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Prediction of Bath Temperature using Neural Networks

H. Meradi, S. Bouhouche, and M. Lahreche

Abstract**—**In this work, we consider an application of neural networks in LD converter. Application of this approach assumes a reliable prediction of steel temperature and reduces a reblow ratio in steel work.

It has been applied a conventional model to charge calculation, the obtained results by this technique are not always good, this is due to the process complexity. Difficulties are mainly generated by the noisy measurement and the process non linearities.

Artificial Neural Networks (ANNs) have become a powerful tool for these complex applications. It is used a backpropagation algorithm to learn the neural nets. (ANNs) is used to predict the steel bath temperature in oxygen converter process for the end condition. This model has 11 inputs process variables and one output.

The model was tested in steel work, the obtained results by neural approach are better than the conventional model.

Keywords**—**LD converter, bath temperature, neural networks.

I. Introduction

LD (Linz and Donawitz) converter process is executed to raise the bath temperature and reduce the impurity level by blowing oxygen into the steel bath surface and adding appropriate amount of flux and coolant into the bath. The main raw materials of the process include main materials (such as hot metal, scrap, pig iron) and sub-material (oxygen, iron ore, lime, dolomite), and the product is the steel bath of which the temperature and content are required to hit the tapping aim.

The ways of LD converter refining control can be divided into two major groups: Static control based on the information obtained before the start of the blowing and dynamic control based on the process signals representing the state of refining during the blowing.

The control method combining the static process control and the dynamic process control is popularly used. Static process control determines the gross requirement of oxygen and coolant for the each heat based on the initial information, and the dynamic model based on sublance is processed successfully in the posterior period to adjust the dynamic requirement of oxygen and coolant based on the measurement result of bath carbon and temperature. The use of sublance is not economic because it has an expensive exploitation and maintenance [1].

The difficulties in developing of predictive control models for steelmaking processes could be summarized as follows:

- process non-linearity;
- dealing with high-dimensional, multivariate matrixes;
- highly inter-reactive process parameters;
- inherent variable process time-delays;
- inadequate and uncertain measurement;
- the incorporation of process safety and environmental considerations;
- unstable external variables such as thermal losses, quality molten pig iron, etc.

With the emergence of Neural Network technology, a new avenue became available to the industry, for developing high fidelity process models. Neural networks are being approved to be a very successful approach for model building, to predict and control of many manufacturing processes [2]-[4].

Neural networks are known for being able to efficiently approximate and interpolate multivariate data. Their ability to deal with nonlinearities and their capability to generalize from the acquired knowledge during the training phase makes them extremely suitable for prediction.

II. The LD Steelmaking Process

The objective of the oxygen converter is to refine molten iron to crude steel through oxidization to achieve a specified temperature and composition at the end blow. Failure to do this leads to the need to reblow.

At the start of the refining process to molten metal along with cold scrap is charged to the steelmaking vessel. This is known as charging. There is usually 80% hot metal, and 20% scrap when charging, and the balance between these amounts is used to regulate the temperature of the steel in the furnace, and also the specification of the required steel.

Lime is added and then an oxygen lance is lowered into the vessel to blow oxygen at supersonic velocities through specially designed nozzles at the tip. The reaction of process is shown in Fig. 1.

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H. Meradi is researcher with the Iron and Steel Applied Research Unit – Welding and Control Research Center, URASM CSC, BP 196 Annaba, 23000, Algeria (phone: 00 213 38 87 18 81, e-mail: meradi213@yahoo.fr)

S. Bouhouche is senior researcher with the Iron and Steel Applied Research Unit – Welding and Control Research Center, URASM CSC, BP 196 Annaba, 23000, Algeria (phone: 00 213 38 87 18 81, e-mail: bouhouche11@yahoo.fr).

M. Lahreche is the director of the Iron and Steel Applied Research Unit – Welding and Control Research Center, URASM CSC, BP 196 Annaba, 23000, Algeria (phone: 00 213 38 87 18 81).

