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Neural Network Breakout Prediction Model for Continuous Casting

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Abstract— Continuous casting is a process in which liquid steel is cooled in a bottomless mould into semi-finished steel products called billets, blooms or slabs depending on their cross section. In the process of continuous casting, two of the major problems encountered are cracks and breakouts. Breakouts usually result in temporary shutdown of the caster and huge amounts of downtime. Primary cracks which form before the solidifying strand exits the mould, are invariably linked to breakouts. Controlling primary cracks results in reduced chances of breakouts. This work aims at designing a breakout prediction neural network model. In this paper, a two-layer feed forward backpropagation neural network model is developed for predicting the existence of primary cracks that might lead to a breakout. The network obtains its inputs in form of temperature values from rows of thermocouples attached to the mould tube. Based on solidification characteristics of steel, the neural network is supplied with various inputs (of temperature values) and targets and is trained to predict the crack status in the mould. Training is performed using the Levernberg-Marquardt (trainlm) training algorithm, and the log sigmoid transfer function was used for both the hidden and output layer. The output from this neural network was a logical 1 (if a primary crack is present) and a logical 0 (if no primary crack is present). The neural network model is validated by simulating in MatLab/Simulink.

Index Terms— **continuous casting,** ***breakout prediction, neural network.***

I. INTRODUCTION

Continuous casting, or strand casting, is the process whereby molten metal is continuously solidified in a bottomless mould into a finished or semi-finished product. Presently, continuous casting is the most common way of producing steel in the world according to [1]. Nowadays, continuous casting process has been widely adopted in the production of semi-finished steel products worldwide, due to its inherent advantages of energy savings, enhanced productivity, higher yield, improved quality, and low cost [2]. Despite having the aforementioned advantages over the tradition ingot casting method, continuous casting is associated with its fair share of hazards. One of the greatest hazards that come with this process is the problem of breakouts. During strand withdrawal, the formed shell is still very thin and may fail to support the billet weight on exiting the mould. Typically the shell thickness should be about 16 – 20 mm for blooms and billets [3]. A breakout is a hazard whereby the thin shell of the strand breaks, allowing the still-molten metal inside the strand to spill out, thus necessitating an expensive machine shutdown. Hence the breakout has a profound influence on the caster availability, affecting the productivity and the cost of production [4]. Thus the aim of the paper is to highlight the development of a neural network breakout prediction model. The rest of the paper is set in the following order: Section II and III related literature, section IV model development while section V gives the output of the results followed by the conclusion.

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II. CAUSES OF BREAKOUTS

Several factors can be linked to the occurrence of breakouts. Breakouts are usually as a result one or a combination of factors described in the following sub-sections.

A. Inconsistent casting temperature

The higher the superheat of the liquid steel, the lower is the shell thickness formed. If the incoming metal is too hot (that is above the desirable or normal casting temperature), it means that final solidification takes place well below the straightening rolls and the strand breaks due to stresses applied during straightening. If the incoming metal is overheated, it is preferable to stop the caster than to risk a breakout.

B. Casting speed

The productivity of both processes is controlled by the casting speed, so higher speeds are always sought. However, the casting speed cannot be increased arbitrarily for several reasons stated by [5]. Often, breakout is due to a too high withdrawal rate, as the shell has not had the time to solidify to the required thickness. At higher casting speeds, mould lubrication becomes insufficient due to lack of mould flux flow from the meniscus into the shell/mould boundary. Increasing casting speed results in decrease of the total heat removal and higher friction at the mould/shell interface. The practical range of operating speeds depends on alloy composition and product geometry. For steel slabs, the casting speed increases with decreasing thickness from 0.01 ms^{-1} (for 300-mm blooms) to over 0.08 ms^{-1} (for 50-mm thin slabs) [5].

C. Improper lubrication between mould and strand

If mould powder gets entrapped in the molten steel below the meniscus, the result is improper lubrication between the mould and the strand. This leads to the sticking of the strand to the mould walls, posing difficulties in withdrawing the strand. Inadequate or uneven lubrication causes sticker breakouts [4].

D. *Ineffective water flow in the mould*

The difference in inlet and outlet water temperature, pressure and flow rate has a bearing on the mould cooling. The cooling water flow rate decreases if there is choking in the mould cooling system and this will result in low heat extraction form the strand, leading to a breakout.

