Control of the Continuous Casting Process Using Neural Networks

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Abstract: - This paper work refers to coming up with a management method for the continuous cast process by using a neural system of crack detection, which may lead to removing all the cover cracking and factory rejects caused by this phenomenon. The output signal of the neuronal network causes an improvement of the water flow used for primary cooling of the casting speed, in case it predicts any crack.

Key-Words: - Neural networks, control, prediction, crack, casting speed, water flow

1 Introduction
During the casting, the crystallizer tank receives the liquid steel in its upper part in precise conditions of temperature and debit, and, at the lower part, a semi-finished product with solidified crust and liquid core is extracted at constant speed. One of the great problems is its cracking or even it’s tearing, due to several factors [1]. An abnormal process of cooling inside the crystallizer tank can lead to the appearance of cracks, especially in its upper part.

Another possible factor of apparition of cracks is too high the casting speed, which can lead to forming too thin a crust in the crystallizer, with no sufficient resistance to the ferro-static pressure of the liquid core [4], [12].

It is important that we pay attention to the fact that alloyed steel must be casted for low speed, because they are highly responsive to middle porousness and cracks. If we analyze each of the causes of cracking, mechanical resistance of the steel crust is very important which is produced inside the crystallizing apparatus, as well as the size of the abrasion force/strength between the inside wall of the crystallizer, each of them having 4 sensors, fig.1 [15].

![Fig. 1 Dispose of the thermocouples on the crystallizer wall](image1)

Fig. 1 Dispose of the thermocouples on the crystallizer wall
- 12 Rows of thermocouples
- a. Crystallizer
- b. Open crystallizer

Not all increases of temperature are cracks in the incipient stage. A real crack has a certain pattern for the temperature, [5] as well as a particularly achieved displacement.

In the figures 2 and 3 were presented the temperature patterns measured by the sensors from a certain row, as well as by the sensors of the very next row. In figure 2, when the crack of the crust reaches the upper row of thermocouples, the temperature registered by them increases. When the crack of the crust reaches the next inferior row of thermocouples, with a certain delay due to the flowing speed, the temperature registered by these thermocouples also increases, following the same pattern of temperature as in the case of the upper row thermocouples.
Fig. 2 Temperature patterns in case of cracks

Another similar temperature pattern is also recognized by the adjacent thermocouples (horizontally).

In the figure 3 are presented the temperature patterns measured by the sensors from a certain row and from the next inferior row, in case the crack did not occur.

Fig. 3 Temperature patterns in case of no cracks

The accuracy of the crack detecting system depends both on the pattern recognition and on the displacement performed by the crack [9].

Neuronal networks prove to be useful for solving some difficult problems, such as: estimating, identifying, predicting, and controlling or for complex optimization [7], [8]. In this way, a neural system can analyze the signals provided by the sensors mounted on the crystallizer’s walls and can recognize the apparition of crack very accurately, and the system managing the process can order the necessary measures to eliminate the crack (correction of the water flow capacity meant for the primary cooling and the casting speed).

3 Neural network architecture for cracks prediction

The phenomenon of apparition of crack is characterized by the dynamic increase and decrease of the temperature recorded by the individual thermocouples (case 1) and by its spatial distribution in the crystallizer (case 2).

In the crystallizer, the temperature can vary, so that, if we take into account only the case 1, its variation can predict the apparition of breakout. In order to achieve a competitive breakout detection system, the neural networks recognized both case 1 and case 2. In order to cover both cases with a single neural network, this will be very complex and will involve many problems, including the difficulty in learning of the internal coefficients.

In the present case, is presented a solution based on a system composed of several multi-layer neural networks, [17]. This system is formed of a neural network receiving as input data the dynamic series of temperature from the individual thermocouples of the upper and lower row, called the dynamic series network and a spatial network, which receives the input data from every pair of adjacent thermocouples from the upper row. These data represent the dynamic series of temperature used to recognize the case 2. To each thermocouple taken aside, both from the upper and the lower row, corresponds a dynamic series network and the spatial networks correspond each taken aside to a pair of adjacent thermocouples from the upper row.

The breaking is predicted by the dynamic series network corresponding to the thermocouples of the lower row and by the spatial network in the following stage. It is considered that the solidified crust is non-uniform when the dynamic series network corresponding to the lower row thermocouples records an important modification of the temperature.

In order to recognize the case 2, the two adjacent thermocouples for the upper row are used and the corresponding ones of the lower row. In this way, the crack of the wire can be detected early, in the initial stage of its propagation, so that there is enough time to act for preventing the breaking.