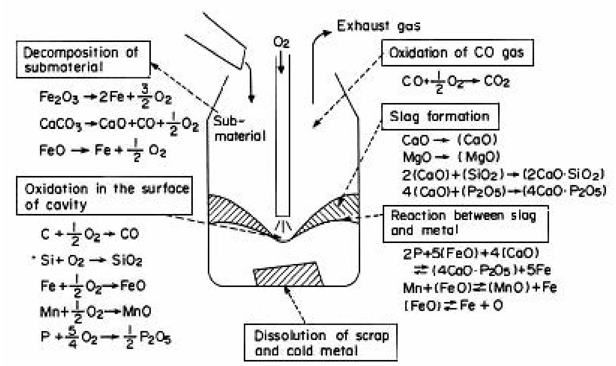

Fig. 1 Steelmaking using the LD converter [5]

To define the charge conditions and oxygen blowing requirements to achieve the temperature and composition, mathematical and thermodynamic models have been developed.

The LD process is of course a very complex batch reaction, which can vary significantly from heat to heat, while many of variables involved are not accurately known. As a consequence, therefore, it is necessary to have a number of coefficients which are used to correct for differences between the theoretical predictions of the process models and the actual results, in order to improve prediction model.

The principle of charge calculation program developed, as show in Figs. 2 and 3, is given for determination of the weight of iron ore, the weight of burnt lime and the volume of oxygen required to meet the weight, temperature and chemistry specifications of a given product.

The left side of Fig. 2 shows the information required for the charge calculation: hot metal analysis and temperature; scrap weight, analysis; ore and flux analysis; and weight, temperature and chemistry specification of the product.

In the center there is a box labeled «Charge calculation program». This program, represents both the computer program and the computer, is often referred to as black box by operators.

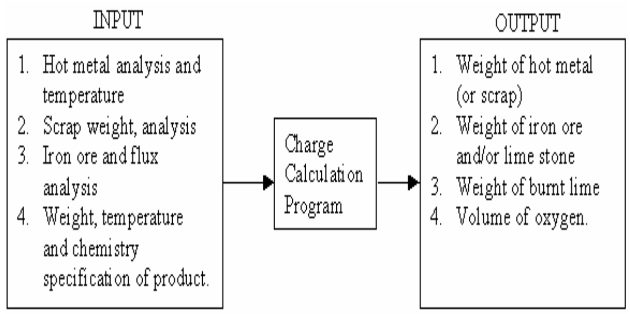

Fig. 2 Charge calculation program in inputs and outputs

The conventional model developed, use closing for oxygen and heat. After the complete heat, the model recalculates using the actual additions to determine the actual loss (or gain) in oxygen and heat, and therefore the charge to parameters needed to keep the output of the model with current operating conditions. The difference between actual and predicted values is taking into account for the next heat. The principle of adaptation is shown on Fig. 3.

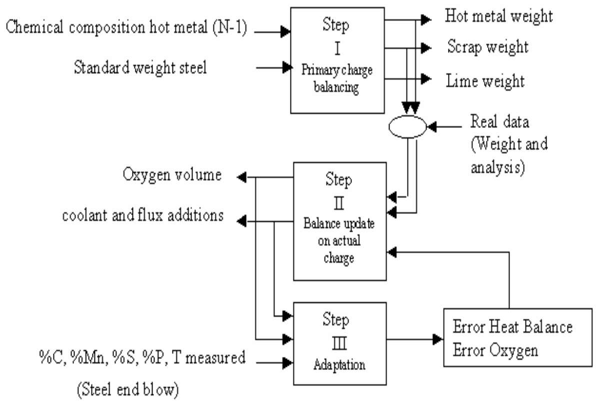

Fig. 3 Step of charge calculation and adaptation

III. Problem Definition

The developed model, suffer from a degree of imprecision. This is due to inherent complexity of the process, the difficulty of accurate measurement of process variables, and the influence of many factors, such as oxygen lance wear, vessel profile, thermal losses (empty converter) and slag retention, that cannot be quantified. These problems cause the need of reblow. Such reblows add significantly to process times and costs, and results in additional wear of the vessel lining refractory. Alternatively, too high temperature at the end of the blow, leads again to increased refractory wear, poor alloy yield and increase in processing time to reduce temperature to acceptable levels for the subsequent casting process. Approximately 50 % of reblow ratio are due for correction steel bath temperature as shown on the Fig. 4.

