APPLICATION OF A NEURAL NETWORK FOR AN IMPROVED CONTROL OF THE METALLURGICAL PROCESS

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Abstract

The factors of influence involved in many metallurgical problems are featured by a non-linear relation, so that their control is not an easy task. On the other hand, the quality of the metallurgical aspects of the product depends greatly on the knowledge of the relation that can allow a successful management of the metallurgical process. The technological control of the process can take advantage from the application of non-linear numerical methods that describe and simulate some not easy-understandable behaviours of the metallurgical systems. The neural network can be applied to build an automatic procedure for the definition of the productive parameters to obtain the desired results. Moreover, the neural networks find not only reliable relation for the forecasting task but also to develope a speedy and reliable classification of the different production cases to be treated. The neural network model here shown is devoted to implement both these issues and has been validated on the definition of the effect of the electromagnetic stirring on the solidification structure of a continuous casting machine, but it can be adapted to treat also other metallurgical processes in the foundry operations and so on.

Riassunto

I fattori di influenza coinvolti in parecchi processi metallurgici sono caratterizzati da relazioni non –lineari, così che il lro controllo non è facilmente realizzabile. D'altra la qualità metallurgica finale del prodotto dipende fortemente dalla conoscenza di una relazione che ossa permettere la corretta gestione del processo. Il controllo tecnologico del processo può quindi trarre vantaggio dall'applicazione di modelli numerici non-lineari, che descrivono e simulano i comportamenti di sistemi metallurgici caratterizzati da relazioni interne tra i fattori non immediatamente comprensibili. Le reti neurali possono essere applicate per costruire procedure automatiche finalizzate ad ottenere i risultati desiderati. Inoltre, la rete neurale non solo è in grado di fornire risultati previsionali attendibili circa l'esito di un processo, ma può consentire una veloce classificazione dei diversi casi trattati. La rete neurale qui presentata consente di raggiungere entrambi questi scopi ed i suoi risultati sono stati ritenuti affidabili dopo la sua applicazione al problema della determinazione della struttura finale di solidificazione di billette colate su macchina di colata continua con stirring elettromagnetico. D'altra parte un tale strumento può essere adattato pure per trattare i processi metallurgici nelle operazioni di fonderia.

INTRODUCTION

The effect of the electromagnetic stirring has many similiarities with other metallurgical processes, that is the non-linear relations among the factors of influences and between these ones and the final microstructure of the product. Moreover, the complete treatment of many problems by means of a precise physical formalism implies hard and long time spending simulation that can never be applied to the in-line control of the process, because the development of the industrial operation belongs to a shorter time scale than the time spent by the computation procedure. This situation makes the use of the physical model very difficult for the application in the industrial practice. An innovative approach that involves the interaction among the different significant parameters of the process is needed, so that the operators can apply a rapid and automatic procedure to produce a metal product which respects the required specifications. In the studied case the billet has to be featured by a solidification microstructure which grants an efficient plastic deformation. Thus, the adjustment of all the productive parameters to implement an efficient process can assure a sucessful plant management. The neural network approach seems to satisfy these needs in metallurgical problems hard to be treated by more classical methods.

Two main types of models can be used to understand and describe a technological process: physical models and statistical models. The neural networks belong to the second category, but their performance is greater than that of a linear regression with which most scientists are familiar, because the neural networks show at least three strong aspects that differentiate them from the classical linear or pseudo-linear regressions [1,2]:

- the users are not constrained to choose a previous hypothesis about the relationship among the factors;
- the neural networks can describe very well non-linear relationships among the inputs factor and between these ones and the outputs.

The model proposed has a significant peculiarity: the use of a classifying algorithm which is able to distinguish a case from another on the basis of the former learning task and on the main factors of influences that feature the case itself. The classification procedure is implemeted by a specific module based on the neural network as well and generally known as SOFM (Self Organizing Feature Map) [3].

