aceptado en su forma final el día 20 de septiembre de 2004.
(*) Dip. di Ing.Chimica, Chim. Ind. e Scienza dei Materiali -Università di Pisa, Italy
(**) Scuola Superiore Sant'Anna, Pisa, Italy

(c) Consejo Superior de Investigaciones Científicas
Licencia Creative Commons 3.0 España (by-nc)
http://revistademetalurgia.revistas.csic.es

Neural networks (NN) are one of the conceivable means to build complex, highly non-linear mappings between many inputs and some outputs so neural networks are general devices to build black-box models for prediction purposes. Neural approach alone is insufficient to predict the process behaviour in non-standard cases. Expert knowledge is incorporated. Predictions are transformed into control actions in order to hit the target parameters. It is observed that large datasets need to be split into smaller ones for obtaining better results. Thus it would be advantageous to keep on tuning the regression models on small batches of datasets progressively, as campaign moves forward. Thermodynamics models of carbon oxygen reaction provide basis of parameters to be chosen for regression models.

2. PROBLEM DESCRIPTION

For establishing the End point in a LD converted, usually the following approximate mathematical equation is adopted:

$$Log\frac{P_c}{[C]^n[O]} = \frac{A}{T} + B \qquad (1)$$

where [C] and [O] are, respectively, the carbon and oxygen content expressed in wt%, T is the temperature expressed in °K, while P_c is a constant pressure value in the range 1:1.5 atm, A, and B are constants whose theoretical values are, respectively, $A=1895$ °K and $B=1.6$, according to[1], while the values $A=1056$ °K and $B=2.131$ are reported in[2]. As far as the n value is concerned, it is commonly assumed equal to unity, but some literature results provide $n\sim0.5$ for [C]<0.08 % and $n\sim1$ otherwise.

Eq. (1) can easily be inverted in order to predict [C], once the constant values has been suitably tuned, but the prediction obtained with the nominal values of the constant parameters is affected by considerable error with respect to the [C] measurements contained in the available experimental dataset.

In the following we will neglect the tuning of the parameter n, as many literature results agree in consider it unitary, while the remaining parameters will be often indicated as a parameter vector $p=[P_c, A, B]$.

If the mathematical model in equation (1) have to be maintained, the parameter vector p has to be suitably tuned in order to fit at best the available data. All the parameter have a precise physical meaning, thus their values must vary within precise and quite narrow ranges, that are shown in table I.

3. PARAMETER OPTIMIZATION

The straightforward solution of exploiting a version of equation (1) linearised with respect to the parameters (by means of a simple logarithmic transformation) and building an overdimensioned linear system of equation (one for each input—output data set) to be solved through pseudoinversion does not lead to an acceptable solution.

In order to suitably tune the parameter values within the allowed ranges, a novel optimisation method, the *BS* algorithm[4], has been exploited as it proved to be more efficient with respect to other traditional optimisation techniques, such as genetic algorithms[5] and simulated annealing[6] . The BS method is an evolutionary algorithm that moves the vector p in the allowed region of the multidimensional solution space in order to minimise a so-called *fitness function*, i.e. a figure of merit that quantifies the goodness of a particular solution.

The numerical analysis of the trend of the difference among real data and values estimated through equation (1) suggested to add a term linearly dependent on the oxigen content [O] to the relation that provides the carbon content as a function of T and [O] itself, as follows:

$$[C] = \frac{P_c}{[O]} \cdot 10^{-\left(\frac{A}{T}+B\right)} + K[O] \qquad (2)$$

where K is a further constant value. The physical meaning of such term lies in the needing to take into account that, when the carbon content is very low, the reaction cannot take place from the kinetic point of view. This is confirmed by numerical

Table I. Variability ranges of the three constant value in equation (1)

Tabla I. Variación de las tres constantes en la ecuación (1)

	Min.	Max.
P_c	1	1.5
A	1700	2500
B	1.5	1.9

(c) Consejo Superior de Investigaciones Científicas
Licencia Creative Commons 3.0 España (by-nc)
http://revistademetalurgia.revistas.csic.es

investigations on the optimal value of the constant K, that provide always a negative value.

4. THE ALTERNATIVE NEURAL APPROACH

Neural networks are a generic parametric model, that is capable of mapping highly nonlinear input-output relations. Thus a completely different approach to the problem of the estimate of the Carbon content consists in designing a feedforward neural network that has two inputs [O] and T and outputs the estimate [C] of the Carbon content. Many different neural paradigms and topologies have been tested. The one that proved to be more efficient is a standard two-layered Multi Layer Perceptron (MLP)[3], that has been trained with the *Levemberg Marquardt* method[7].

This approach is quite simple to be pursued, as it is based on consolidated automatic procedures, and has the considerable advantage of being capable of self-adaptation to the existing operating condition, because the internal model parameters are tuned by exploiting experimental data. Moreover, there is non needing to formuate an analytical model, such as those in (1) or (2). On the other hand, the model parameters have not a direct physical meaning, thus the model, even if perfectly tuned, does not increase our knowledge of the process under concern.

5. RESULTS AND DISCUSSION

In this section the results obtained with the above described estimators are presented and compared.

For all the proposed estimators, the whole data set has been split in two subsets, the *training set*, composed of about 75 % of all the available data, that has been used for tuning the model parameters or the neural network, and the validation set, that is used to assess the real behaviour of the estimator. Usually the performance on the training set is better with respect to the one obtained on the validation set, because the parameters have evolved during the different iterations of each algorithm, usually so as to minimise some sort of estimate error on the training set itself.