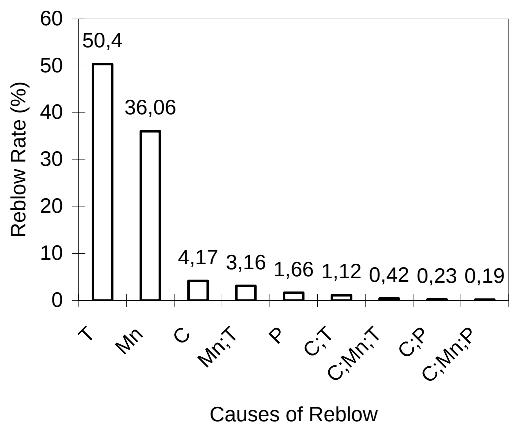

Fig. 4 Reblow ratio versus causes reblow

With the sight of these results, we decided to develop a more advanced model based on neural networks for temperature control in a first step.

IV. Neural Networks Modellisation

Artificial Neural Networks (ANNs) have become a powerful tool for many complex applications such as function approximation, optimization, non-linear system identification, and pattern recognition. This is due to the fact that they are capable to learn from examples and to perform non-linear mappings. It is confirmed that neural networks can reduce considerably the task of engineers by allowing an effective and generic approach of nonlinear problems [6]. The backpropagation has been applied to a wide variety of practical problems and it has proven very successful in its ability to made nonlinear relationships. A typical backpropagation net is show in Fig. 5.

Data are used to develop the model. Before modelling, the data base is divided into three parts, that is, training set, validation set and test set. The training set is used to train a model, the validation set is used to validate the model in order to prevent the model from overfitting, and test set is used to test the model in order to select an accurate model.

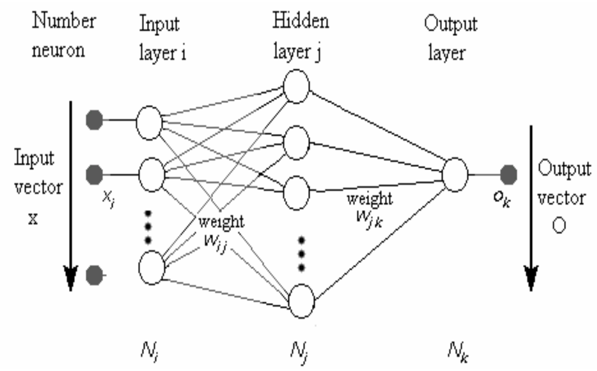

Fig. 5 Typical backpropagation net

The neural technique is a powerful method of fitting non-linear function to data, however, the number of hidden layers and iterations used to train the network should reflect the problem complexity. The difference in vocabulary between statistics and neural networks can summarize in Table I.

TABLE I
EQUIVALENCE BETWEEN STATISTICS AND NEURAL NETWORKS

NEURAL NETWORKS	STATISTICS
Choice of architecture	Choice of functions family for ¶approach the function of regression
Together of training	Observations
Training	Estimate of parameters for approximation ¶ the regression function ¶
Generalization	Interpolation, extrapolation

V. Architecture Configuration Data Collection and Preprocessing

The preprocessing of data consists in the identification of the relevant information that permits the distinguishing of different classes. Consequently, the emphasis is placed on the elimination of such problems as noise, erroneous or missing data.

If too many factors are considered, it is difficult to design a practical model. On the other extreme, the model couldn't reflect the nature of steelmaking if certain important factors are overlooked.

Before constructing a model based on industrial process data, it's important to indicate how faulty data points might be detected.

To locate these faulty data points, four main techniques were used [7]–[10]:

- basic (maximum, minimum and correlation)
- structured (analysis of similar input vectors)
- multivariate (principal component analysis)
- learnt detection (model based analysis)

Visualisation and statistical tools are provided to make this task very easy.

According to this assumption and after treatment of data base and the choice of most significant variables [11], results are presented in Table II. These variables are the input vector in neural model.