Structure of the developed neural networks

A neural network model is composed of different layers of nodes. Generally, the first layer of nodes is the input layer, while the last one is the output layer. These extreme layers are linked by a network formed by other layers, named hidden layers, which are linked in a complex network that permits the information transfer from a node to the other ones (fig.1). The input data are multiplied by weights which characterize every single linkage between the nodes (w_i) and the sum of all the product becomes the argument of a non-linear function, that in the case of the present model is the hyperbolic tangent (hidden function):

$$h = \tanh(\sum_i w_j^{(1)} x_j + k)$$

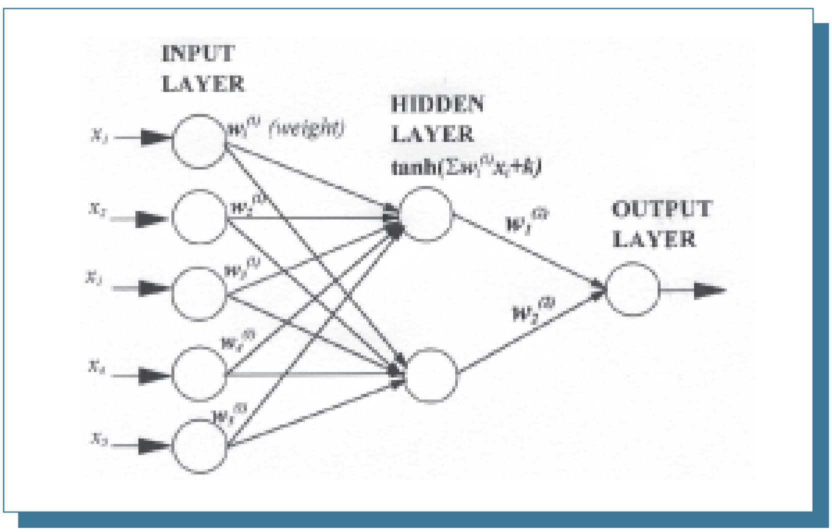

Fig. 1: Structure of the neural network with three layers [ ]

where k is a constant value, named bias value, and x_j is the input value coming from the former layer.
The weights of the successive layer eventually present are indicated as $w^{(n)}$.
The core of the method consists in the definition of the weights that link the different nodes and the procedure for this definition is the training of the neural networks, that needs some experimental tasks. The weights that define the interactions between the factors are adjusted on the basis of the experimental tasks, in which the value of the chosen factors of influence (input factors) were known and the output values were measured. Through a drawback propagating algorithm the network is trained by the computation of the weights. In this case a genetic algorithm [4] of back propagation was developed on the basis of a previous model proposed by Cormier and Raghavan[5].
The correct number of nodes and layers is fundamental for the stabilization of the weights of the networks. In the present case, the neural network is composed of three layers (one input layer, one hidden layer and one output layer) and the number of the nodes are defined by an empirical procedure [6], provided that there are six input nodes and one output node.
The aim of the development of a statistical numerical model based on the neural network method permits the suitability of its results to a wide range of products and the possibility to support the operators by an automatic computation of the interesting aspects which in this case are the size of the different structure of the inner region of the billet solidified under the action of the electromagnetic stirring. The correct control of the inner solidification structure can allow to increase the performance of the productive plant by increasing the homogeneity of the billet structure and to improve the coordination between two different subjects involved in the process, the steelmaking unity and the rolling one that has to deform a material with a known inner structure.
The approach described here allows the definition of a mathematical model that can represent the measure of the different area of the microstructure conditioned by the electromagnetic stirring action: the chill zone, the dendritic zone and the central equiaxic zone.
The classifying step is needed in the architecture of the designed model for the following forecasting step. During the learning period the weights of the network have been defined by means of the back propagation genetic algorithm for every experimental case that is introduced for fixing the correct weights to be applied to the neural network. The basic idea is that two cases are similar if they have similar weights relating the input factors of influence with the output. The condition of similarity is determined on the basis of the eulerian distance between the set of the weights belonging to the different cases. If the weights of two cases are represented in this way:

$$\{w_1^A, w_2^A, w_3^A, w_4^A, w_5^A \ldots w_n^A\}$$
$$\{w_1^B, w_2^B, w_3^B, w_4^B, w_5^B \ldots w_n^B\}$$

the eulerian distance is:

$$\delta = \sum_{i=1}^{6} (w_i^A - w_i^B)^2$$

where A and B are two different cases compared by the difference between the homologous weights. This expression has the properties of a distance also in a multidimensional system because it respects the following relations:

$$\delta \geq 0 \qquad \forall w_i$$
$$\delta_{AB} = \delta_{BA}$$
$$\delta_{AB} \leq \delta_{AC} + \delta_{CA}.$$

