A&QT-R 2002 (THETA 13)
2002 IEEE-TTTC International Conference on Automation, Quality and Testing, Robotics
May 23 - 25, 2002, Cluj-Napoca, Romania

THE USE OF NEURAL NETWORKS IN CONTROLLING THE SURFACE QUALITY OF CONTINUOUS CAST PRODUCTS

Nicolae Rusu, Stela Anghel

The “Politehnica” University Timisoara, The Faculty of Engineering of Hunedoara,
5 Revolutiei Str., 2750 Huneodara, Romania, tel. 054-712538, fax. 054-207000,
e-mail decan@fih.utt.ro

ABSTRACT

The paper introduces the structure of a neural system to be used in the prediction of skin cracking on steel continuous casting in order to diminish the surface flaws it engenders or the total discarding of the semi-finished part.

KEY WORDS: neural network, prediction, continuous casting

1. INTRODUCTION

In the process of continuous casting, the molten steel in the ladle passes through the distributor into the mold, which is water-cooled (primary cooling). Here, a solidified skin appears, and one of the major problems encountered is its cracking, which may happen because of several factors. When the cracked area gets out of the mold, the molten steel overflows and the process of continuous casting has to be halted. Such an accident has to be avoided by detecting the fissures and by reducing the casting rate, thus allowing the solidification of steel. It was noticed that when the skin cracks, the liquid steel comes into contact with the wall of the mold, which leads to an increase of its temperature. Starting from this finding, a predictive system can be designed, using a series of temperature sensors mounted on the walls of the mold; their signals are analyzed by a neural network. The paper introduces such a system.

2. DESCRIPTION OF THE METHOD

The thermocouples are integrated into the outer wall of the mold at specific intervals, according to the desired precision. (Fig.1)

On cracking, the temperature detected by the thermocouple in the respective area (for instance 1-1) varies as in figure 2 (the full line). Element 1-2, placed under 1-1 will detect a temperature variation as in figure 2 (the dotted line).

Figure 3 gives the functional diagram of the fissure prediction system. One of the sensors 2 is selected as central sensor (e.g. 2-0) with respect to which we define the adjacent sensors left- right (2-1; 2-2) positioned on the same level with 2-0, as well as a sensor (2-3), positioned under the central one.

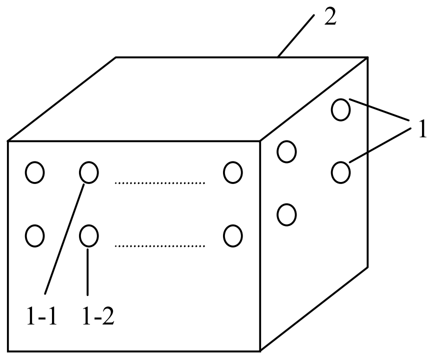

Fig.1
1 – thermocouple; 2 – mold;
1-1 – thermocouple no. 1
1-2 – thermocouple no. 2

