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NOZZLE CLOGGING PREDICTION IN CONTINUOUS CASTING OF STEEL

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Abstract: Submerged entry nozzle connects the tundish and the mold in the continuous casting of steel. Continuous casting is usually done in series including 3–6 successive heats. Casting of a heat takes about 35–50 minutes. The nozzle is changed after each series and the new series is started with a new nozzle. About 360–720 tons of steel goes through a nozzle during its lifetime.

The casting speed and the stopper rod position give the indication of nozzle clogging, but they cannot, however, answer the question, how long time the casting can continue and when the nozzle should be changed. In this paper, feedforward neural networks with backpropagation training were used in modelling the nozzle clogging behaviour at Rautaruukki Steel mill, at Raahe site. *Copyright © 2002 IFAC*

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1. INTRODUCTION

This paper shows the results of a research project that aimed to find reasons for nozzle clogging in the submerged entry nozzle in continuous casting of steel, and also to develop tools for predicting the occurrence of this phenomenon. It is known that better management of casting brings along considerable potential for production increase and quality improvement.

The casting plant at Rautaruukki Raahe Steel consists of five single strand continuous casters. Casting process starts by opening the steel ladle (see Fig. 1). Then the steel flows in a continuous stream through the ladle into the tundish. From the tundish the steel flows through a submerged entry nozzle into a mold where the solidification of steel starts. Partly solidified cast strand is pulled out from the mold by rollers. The inner part of the cast strand is solidified in the secondary cooling zone by air-water spray cooling. At the end of the casting machine, a torch cutting machine cuts the cast strand to slabs.

2. NOZZLE CLOGGING PROBLEM

2.1 What is nozzle clogging?

Submerged entry nozzle connects the tundish and the mold in the continuous casting of steel (Fig. 2). It is a tube with a diameter of about 15 cm and it divides the molten steel into two directions on the both sides of the nozzle. The direct flow downwards should be avoided, because in this case aluminium compounds in slag would stay in molten steel. The nozzle transfers molten steel from the tundish to the mold and separates steel from the atmosphere.

Usually one cast series includes 3–6 successive heats meaning the same number of ladles. Casting of a heat takes about 35–50 minutes. Each series is designed to consist of the same steel quality. The nozzle is changed after each series and the new series is started with a new nozzle. About 360–720 tons of steel goes through a nozzle during its lifetime. The risk of nozzle clogging increases all the time so that when about 360 tons of steel has been cast (after the third ladle) the nozzle condition must be monitored carefully. The operators estimate, based on vision and the casting plan, if the clogging should be removed or the nozzle changed in the middle of the cast series. Nozzle clogging is not an instantaneous phenomenon, but rather it develops with time.

The clogging can be removed by pumping the stopper rod and in this way continue the casting series without changing the nozzle. Different nozzle materials and designs and dimensions of the nozzle are available.

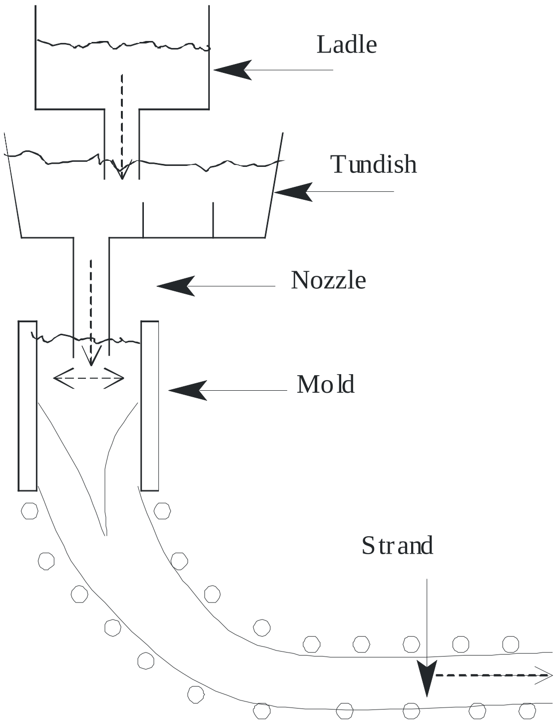

Fig. 1. The continuous casting process.

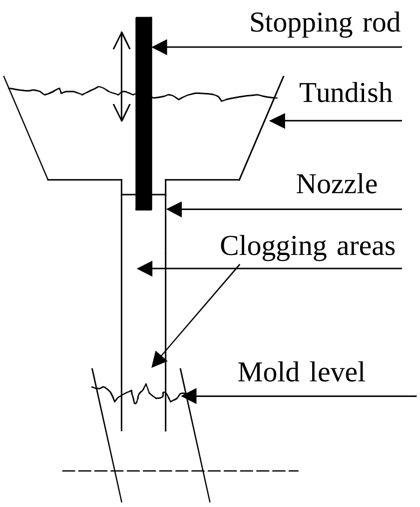

Fig. 2. Location of the submerged entry nozzle in the continuous casting process.