E. *Improper mould geometry*

Continuous casting moulds are tapered so as to accommodate the shrinkage of steel on solidification [4]. This taper helps to increase and maintain the metal-mould contact area, thereby increasing the heat extraction from the mould. The higher the rate of heat extraction, the thicker is the shell of the strand on mould exit. If the taper provided does not match the requirements, an air gap is introduced between the mould and the metal shell. Since air has the highest resistance to heat in the mould heat transfer system, it greatly hampers the formation of the shell of required thickness eventually leading to a breakout.

F. *Dummy bar irregularities*

Once a shell of sufficient thickness is formed in the mould, the dummy bar is gradually withdrawn. Inappropriate withdrawal and loose packing of the dummy bar leads to molten metal flow out of the mould, resulting in a breakout. If the dummy bar separates from the strand prior to lifting of the dummy bar head, premature separation occurs which can lead to breakout occurrence.

III. PREDICTION OF BREAKOUTS

According to [6], when a primary crack (crack during primary solidification stage) occurs, the liquid steel touches the crystallizer's wall, causing an increase in its temperature. Therefore, the crack can be detected by means of several heat sensors mounted on the crystallizer's wall both on its width and on the direction of casting. Because primary cracks are almost invariably linked to breakouts, unusual temperature increases recorded by the heat sensors could mean an impending breakout.

A. *Neural networks in prediction problems*

One efficient way of solving complex problems is to "divide and conquer" [7]. A neural network is a mathematical (or computational) model that is inspired by the structure and function of biological neural networks in the brain [8]. In this neural network structure, a complex system is broken down to simpler elements in order to understand it. The interactions of nodes though the connections lead to a global (emergent) behaviour of the network, which cannot be observed in the elements of the network as shown in Figure 1. This means that the abilities of the network supersede the ones of its elements, making networks a very powerful tool [9].

The basic building block of every neural network is a simple mathematical model called the artificial neuron. Such a model has three simple sets of rules: multiplication, summation and activation [10].

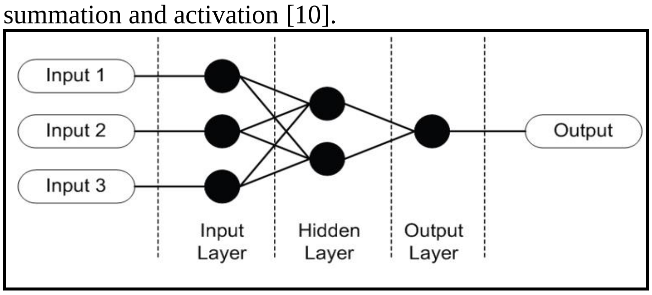

Figure 1 Basic neural network structure [10]

An activation function *f* performs a mathematical operation on the signal output. If the input signal is *m* and its weight *w*, and for a bias *b*, then the output signal *y* in response to this input is given by:

$$y = f(wm + b) \dots\dots\dots\dots Equation\ 1$$

B. *Types of neural network topologies*

There are several neural network topologies, amongst them feed forward, recurrent, Hopfield, Elman and Jordan, long term short memory, bi-directional, self-organising map (SOM), stochastic, and physical. For a feed forward neural network (FNN), the artificial neurons are set into layers. Signal propagation occurs from input to output layers, passing through the hidden layers of the FNN [7]. The guiding condition for FNN is that information must flow from input to output in only one direction with no back-loops. There are no limitation on the number of layers, type of transfer function used in individual artificial neuron or number of connections between individual artificial neurons [10].

IV. METHODOLOGY

The cracks that are directly linked to breakouts are primary cracks. Therefore this design is meant to predict primary cracks, that is, those cracks that form in the mould tube during primary solidification. The design of the predictive system is based on the dynamics of the temperature recorded by thermocouples attached to the sides of the mould tube at different points along the length of the mould tube.

A. *Breakout prevalence as a function of casting temperature and speed*

Casting temperatures vary according to the steel analysis or chemical composition of the steel being cast. Table 1 shows how changing the casting temperature affects the rate of breakout occurrence. For this measurement, the casting speed is at an optimal of 2.2 – 2.4 m/min. The relationship between casting temperature and breakout occurrence is directly proportional as can be seen from the audit in Table I.

Table I Casting temperature versus breakout rate

Temperature (°C)	Breakout rate (%)
1615	22
1580	12
1550	8
1530	3
1515	0

From the case study, it was observed that in the majority of cases, breakouts occur at high casting speeds. These results are shown in the Table II. It is clear that breakout rate is directly proportional to casting speed when moderate casting temperatures of 1535 – 1560°C are used.

Table II Casting speed versus breakout rate

Casting Speed (m/min)	1.8	2.2	2.4	3.2	4
Breakout Rate (%)	9	12	16	20	32

B. *Mould temperature profile measurement*

Thermocouples were used for measuring the temperature profile along the mould tubes. An unusual rise in temperature indicates that a primary crack is about to form, or has already formed.