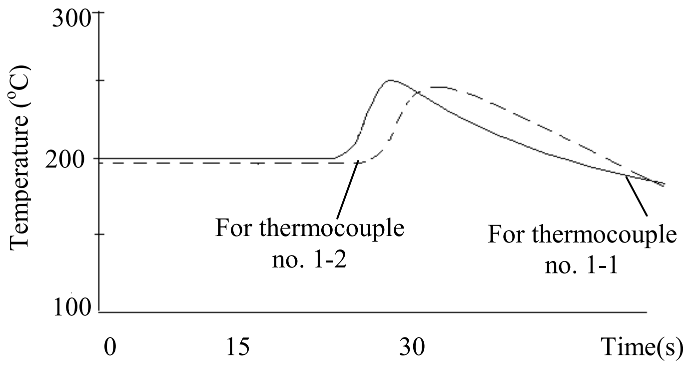

Fig.2

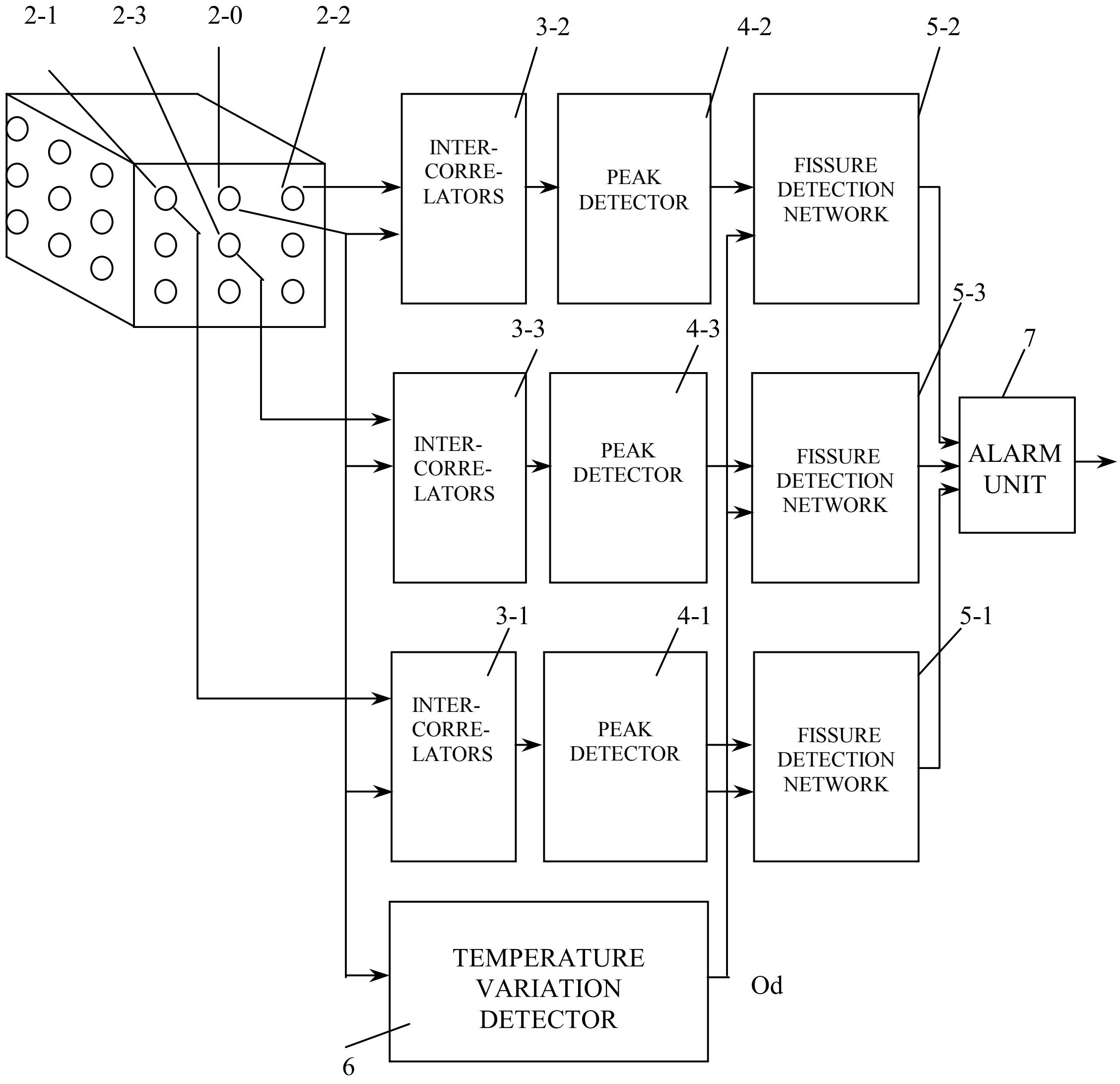

Fig. 3

The decision-making section of the prediction includes: inter-correlators 3-1, 3-2, 3-3; the peak detectors 4-1, 4-2, 4-3; the temperature variation detector 6; the fissure detection network 5-1, 5-2, 5-3 and the alarm unit 7.