2.2 Reasons and remedies

There are several reasons that contribute to nozzle clogging:

- metallurgical factors: steel cleanness and aluminium content,
- hydrodynamic factors: steel flow rate and nozzle geometry,
- thermodynamic factors: cold steel and heat transfer inside the nozzle,
- nozzle material, and
- unpredictable disturbances and operational faults.

Clogging mechanism depends on the cleanness of steel (Miyazawa, 2001). With clean steels, the clogging consists of solidified steel, but in other cases powdered aluminium oxide dominates.

Several methods have been used in avoiding nozzle clogging (Rackers and Thomas, 1995, Pilet and Bhattacharaya, 1984, Okamoto et al., 1982, Takasugi et al., 1990):

- calcium silicate injection,
- improving steel cleanness,
- argon injection into the nozzle, and
- nozzle material, construction and geometry.

The effects of nozzle clogging to mold level control has been studied by Dussud et al. (1998) and Graig et al. (2001).

2.3 Nozzle clogging detection

There are some variables that can tell about increased risk for nozzle clogging. Fig. 3 shows trends of casting speed and stopper rod position in two cases. The uppermost figure shows the case without any nozzle clogging and the lower one shows the opposite case. The difference is clear and the experiences have shown that these two variables can give the first indication of nozzle clogging.

Using the casting speed and the stopper rod position cannot, however, answer the question, how long time the casting can continue and when the nozzle should be changed. Figure 4 shows a block diagram for the system that aims to estimate also the time available for undisturbed casting.

3. DATA ACQUISITION AND ANALYSIS

This paper reports the study that concerns with the possibilities to predict nozzle clogging or, more exactly, to estimate the amount of steel that can be cast without changing the nozzle. This is based on historical data collected from Rautaruukki Steel Mill’s converter plant and two casters. The first analysis revealed that nozzle clogging exists with aluminium-killed steel grades that have gone via the stirring station to the casters. Modelling was done with feedforward networks trained by backpropagation.

3.1 Data

Data was collected from casters 5 and 6, from 5800 heats from each. All the heats were not used in modelling. Clogging occurs with aluminium-killed heats and other heats were left outside. Four steel grade groups were concerned and they will be called grades 1, 2, 3 and 4 in the following. The heats that had gone via the ladle furnace were omitted. Silicon-killed heats were also left without further consideration as also heats with serious disturbances.

3.2 Correlation analysis

The analysis considered only these heats where nozzle clogging existed. First attempts were made keeping all the heats for casters 5 and 6 together. Correlations were, however, weak, and therefore the data was first divided according to the caster and further into smaller data groups based on four steel grades (1–4).

So, correlation analysis was made separately for two machines and four grades. It meant eight data groups and the results were used in defining the potential variables for nozzle clogging models.

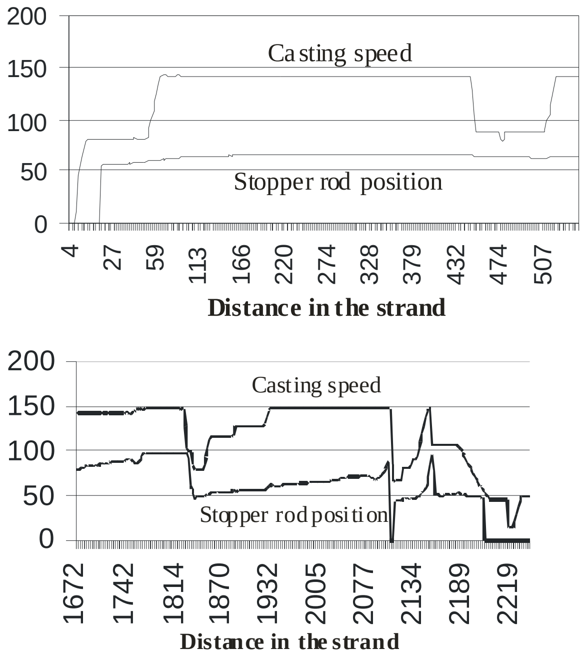

Fig. 3. Examples of casting speed and stopper rod position in undisturbed case (upper figure) and in a nozzle clogging case (lower figure).