TABLE II
INPUT AND OUTPUT RANGES FOR THE DATA SD IS THE STANDARD DEVIATION

Variable		**Min.**	**Max.**	**Mean**	**SD**	**Unit**
Mn cast iron	Input	1,76	3,04	2,51	0,21	weight %
Si cast iron	Input	0,31	1,59	0,86	0,13	weight %
C cast iron	Input	3,83	5,81	5,07	0,26	weight %
Temperature cast iron	Input	1290	1436	1396	15	°C
Weight cast iron	Input	76	80	77,6	1,33	ton
Weight scrap	Input	20	24	22,32	1,47	ton
Volume of oxygen	Input	4189	5643	5090	188	Nm^3
Weight lime	Input	4	8,5	6,95	0,64	ton
Weight limestone	Input	0	2,5	0,66	0,55	ton
Wear of lining refractory	Input	17	918	480	264	
Wait between heats	Input	4	2160	119	218	Minute
Steel temperature	Output	1590	1746	1687	21	°C

Several configurations have been tested, and the best is given by the following diagram:

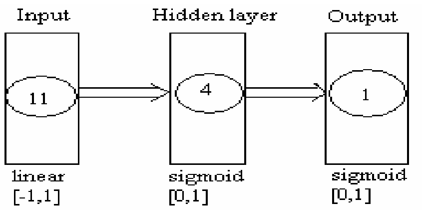

Fig. 6 Structure of back propagation network for temperature prediction

The simulation was carried out from 1200 heats distributed as follows:

- *900 heats for training*
- 200 heats for validation
- 100 heats for test.

Algorithm of Training

In order to find the best non-linear fit of the output to the data, the following steps must be taken:

(i) Choose the architecture of the network, i.e. the network inputs (the relevant variables), the topology and size of the network: this determines a family of non-linear functions with unknown parameters (the weights of the network) which are candidates for performing the data fitting.

(ii) Train the network, i.e. compute the set of weight values that minimize the approximation error over the data set used for training (training set).

(iii) Assess the performance of the network on a data set (called test set) which is distinct from the training set, but which stems from the same population.

The backpropagation is the popular algorithm used in practice [12]–[17].

This network is called backpropagation because the errors in the network are fed backward, or backpropagated, through the network.

This model has been adapted to problems in steel industry in the present work, and also has found lots of applications in various domains of science and technology [18].

The input to any neuron i without bias is given by:

$$I_i = \sum_j w_{ij} x_j \tag{1}$$

where W_{ji} are the weights of interconnects between neuron i and j, x_j represent the signal at the connection concerned.

The sum is transformed by the activation function. The overall transfer function of a neuron is thus structured as follows:

$$O_i = A_i = f\left(\sum_j w_{ij} x_j\right) \tag{2}$$

In this equation O_i is the output of the neuron, A_i is its activation, x_j is identical to the output of the preceding neuron, with index j of the observed element.

The aim of the learning process is to minimize the global network error:

$$E = \frac{1}{2}\sum_i (y_i - O_i)^2 \tag{3}$$

where y_i is the target output values.

Adaptation of the weights is effected according to the equation as follows [19]:

$$\Delta w_{ij} = w_{ij}(t+1) - w_{ij}(t) = -\alpha \frac{\partial E}{\partial w_{ij}} \tag{4}$$

where α is defined as the learning rate, this results in:

$$\Delta w_{ij} = \alpha\, \beta\, x_j \tag{5}$$

where the local error of a hidden element is calculated via:

$$\beta_i = f'(I_i) \sum_j \beta_j w_{ij} \tag{6}$$

The β_j components represent the errors of the elements in the following layer, while w_{ij} represents the connection weights for these elements.

The error of a neuron of the output layer is obtained via:

$$\beta_i = f'(I_i)(y_i - O_i) \tag{7}$$

The error is first of all calculated and then back-propagated into the hidden layer located before the output layer.

The connection weights can then be modified according to the calculated Δw_{ij} in the concluding stage of this process.

To resolve a problem of local minimum of the error space, we have introduced a momentum term. The equation for adaptation of the weights is modified as follows:

$$\Delta w_{ij}(t) = \alpha\, \beta_i\, x_j + \mu\, \Delta w_{ij}(t-1) \tag{8}$$

μ is defined as the momentum , t is the current learning step and t-1 the previous learning step.