All temperatures are measured according to a certain sampling period, for instance one second. Temperature at moment "i" is $T_d(i)$.

Figure 4 gives the functional diagram of the detector of the temperature variation curve (6).

The normalizing unit 6-4 carries out the following operations:

$$\overline{T}_d = \frac{1}{n+1}\sum_{K=i-n}^{i} T_d(K) \tag{1}$$

$$\sigma_d = \sqrt{\frac{1}{n+1}\sum_{K=i-n}^{i}\left[T_d(K)-\overline{T}_d\right]^2} \tag{2}$$

$$T_d(j)' = \frac{T_d(j)\cdot \overline{T}_d}{\sigma_d} \qquad (j = i-n...i) \tag{3}$$

offering the normalized temperature values at its output $T_d(i)' \rightarrow T_d(i-n)$.

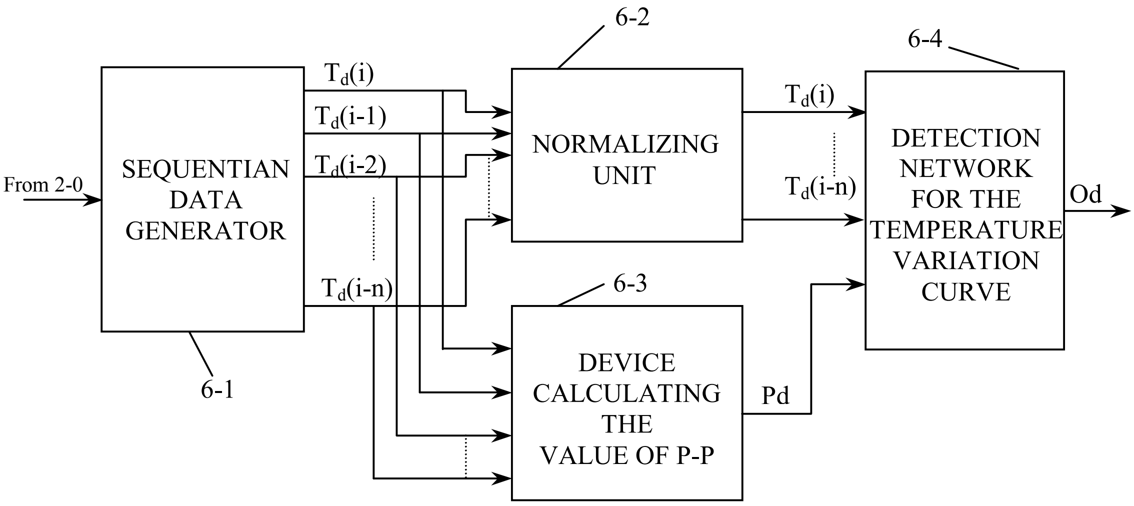

Fig. 4

The peak value calculation unit (6-3) realizes the difference between the maximal and the minimal values of the temperature levels $T_d(i) \rightarrow T_d(i-n)$:

$$P_d = \max[T_d(i-n),...,T_d(i)] - \min[T_d(i-n),...,T_d(i)] \tag{4}$$

Figure 5 gives the neural network meant to detect temperature variation and including: an input level (71) made of (n+2) nodes whose inputs are the normalized values $T_d(i)'$ …$T_d(i-n)'$ şi P_d, an intermediate level with several units (72) and an output level (73) with just one node.