If a case is found that has a distance from the other cases under a limit value, this case will represent well the behaviour of the nearest cases and it is possible to call it a model item for every case.
The role of the SOFM is to define the set of weights that represents a model item. The algorithm used to implement the SOFM is known as the Kohonen's algorithm [3]. The idea of this procedure is to start from randomly chosen weights that characterize some different possible model items that have some initial relations with the experimental cases featured by the measured value of the input factors of influence and the correlated value of the output parameter. After some iterations the randomly chosen model items converge in a position within the multidimensional weight space and these movements permit them to characterize well the adjacent cases. It is possible that two or more randomized cases converge in the same position, thus reducing the number of the model items.
The model items are constituted by the sets of weights that characterize the whole population has been introduced during the learning step. When a case characterized by a particular input set is introduced to the numerical model, the particular weight of a single model item is applied to that. The choice of the more suitable and reliable model item to be applied to the introduced case is operated by the comparison of the inputs of the introduced case and the inputs of all the experimental cases that have been used for the training of the algorithm and for the definition of the model items. The comparison between the input values is still performed by the computation of the Eulerian distance. When among the real experimental cases used for the training the nearest one to the case to be forecast is found, the numerical model evaluates what is the reference model item of that experimental case. So, the set of weights of this model item are used for the forecasting step of the introduced case to be forecast. The numerical model performance can be adapted by a continuous learning task richer and richer in experimental samples to train the neural network model and to enrich it of other model items.

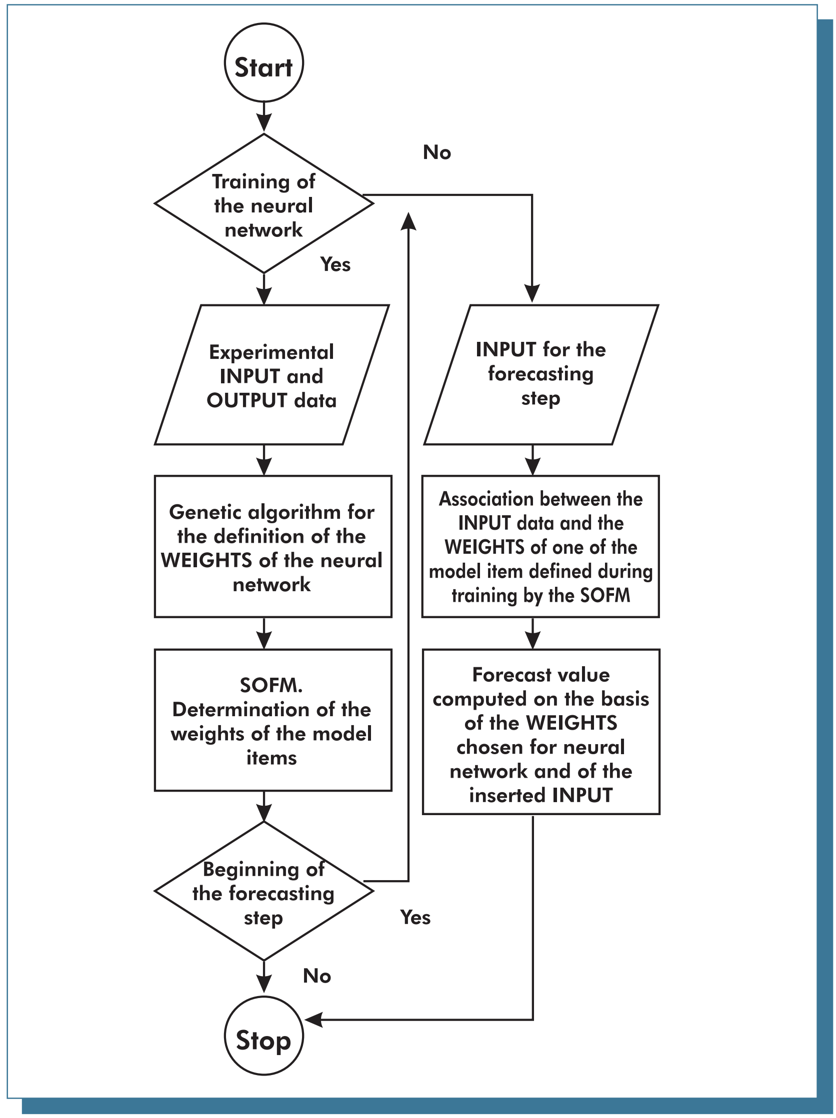

Fig. 2: Flow chart of the implementing software

Thus, this model is organized by two cooperating software modules developed by a C++ language code, one devoted to the forecasting and endowed with the SOFM procedure while the training procedure is performed by the genetic algorithm. The peculiarity in the system architecture is represented by the presence of a SOFM algorithm that is able to distinguish several fundamental cases to which all the cases that can undergo the treatment of the numerical model (fig.2).can be reconducted.