As a performance index, we adopt the Standardized Root Mean Square Error (SRMSE) [8], which is defined as:

$$\varepsilon = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left\{\hat{y}_i - y_i\right\}^2}$$

where M is the number of samples in the training (or validation) set, y_i and $\hat{y}_i$ are, respectively, the estimated and real quantity to estimate (i.e. the carbon content *[C]*) corresponding to the *i*-th sample data and σ_y is the standard deviation of such quantity. The quantity $-\varepsilon(p)$ has been used as fitness function to be minimised by means of the BS optimisation algorithm and it is obviously function of the parameter set p.

Table II compares all the above described estimators in terms not only of performance, but also of time required for the training.

The nominal parameter values suggested in[2] provides unreliable estimates, thus have not been considered.

It is appearent that equation (2) with parameter values optimised through the BS methods leads to the best results, although neural networks provide very similar NSRMSE, but requires more time for tuning.

Figure 1 compares the experimental data and the estimate obtained with equation (1) with nominal parameters and values optimised through the BS method: the improvement achieved through optimisation is quiteevident. The shown data refers to the validation data set.

Similar estimates are achieved through the neural network approach.

Table II. Parameter values and performances of the described predictors

Tabla II. Valores de los parámetros y rendimientos de los predictores

Algorithm	P_c	A	B	K	Time (sec.)	ε
Equation (1) with nominal parameters values	1	1895	1.6	–	–	1.70e-3
BS method applied to equation (1)	1.41	2359	1.54	–	17	1.55e-4
BS method applied to equation (2)	1.12	1794	1.72	-0.07	10	9.88e-5
Neural network	–	–	–	–	15	1.01e-4

(c) Consejo Superior de Investigaciones Científicas
Licencia Creative Commons 3.0 España (by-nc)

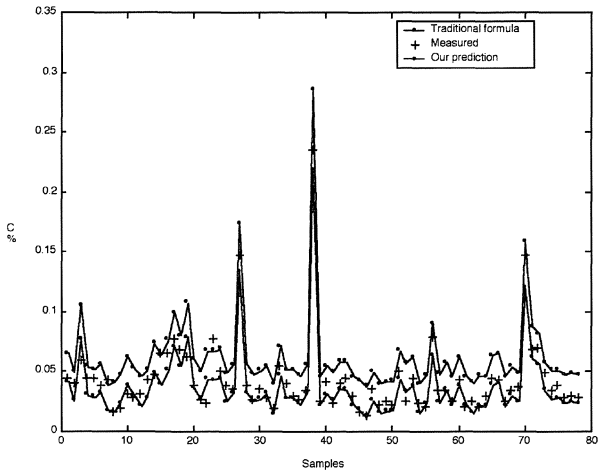

Figure 1. Comparison among the experimental data, the estimates obtained with equation (1) and nominal parameter values and the estimates provided by equation (2) and parameters reported in table II.

Figura 1. Comparación entre datos experimentales, estimaciones obtenidas con la ecuación (1) y valores nominales de los parámetros y estimaciones previstas por la ecuación (2) y parámetros contemplados en la tabla II.

6. CONCLUSIONS

This paper presents an alternative approach to the final carbon content prediction in an LD converter, which is based on neural networks, and compares it with a more traditional method, based on a traditional mathematical formulation, whose parameters are anyway optimised through a novel optimisation algorithm. The system has been trained and tested with real industrial data and its performance overcomes those provided by the analytical model with parameter values extracted from literature results, due to the capability of neural networks of inferring highly non linear relationships from experimental data.

On the other hand, the neural approach does not work well upon establishing a useful online dynamic model for LD without extra means because raw data from online database are often full of noise.

As the traditional model, even after optimisation of the parameter values , cannot provide results comparable with those obtained through neural networks, the numerical analysis of the estimate error trend suggested to introduce a further term in the traditional formula that depends linearly on the oxigen content. The obtained results are very satisfactory and are even better than the NN model in the respects both of simulation and real production test.

The fact that the modification of the traditional formula has a precise physical meaning demonstrates that numerical analysis can be used also for achieving a deeper understanding of the process under concern.

Acknowledgements

The authors wish to thank Dr. Sergio Fera for the fruitful discussions which led to the present analysis.

REFERENCES

[1] G. VIOLI, *Processi siderurgici*, Kompass, Milano, 1972
[2] E.T. TURKDOGAN, *Fundamentals of Steelmaking*, The Institute of Materials, London, 1996
[3] S. HAYKIN, *Neural Networks, A Comprehensive Foundation*, Mc Millan College Publishing Company, New York, 1994.
[4] M. VANNUCCI, V. COLLA, G. BIOLI and R. VALENTINI, *Proc. 7th Int. Conf. Knowledge-Based Intelligent Information & Engin. Syst. KES 2003*, 2003 Oxford (UK).
[5] H. MUHLENBEIN, *Proc. 2nd Conf. Parallel Problem Solving from Nature PPSN-II*, North-Holland, 1992.
[6] S. KIRKPATRICK, C.D. GELATT JR, and M.P. VECCHI, *Science* 220, 4598 (1983) 671-680.
[7] D. MARQUARDT, *SIAM J.Appl. Math.* 11 164-168.
[8] Q. ZHANG, *IEEE Trans. Neural Networks* 8 (1997) 227-236.

(c) Consejo Superior de Investigaciones Científicas
Licencia Creative Commons 3.0 España (by-nc)
http://revistademetalurgia.revistas.csic.es