VI. Simulation Results

After training, the capacity of the network is examined using other data in the so-called test. The network is presented by new examples which also contain output information (as in training). The procedure corresponds to that of the training phase, but the data are not used for learning. In this test, the most important information is the error generated by the network. If this considered to be too large, training should be continued.

If the results achieved by the network are satisfactory, it can be used for problem solving. The data used here no longer contain desired output values. They now consist of the input information only.

This action on the network is called test. The obtained results from 100 heats are showed in Fig. 7 which illustrate the predicted and measured temperature, Fig. 8 illustrate the error between predicted and measured temperature. Optimal values found for momentum factor and learning rate are 0.3 and 0.7.

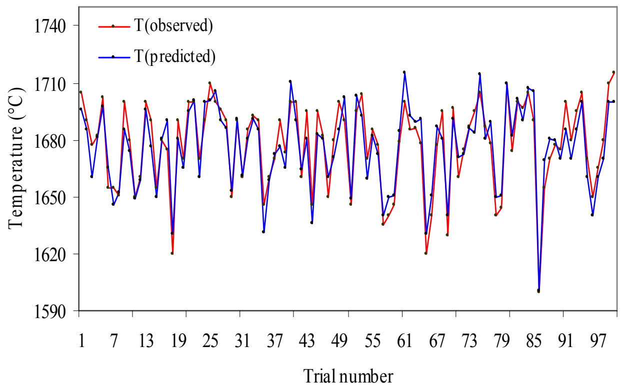

Fig. 7 Predicted and measured temperature

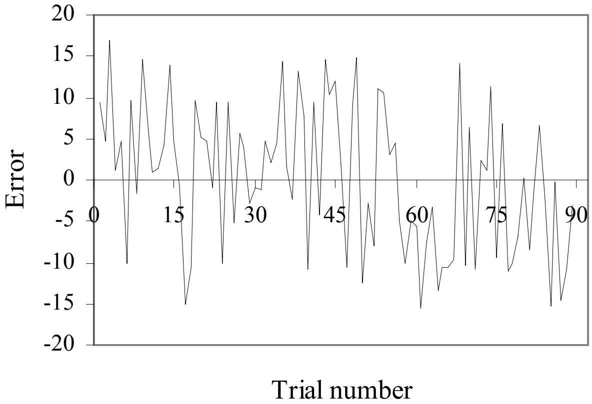

Fig. 8 Error between predicted and measured temperature

A mean absolute error of 8 °C with a standard deviation of 7 °C is achieved.

A further important consideration is the performance of the neural technique in comparison with the conventional prediction model. Taking end blow bath temperature prediction, Fig. 9 shows the performance of prediction bath temperature between conventional and neural net model. The mean absolute error was 8 °C for the neural network, compared with 30 °C for the conventional technique. This result represents a very significant improvement.

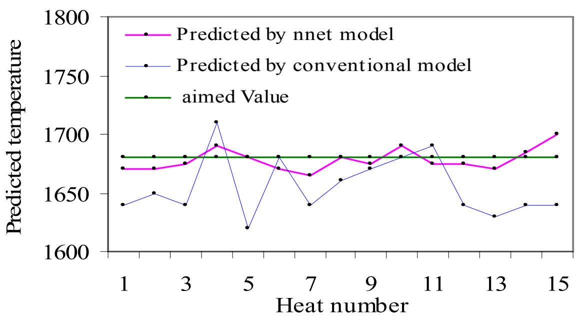

Fig. 9 Comparison conventional model versus neural net prediction of bath temperature

VII. Conclusion

A nonlinear observer is shown to correctly estimate final temperature of molten metal in the Linz and Donawitz (LD) converter process. The mean absolute error was 8 °C for the neural network, compared with 30 °C for the conventional technique. This therefore represents a very significant improvement.

A mixed neural network and knowledge base modeling method shows a very satisfactory result that is much better than the algebraic model. In our approach, the conventional model was used to charge calculation¶ and the neuronal model for temperature prediction in end blow.

This results show that the neural network can be successfully used in modelling of LD converter in complement with the conventional model.

The objective of the first stage is achieved; we project to generalize this method for process control (prediction bath temperature and composition of steel in end blow).

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