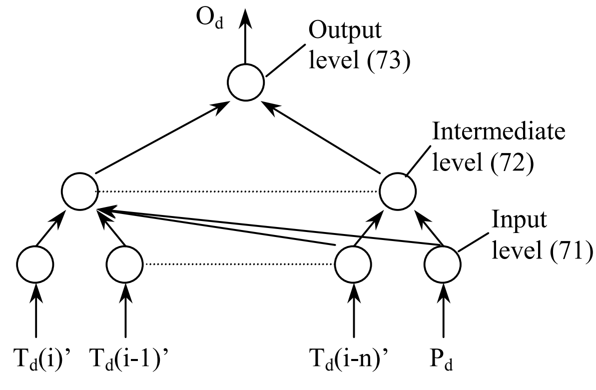

Fig. 5

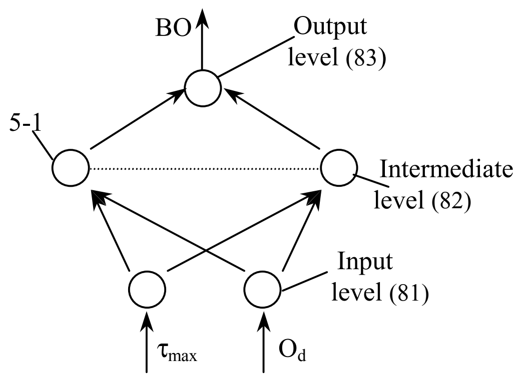

Fig. 6

Through a learning process, the neural network will give at its output signal O_d, whiose value is 1 when a temperature variation occurs, as in figure 2, otherwise being $O_d = 0$.

We marked as $T_a(i),\ldots,T_a(i-n)$ the temperatures detected by sensor 2-1 at the same sampling moments as $T_d(i),\ldots,T_d(i-n)$ determined by the central sensor 1-0. The temperature levels detected by sensors 2-0 and 2-1 are processed by the first correlator 3-1, leading to normalization, i.e. the values $T_d(i)',\ldots,T_d(i-n)'$ and $T_a(i)',\ldots,T_a(i-n)'$, the calculation of the inter-correlation value being:

$$C(\tau) = \frac{1}{N+1}\sum_{j=i-N}^{i} T_d(j)' \cdot T_d(j+\tau)' \qquad (5)$$

where τ = -n…n.

If value K in $T_a(K)'$ is out of the domain (i-n) and I then:

$$T_a(K)'=0 \qquad (6)$$

Block 3-1 (the first correlator) gives on its output the intercorrelation value $C(\tau)$, which is input to the peak detector 4-1. It gives value τ_{max}, i.e. the maximal value of the inter-correlation magnitude for: $-n \le \tau \le n$.

The fissure detection network 5-1 has the structure given in figure 6 and includes: an input level (81) with two nodes, having as input signals τ_{max} and O_d, given by 4-1 and 6, an intermediate level with several nodes (82), an output level (83) with just one node.

The learning process for both neural networks (fig.5 and 6) is based on the following steps: the temperatures collected by each sensor are memorized both for the normal situations and for the fissure occurrence, the temperatures are currently measured and, in correlation with the ones previously memorized, they lead to the generation of O_d, BO signals, corresponding to the momentary state (there is or there is not the risk of fissure occurrence); the alarm unit 7 receives at its input the BO result given by networks 5-1, 5-2, 5-3 and if one or several of these signals go over a previously determined value, it triggers the alarm and has the casting rate decrease until the skin cracking danger dims out.

3. CONCLUSIONS

The method we introduced allows a control of the skin fissure occurrence, using a network of thermocouples placed inside the mold walls. Their signals are processed by two neural networks, which predict such a flaw and take steps towards avoiding it. Due to its major economical implications, the method we introduced is extremely important, the general investment implied by its implementation being cleared off very soon.

BIBLIOGRAPHY

1. Şt. Preitl, R. Precup, 1997, Introducere în conducerea fuzzy a proceselor, Editura Tehnică, Bucureşti, pag.15-21 ;
2. C. Voloşencu, 1997, Reglare fuzzy şi neuronală, Editura Eurobit, Timişoara, pag.35-39 ;
3. A. Nakamura, 1996, U.S. Patent 5548520, pag. 1-6.