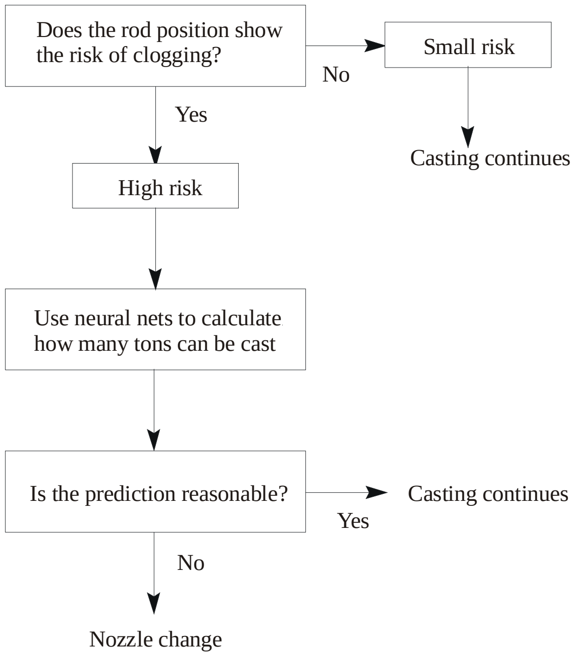

Fig. 4. Nozzle clogging detection based on the stopper rod position and neural network model.

In correlation analysis, a total of 67 variables were considered. All main temperatures and compositions were included starting from the converters until the casters together with other process variables and some additional variables that were calculated from process variables. The most significant are listed in Table 1 later in Chapter 4. It was also found that in some cases data from two successive heats were needed.

4. MODELLING APPROACH

Nozzle clogging was modelled using neural networks. Modelling with neural networks consists of two phases: training and testing. In training, network parameters are updated aiming to minimise the difference between estimated and actual response values. In this case, training utilised backpropagation procedure. In testing, response is calculated using constant network parameters. Testing is done with a data set that was not used in training. Training is continued, until the error in the testing phase reaches its minimum. Excessive training must be avoided.

4.1 Pre-Processing for Neural Networks

Before training, all input and output variables were scaled. Usually, the scaling is done in intervals -1 – +1 or 0 – +1. Most of the inputs were scaled using the Matlab-function prestd() that scales the variables to the average value of zero and the standard deviation 1. The serial number of the heat is scaled inside the interval 0.16–1.16 by dividing it by 6. The serial number starts from 1 and the longest series count to seven heats. The mold width (koklev) was scaled inside the interval 0 – +1 using equation 1:

$$Koklev=(koklev-1000)/800 \quad (1)$$

The output variable of the network is the amount of cast tons with a certain nozzle without pumping. Its values were scaled inside the interval 0.16–1.16 by dividing the actual measurement value by 720 that is the total amount of six heats in tons.

4.2 Network Structure

Modelling used feedforward networks with only one hidden layer. These networks model steady-state dependencies between input and output variables. Two activation functions were applied, namely a hyperbolic tangent (y = tanh(x)) and a linear function (y=x). Modelling used Matlab's NN-toolbox. The first layer included non-linear tanh-functions and the second layer a linear y= x function. This made non-linear modelling possible.

4.3 On the Training Data

Three principles were used while selecting the input variables for the neural networks:

- The variables had a correlation with cast tons over 0.20
- They were not the set points for process controllers
- They were not correlating with each other. The limit was chosen as 0.50.

The amount of data limits the size of the network. The number of training parameters should not exceed the number of training points. In practice, network modelling is difficult if the number of data point is less than 60, because training requires 30 points at minimum and almost the same number is needed for testing. With five inputs and 30 training points, a conventional network can include only 5 neurons. These limitations were especially met in the caster 6.

5. MAIN RESULTS

5.1 Significant Variables

Several models were developed for both casters. The best models can predict the cast tons with ±60 tons accuracy in over 80 % of cases. Models for caster 6 show a better accuracy. Fig. 5 shows a typical example. Table 1 shows a summary of 12 models for caster 5 and 14 models for caster 6. It shows the variables that were used in the models. There are no surprises in this table; the listed variables can be assumed to effect on nozzle clogging also by a priori knowledge. The original results are shown in project reports (Ikäheimonen, Leiviskä, Ruuska, 2001).

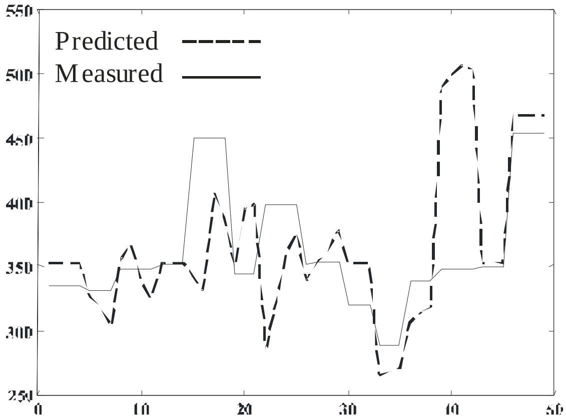

Fig. 5. An example of test results.