Experimental Procedure and validation

The shown model is validated by the observations developed on the effect of the electromagnetic stirring on the solidification microstructure of the round billets solidified within a continuous casting machine equipped with that electromagnetic device.
The studied materials are four types of resulphurised steel (tab.1)

Table I. Chemical composition of the four studied steels

Elements %wt	1	2	3	4
C	0,17	0,2	0,25	0,17
Mn	1,4	1,4	1,6	1,2
Si	0,26	0,27	0,35	0,4
P	0,013	0,012	0,014	0,013
S	0,02	0,025	0,035	0,015
Al	0,025	0,024	0,025	0,025
Ca	0,001	0,001	0,001	0,001
N_2	0,008	0,008	0,009	0,007

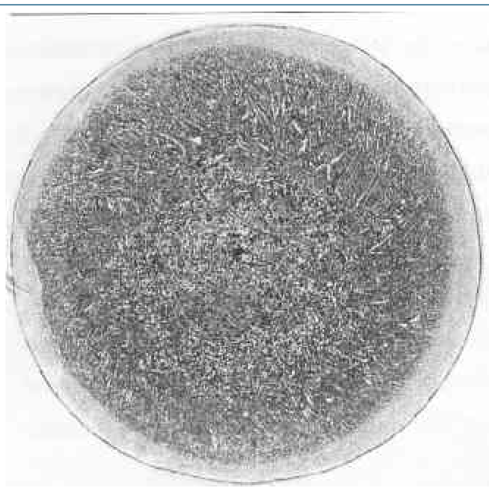

Fig. 2: A macrographic billet structure etched by the Baumman's etchings

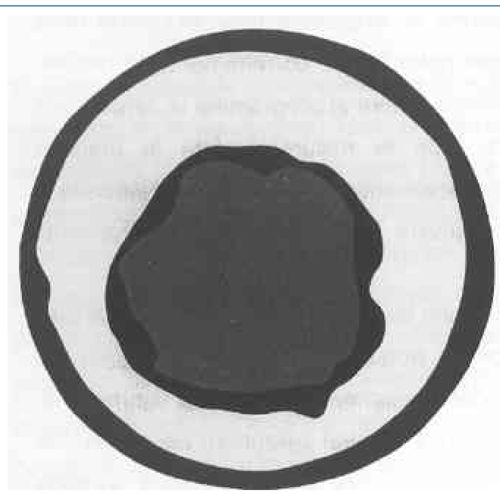

Fig. 3: Example of a treated image of the billet surface in which the different main zone are recognized: chill zone, dendritic zone, dendritic-equiaxic zone, central equiaxic zone (from the outer side to inner side)

The presence of the sulphur allows the application of the Baumman's etchings requiring the use of a 92% H_2SO_4 concentrated solution that points out the sulphur prints on photography paper and permits to well recognize the different four main zones of the billet solidification structure: the chill zone, the dendritic zone, the dendritic-equiaxic zone and the central equiaxic zone (fig.2, fig.3).

The measurements of the area of 250 etched billets are performed after the Baumman's etchings by means of an image analyzer which permits to measure the areas of interest.

The model has been trained on 210 samples and then validated on the other 40 samples whose significant input data are introduced to perform the forecasting task devoted to define the area of the different inner microstructure of the billets.

The results of the model are very satisfactory, provided that the number of samples introduced to train the neural network can be considered smaller than that often used for these trainings (fig.3, fig.4, fig.5).