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This is so because when the surface of the solidifying strand cracks, the still molten steel is exposed and gets in direct contact with the mould. This results in the thermocouple recording an abnormally higher temperature. The observed temperature profile is presented in Table III.

Table III Typical temperature variation along mould tube

Distance from meniscus (mm)	**Typical temperature range (ºC)**
150 (Thermo1)	1350 – 1400
350 (Thermo2)	1300 – 1350
550 (Thermo3)	1240 – 1300
750 (Thermo4)	1200 – 1240

C. Generation of training data

Four sequences of input/output are considered. Each sequence is made up of temperature values (together with their weights). For each sequence there must be an output (0 or 1) to show presence or absence of a primary crack. The normal temperature for different thermocouple positions is based on the experimental measurements recorded in Table 3. This is the profile for which no cracks are detected.

Based on various temperature values sampled, and using *Equation 1* we have:

$$f(Thermo4 * w_1 + Thermo3 * w_2 + Thermo2 * w_3 + Thermo1 * w_4) = y$$

In this case y (the output) assumes a logical 0 and 1 for presence and absence of crack respectively. Since the transfer function being used is log sigmoid, the training sequence can be presented as follows:

$$logsig(1400w_1 + 1350w_2 + 1300w_3 + 1240w_4) = 1$$
$$logsig(1350w_1 + 1300w_2 + 1240w_3 + 1200w_4) = 0$$
$$logsig(1356w_1 + 1308w_2 + 1249w_3 + 1215w_4) = 0$$
$$logsig(1389w_1 + 1342w_2 + 1244w_3 + 1220w_4) = 1$$

The unweighted training data obtained from the above data is presented to the network manager as the “inputs”. The weights are the generated by the network depending on each output target required. Both the training input and target data are presented as matrices.

(i) Training input data matrix
[1400 1350 1300 1240; 1350 1300 1240 1200; 1356 1308 1249 1215; 1389 1342 1244 1220]

(ii) Training target data matrix
[1 0 0 1]

The weights are initialised before training the network. Depending with the error between actual outputs and targeted outputs, these weights can be re-initialised until satisfactory results have been reached (that is when regression R = 1).

Depending on the performance of the model, more testing data can be provided and the network can be retrained. Initially four samples of each of the inputs were supplied but performance of the network was unsatisfactory. The final matrices used for training are given below.

Input matrix

[1200 1213 1236 1240 1217 1231 1206 1229;
1240 1256 1273 1300 1245 1273 1249 1288;
1300 1307 1324 1350 1311 1341 1313 1343;
1350 1361 1396 1400 1359 1391 1360 1397]

Output matrix

[0 0 1 1 0 1 0 1]

D. Training parameters

The training method used is the Levenberg-Marquardt (trainlm) with the mean square error performance function. The Levenberg-Marquardt method is adopted because it is the fastest training method. The network accepts four inputs (temperature), and a total of four neurons make up the input layer. The hidden layer is increased or reduced in the iterative training process. However, after iterating, 20 neurons were used for the hidden layer. The transfer function is the log-sigmoid because of its ability to accept large positive or negative inputs and squash them to between 0 and 1. The summary of the training parameters are:

Network type: Feed-forward backpropagation
Training function: Trainlm (Levenberg-Marquardt)
Adaptation function: LEARNGDM
Performance function: MSE (Mean-square error)
Transfer function: LOGSIG

The general predictive neural network model with 4 inputs, 20 hidden neurons and one neuron in the output layer is shown in Figure 2.

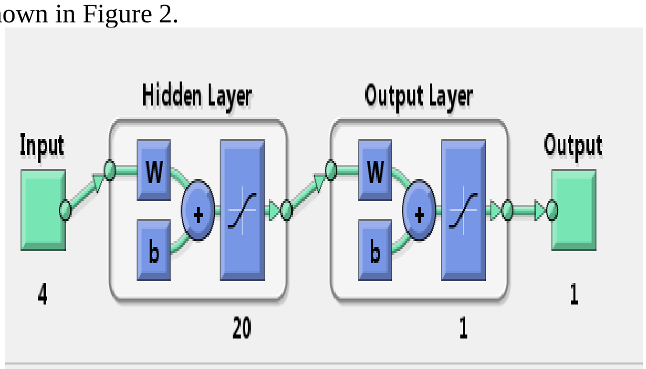

Figure 2 Neural network model architecture

E. Using the neural network

In order to use the network, a Simulink model of the predictive neural network is developed using the pattern recognition tool and is shown in Figure 3. The model can be given different inputs and should be able to predict presence or absence of primary cracks. The input labelled Thermoseq is the sequence of temperature values that have been measured by the thermocouples.

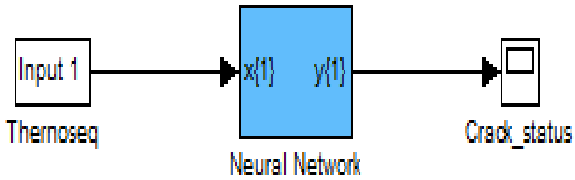

Figure 3 Simulink model of the predictive neural network

V. RESULTS

The input vector of the neural network model can be changed in Simulink. The different vectors that can be input should show crack status based on the training the network was exposed to. The first set of simulation results presented was based on the following inputs: 1240ºC (Thermo4), 1300ºC (Thermo3), 1350ºC (Thermo2) and 1400ºC (Thermo1). This sequence of inputs represents the extreme high values of temperature for each of the thermocouples. The temperature profile decreases as the strand moves down the mould tube, that is, from Thermo1 up to Thermo4. As shown in Figure, when there is a primary crack, the output is 1.

The second sequence of inputs used for the simulation was the extreme low values of temperature for the thermocouple positions.

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These inputs are 1200ºC (Thermo4), 1240ºC (Thermo3), 1300ºC (Thermo2), 1350ºC (Thermo1). These results, illustrated in Figure 5, show an output of 0 (no primary crack present). It is also possible to use input vectors that are in between the temperature range and these will give either a 1 or a 0 output.

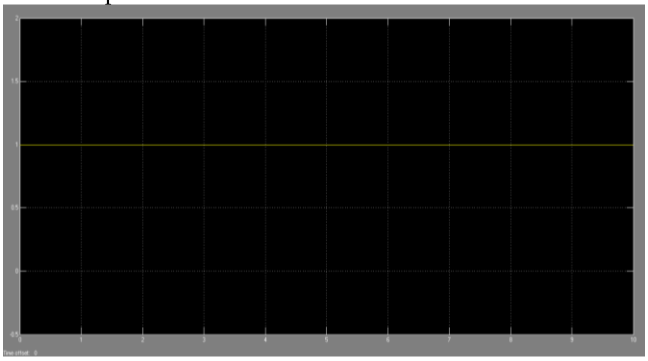

Figure 4 Model behaviour in case of a crack (1)

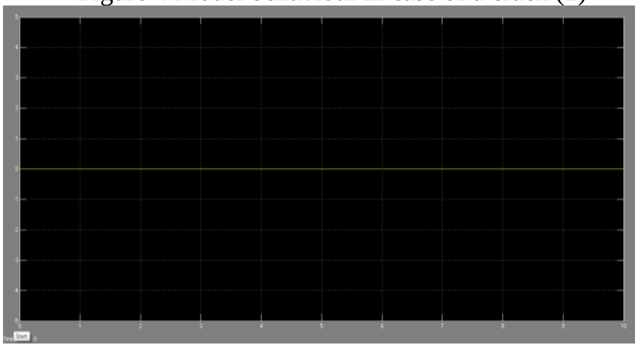

Figure 5 Model behaviour in case of no crack (0)

VI. RECOMMENDATIONS

In order to ensure safe caster operation with minimum downtime due to breakouts, the following practices should be adhered to:

- Good caster practices that include consistent use of mould powder and general mechanical equipment maintenance and operation should be adhered to at all times. Dummy bars should be cleaned thoroughly after each heat so that breakout problems linked to them can be eliminated.
- Cooling water quality should not be compromised as doing so can lead to blockage of spray cooling pipe nozzles. When this happens, the cooling efficiency in both the primary and secondary zones is compromised, leading to possible breakouts.
- Good teeming practices (that is adhering to correct teeming speeds) lead to reduced turbulence in the tundish and consequently less likelihood of non-metallic inclusions. The probability of crack formation due to non-metallic inclusions is therefore reduced. As a result, breakouts directly linked to primary cracks can also be eliminated.

VII. CONCLUSION

The predictive neural network was developed from a set of temperature values along the mould profile. The output is either 1 or 0 (crack present and crack absent respectively). The neural network was trained with the trainlm function using the backpropagation algorithm. Simulation in MatLab/Simulink was done to show how the model predicts (cracks and) breakouts. For the continuous casting of steel, the developed neural predictive network comes in handy as a safety measure to help operators be alert and evacuate areas of risk. The use of the neural network results in a safe working environment.

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