5.2 Cross-Testing

Cross-testing considered applying the model developed for caster 5 to the data from caster 6. Only grade 1 showed reasonable results. This confirms the earlier results claiming that different variables effect the nozzle clogging in different casters.

Table 1. The most significant variables. N denotes how many times the variable was included in 26 models considered.

Variable	N
Serial number of heat in the series	15
Casting speed*mold width	10
Mold width	9
Tundish temperature of the first heat	8
Steel temperature after stirring station	6
Nitrogen content at stirring station	6
Average tundish temperature	5
Aluminium oxide content at stirring	4
Temperature deviation in tundish	4

5.3 Testing with Successful Cases

Modelling used only data from cases where clogging occurred. Models for caster 6 were tested using data from corresponding successful heats. The result was as expected. It is impossible to tell how many tons could have been cast in successful cases, if casting had continued with the same nozzle. Therefore, the predicted cast tons given by the models remain in these cases lower than actual. The average error is about one heat, 120 tons. The result is important from the model application point of view: models never predict too high cast tons. The opposite result could lead to erroneous operator actions: cast could continue in spite of increased clogging risk. Fig. 6 shows an example run.

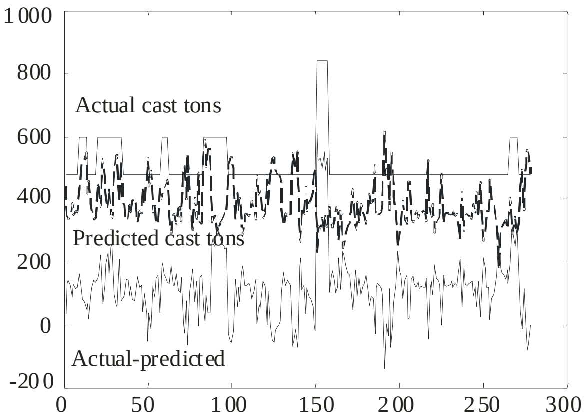

Fig. 6. An example from testing the NN-model with data from successful cases.

6. CONCLUSION

Nozzle clogging problem causes production losses and quality impairment in continuous casting, especially with aluminium-killed steels. Variations in stopper rod position and casting speed provide the operator with the first information on increased risk of nozzle clogging. This cannot, however, answer the question, how long time the casting can continue and when the nozzle should be changed. In this paper, a system is proposed that aims to estimate also the time available for undisturbed casting.

The estimate of the amount of steel that can be cast without changing the nozzle is predicted using neural network models. These models are based on data collected from Rautaruukki Steel Mill's converter plant and two casters; numbers 5 and 6. A total number of 5800 heats and 67 variables were analysed. However, the number of variables effecting nozzle clogging is quite small. Feedforward networks with backpropagation were applied. Separate model for both casters were needed and, in addition to this, data had to be divided in four quality groups. This shows that different variables dominate in different cases.

Results seem promising; in several cases the cast tons are estimated with the accuracy of ±60 tons in more than 80% of cases. Not so encouraging was the finding that different variables become dominating in different machines. The models were trained using clogging cases, only. When testing the models with successful castings, it was found that the models never gave too high predictions.

REFERENCES

Craig, I.K., F.R. Camisani-Calzolari, P.C. Pistorius (2001). A contemplative stance on the automation of continuous casting in steel processing. *Control Engineering Practice* **9**, pp. 1013-1020.

Dussud, M., S. Galichet, L.P. Foulloy (2000). Application of fuzzy logic control for continuous casting mold level control. *IEEE Trans. on Control Systems Technology*, **6**. no. 2, pp. 246-256.

Ikäheimonen, J., K. Leiviskä, J. Ruuska (2001). *Report B32*, University of Oulu, Control Engineering Laboratory. (In Finnish)

Miyazawa, K. (2001). Continuous casting in Japan. *Science and Technology of Advanced Materials*, **2**, pp. 59-63.

Pielet, H.M., D. Bhattacharya (1984). Thermodynamics of nozzle blockage in continuous casting of calcium-containing steels. *Metallurgical Transactions B*, **15**, pp. 547-562.

Rackers, K.G. and B.G. Thomas (1995). Clogging of continuous casting nozzles. *Steelmaking Conference Proceedinfs*, pp. 723-734.

Okamoto, K., T. Nakamura, M. Kondo (1982). Development of alumina-graphite immersion nozzle for continuous casting. *Iron and Steel Engineering*, no. 9, pp. 47-52.

Takasugi, H., T. Masaoga, A. Shirayama, T. Mori, H. Murakami (1990). Prevention of alumina build-up in submerged entry nozzles for continuous casting of low carbon Al-killed steels. *6th International Iron and Steel Conference*, Nagoya, pp. 462-469.