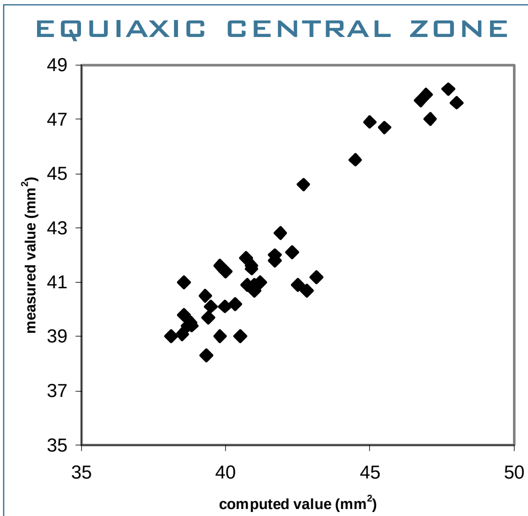

Fig. 3: Comparison of the measured and computed chill zone area

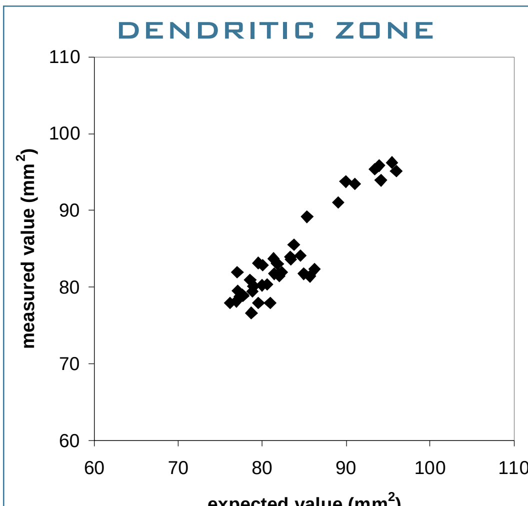

Fig. 4: Comparison of the measured and computed dendritic zone area

The factors of influence chosen in these tasks are the super-heat temperature of the continuously cast steels, the total heat extracted from the billet by the mould and the involvement of some different parameters related to the chemical compositions (%Mn, %C, %S, %Cr) which can variate and influence the solidification structure by modifying the liquidus temperature, the solute partition during the solidification and the thermal conduction of the solidifying metal. The working parameters of the electromagnetic device are mantained constant in all the observed cases, so they have not been included in the factors of influence used in the neural network. I

The average value and the variance of the difference between the computed and the expected values offer a good reliability for the numerical model (tab.2).

However, this model can represent a good tool for the understanding and the description involved in problems related to the control of other metallurgical processes implemented by several industrial systems, provided that the main factors of influence are known. If one of the input factors is related to a less important factor of influences its neural connection linking it to the other nodes should be made unactive after several iterations of the training steps.

TABLE II. AVERAGE AND VARIANCE OF THE DIFFERENCE BETWEEN COMPUTED AND REAL EXPERIMENAL VALUE DURING THE VALIDATION TASK

	Central equiaxic zone	Dendritic zone	Chill zone
Average	-0,36	-0,71	-0,18
Variance	1,03	2,07	0,51

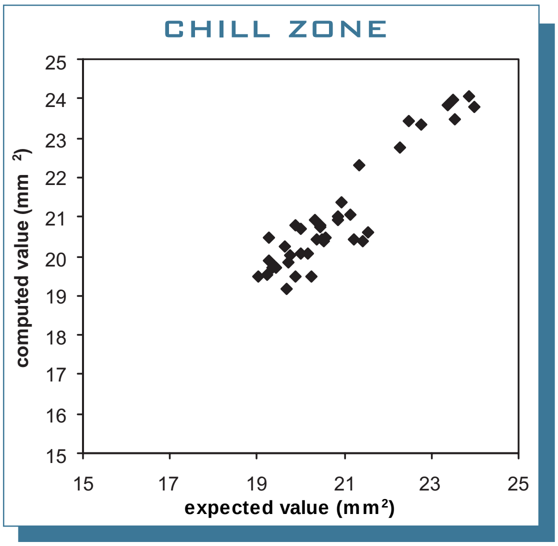

Fig. 5: Comparison of the measured and computed dendritic zone area

CONCLUSIONS

The neural network approach can be used profitably to describe and control the evolution of some metallurgical processes governed by several non-linear relations among the main factors of influence and between these ones. The other great advantage of these method is that they are short time spending, if compared with precise simulation physical softwares that for this aspect cannot always find a good and speedy application needed in the indutrial practice.

The neural network software here developed and validated on a steel making continuous casting plant of a steelmaking unit shows an architecture that is endowed with a SOFM algorithm which can permit also a classification of the case used for the learning and more important can recognize what are the model items which well represent the population in which the main possible cases of the studied phenomenon can be classified.

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