3.1 The architecture of the dynamic series network

It is adopted a model of the artificial neural network of the type of multilayer perceptron, [3], [13] because this type of network is efficient in recognizing patterns. The inputs chosen are of analogical type. The network receives the data from the individual thermocouples of the upper and lower row; these data are then differentiated in order for the network to perceive the variation of temperature [15]. The data differentiated in this way are coupled in 10 buffers for each cycle of sampling and are stored in 10 data storing units. The presentation of data at the network input is made sequentially, through the displacement with a sampling step equal to one, of the each input data in the 10 buffers.

The number of input neurons of the network is chosen to be equal to 10 (Fig. 4).
Based on experiments, the conclusion was reached that a number of 8 neurons for the hidden layer are benefit for a quick process of training, and the network presents a very high accuracy in recognizing the patterns brought at input. The number of output neurons is equal to 1. This neuron indicates whether the temperature pattern presented at input is a suspicious pattern able to indicate the crack in the wire or not. The result present at the output of this neuron is a number in the range 0...1 and results based on the recognition process of the results by the network [16].

It is used as training algorithm, Scaled conjugate gradient backpropagation, which is a network training function that updates weight and bias values according to the scaled conjugate gradient method [14]. This algorithm can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance with respect to the weight and bias variables, [11]. The scaled conjugate gradient algorithm is based on conjugate directions, but this algorithm does not perform a linear search at every iteration.

The functions used as activation functions are the hyperbolic tangent sigmoid transfer function and logarithmic sigmoid transfer function [14].

3.2 Architecture of the spatial network

The adopted model of neural network was always that of multi-layer perceptron. The spatial network receives as input data the output values from two dynamic series networks in order to recognize the relationship between the adjacent thermocouples. The input value [6] resulted from the output of a dynamic series network is applied for sampling to the 6 buffers and retained by 6 storing units. Only the maximum value of the 6 storing units is introduced at the input level of the spatial network, being also used to rectify the propagation time of the crack in the crust, for the adjacent thermocouples of the upper row.

The input level of the spatial network is formed of two neurons, and the number of neurons of the output level of the spatial network (Fig. 5) is equal to 1. It provides the breaking alarm when the output value exceeds a predetermined limit value [16]. The result presented at the output of the network will be: 0 (in case there is no crack) or 1 (in case the crack is detected in the wire).

A single hidden layer was chosen, containing 4 neurons.
The Levenberg–Marquardt back-propagation, [12] was chosen as training mechanism that is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. There were used as activation functions, the functions: Hyperbolic tangent sigmoid transfer function and Logarithmic sigmoid transfer function [14].

The breaking is predicted by the dynamic series network corresponding to the thermocouples of the lower row and by the spatial network in the following stage. It is considered that the solidified crust is non-uniform when the dynamic series network corresponding to the lower row thermocouples records an important modification of the temperature.

4 The structure of the control system
This process is led by a complex system based on fuzzy logics and by individual regulation lock PID. This system tries to consider the anticipation effects that the adjustment of the metal level inside the crystallizing apparatus and the decrease slope of the material temperature (based on specific knowledge used by specialists – a set of rules representing the basic argument which helps specialist analyze the real values of the variable data); the system elaborates the required values for the classic regulation locks of all sizes using adequate inference mechanisms. This system has one main flaw: it cannot predict very precisely any cover crack when the steel turns solid. Therefore the control system has been completed by a neural system that is able to predict any possible cracks (fig. 6).

As a rule, changing the casting speed and the cooling-off system of the semi-product commanded by the crack prediction system will lead to remove the cover cracking and any other reject caused by this phenomenon. In order to implement the new system, the space division of the crystallizing apparatus’ temperature is measured by a temperature sensor matrix and it is analyzed by a neuronal net who is able to predict any crack.

The output signal of the neuronal net causes a correction of the water flow capacity meant for the primary cooling and the casting speed, in case it predicts any crack. The percentage of such
corrections is made off-line, according to the mathematical model of the solidifying process and to some technological experiments. This percentage depends on the quality of the cast steel and the shape of the semi-product.

5 Conclusions
There was established that when a crack occurs, the liquid steel touches the crystallizer’s wall, causing an increase in its temperature. Based on that, we have made a system meant for predicting any fissure, by using a number of temperature sensors mounted on the wall of the crystallizing apparatus, and whose signals are analyzed by a system of multi-neurons. This system is able to analyse all the data received from the thermal-couples and give the right answer.

As a rule, changing the casting speed of the cooling system of the semi-product caused by the crack prediction system shall lead to correcting the cover crack phenomenon and therefore, to removing all factory rejects caused by this phenomenon.

![Control system structure](image)  
Fig. 6 Control system structure
References:


