Quality prediction in continuous casting of stainless steel slabs

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Synopsis

Surface defects on continuously cast slabs require treatment by grinding. This extra phase in the process causes lower throughput of final product and extra energy costs. The elimination of slab treatment after casting implies that slabs can be direct rolled or hot charged, resulting in higher throughput and lower energy costs. To increase the number of slabs that can be direct rolled or hot charged, defects have to be predicted before a slab has completed the casting process. Transversal and longitudinal cracking, casting powder entrapment and other inclusions, bleeders, deep and uneven oscillation marks, stopmarks and depressions are the defects that are considered for prediction.

A structure with two models is proposed. The first model describes the effect of mould level, water inlet temperature and casting speed (MV—manipulated variables) on 38 thermocouple temperatures (IV—intermediate variable). Casting speed is a manipulated variable while mould level and water inlet temperature are treated as measured disturbances. This model is known as the MV to IV model, and is used to control the occurrence of defects.

The second model describes the effect of the thermocouple temperatures on the defects at different positions and locations on the slabs (OV—output variables). This model is known as the IV to OV model and is the predictor of defects. The models are determined using time-series methods in the form of auto regression with exogenous input using data of approximately 500 slabs cast over a period of 6 months.

The models are validated using plant data from 44 slabs gathered three years later, with good results. As an example, published results give a sensitivity and specificity of 61.5 per cent and 75 per cent respectively for longitudinal cracks on validation data, while the presented method gives 63.6 per cent and 93.5 per cent, respectively. The IV to OV model is used in an inversion to determine the optimal thermocouple temperatures for each slab width.

Keywords: Continuous casting, model, defect, prediction, direct rolling, hot charging, goodness-of-fit, correlation, time-series, soft sensor, ARX.

Introduction

The continuous casting of steel slabs is an established technology to solidify molten steel. Surface defects form during the continuous casting process. As a consequence of these defects, an intermediate grinding stage between casting and hot-rolling is needed to remove these defects. This causes large delays before slabs can be rolled, implying reduced throughput. These delays also mean that energy costs are increased because grinding cannot take place at the elevated temperatures of a cast slab; and hot-rolling must occur at an elevated temperature. The slab must therefore be cooled, ground and reheated. These defects also make technologies such as direct rolling and hot charging infeasible, since the defects have a detrimental effect on post-casting operations.

The problem addressed in this work is to determine a model to relate mould variables to surface defects[1]. This model can be used as a predictor to determine when defects will occur, thus making scheduling for direct rolling or hot charging[2,3] of some slabs possible. Only defected slabs are then sent for treatment.

Many researchers have attempted to improve the surface quality of the cast product by Computer Aided Quality Control (CAQC) methods[4–8]. In these methods, some form of non-human surface defect measurement is employed and used to 'train' a database linking mould and secondary cooling zone conditions to the different defects. The database can then be used in conjunction with continuous casting process measurements to 1) predict the quality of the cast product, 2) determine whether the slab can be hot charged or direct rolled, 3) update the database in cases where new defects or steel types occur, and 4) apply control to eradicate the occurrence of defects.

The defect detection databases are usually in-house, and literature on the matter is very limited (see e.g. Hatanaka et al.[9], Hunter et al.[10] and Creese et al.[7]); with most discussions covering only a fraction of the procedures (see e.g. Matsuzuka et al.[11]).

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Some steel-making companies report hot charging of 30 per cent of their slabs without any conditioning[12] while other companies report direct rolling and hot charging of up to 80 per cent of their cast slabs[13,14] and blooms[15] without any conditioning. Some companies even implement direct rolling when the caster is far from the hot-rolling mill[16]. In general, hot charging is more successful in billets than in slabs[17,18].

If defects can be predicted with high accuracy, more slabs can be sent for hot charging directly after casting. Those slabs that do have defects will be sent for grinding, making the scheduling task easier.

To be able to predict when defects are going to occur, a model must be found that relates mould parameters to the defects. The aim of this work is therefore to determine such a model.

The specific defects considered are transversal and longitudinal cracks, inclusions, oscillation marks, stopmarks, bleeders, and depressions, as these are the foremost defects that occur. The occurrence of these defects are the outputs of the model. The inputs of the model are the casting parameters. Since it has been found that the above defects originate in the mould, only mould parameters are considered as inputs. Pre- and post-mould processes are assumed to compound any defects that may occur, and thus act as disturbances.

Since first-principle models presented in the literature are usually 1) vague in terms of effectiveness or accuracy, 2) do not clearly show that they work, 3) have no relation to mould variables so that prediction cannot be performed based on mould variables, and 4) are complicated, a system identification approach to modelling was used. Artificial intelligence (AI) techniques such as artificial neural networks (ANN) have previously been used to predict defects[10], and are not considered in this work as a modelling tool, except to compare published results and results of this work.

The approach followed in this work is to find a model describing the effect of mould variables (inputs) on the formation of defects (outputs) using data from a continuous caster of a South African steel manufacturer. The mould variables are obtained from the level 2 system of the continuous caster, and the defects are obtained by plant personnel inspecting the slabs off-line. The defect data are entered into a computer for analysis and model training. A reduction of the number of mould variables (inputs) is carried out using statistical hypothesis testing and correlation analysis and compared to causes of defects described in literature.

From this data, it also becomes clear that the mould/defect data can be split into two models, one describing the effect of casting speed, mould level and inlet temperature on thermocouple temperatures and another describing the effect of thermocouple temperatures on defects. The outcome of the model split is that the continuous measurement of thermocouples makes it possible to apply feedback control. The thermocouple temperature set-points are then determined such that no defects will occur due to mould temperature. The model is derived and validated using ARX (auto regressive with exogenous input) methods together with plant data.

Continuous casting process

The description of the continuous casting process is done for a bow-type continuous caster (see Figure 1) since it is the most predominant caster found in practice. Each critical component of the caster is described[19].

Molten steel arrives at the continuous casting machine in a container known as the ladle. In steel casters, the ladle contains from 70–300 tons of molten steel at between 1500 and 1600ºC[19]. The ladle is then placed on one end of a rotating platform known as the turntable. The turntable can accommodate at least two ladles simultaneously. When all the steel from one ladle is cast, the turntable swings around and casting proceeds from the second ladle. This method of ladle switching ensures that steel is usually available for casting. The turntable method is the most widely used mechanism to switch ladles. At the bottom of the ladle there is usually a slide-gate mechanism that controls the rate of flow of molten steel into another container known as the tundish.

The tundish acts as a reservoir of molten steel. The reason that liquid metal is not poured directly into the mould from the ladle is three-fold. Firstly, if a ladle is not available for casting, continuity is not assured. Secondly, the tundish is designed to accommodate complex mechanisms to control the flow of steel into the mould. Thirdly, the tundish can be designed to provide liquid steel to several moulds as is the case with multi-strand casters.

At the bottom of the tundish there are mechanisms to allow the flow of steel into the mould (see e.g. Hill and Wilson[20] for a discussion on the importance of the design of the mould inflow). The mould is usually a water cooled copper sheath (Figure 2).

The level of molten steel in the mould is known as the meniscus and is measured by either a radiometric device or an eddy current device. As the liquid steel moves down the mould at the casting speed, it forms a shell that is strong
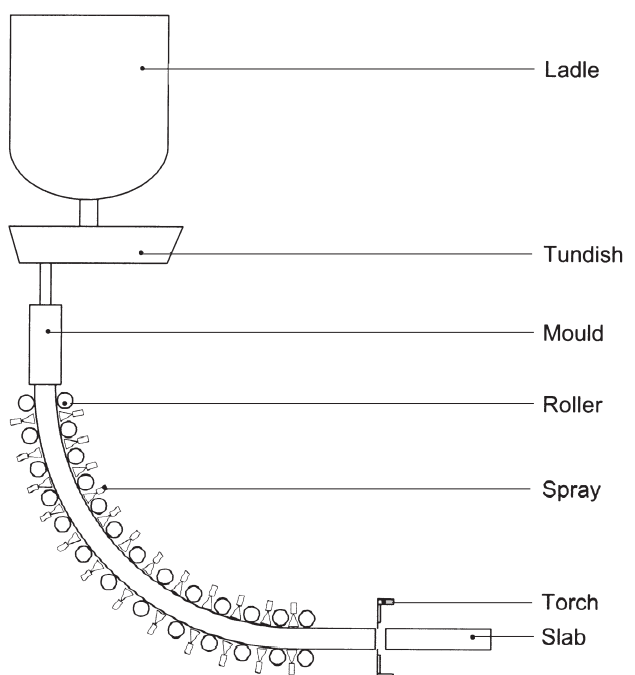

Figure 1—Side view of a bow-type continuous caster

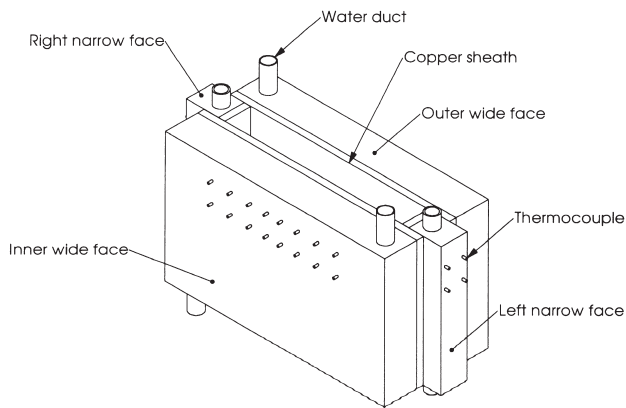# Quality prediction in continuous casting of stainless steel slabs

Figure 2—Isometric view of a continuous caster mould

enough to withstand the ferro-static pressure of the liquid steel within the strand. The mould is typically about one metre long. To ensure lubrication of the solidified shell within the mould, mould powders or oil are added at the top of the mould[21]. These additives form a thin crystalline layer as well as a liquid layer between the steel and the copper plate (sheath) to reduce friction. The fluxes also provide insulation from the atmosphere at the top of the mould to prevent oxidation. Thermocouples are sometimes inserted in the mould to measure temperature gradients from the top to the bottom of the mould (see Figure 3).

Should the temperature gradient be too large, a break-out may occur. The thermocouples act as a break-out detector, warning the operator of possible break-outs. The mould oscillates to aid in the extraction of the solidified strand (see Burgess *et al.*[22]). The mould width is adjustable by moving the narrow sides in or out. Typical widths for slab casters are 1000 mm, 1280 mm and 1575 mm.

On exit from the mould, the strand enters the secondary cooling zone, which ranges in length from 6 to 20 metres. In the secondary cooling zone, rollers support the strand and aid in bending and straightening in the case of bow type casters. Water sprays extract the heat from the strand. These

sprays are grouped in three to six spray zones. Water flow in each spray zone is independently controlled by valves.

On exiting from the secondary cooling zone (SCZ), the strand moves into the radiation zone where the strand cools off naturally. Once the entire cross-section (transversal slice) is below the solidus temperature, the strand is cut and transported to a finishing process such as grinding, rolling, punching etc. The length of the strand from the meniscus to the point where the transversal slice is below solidus temperature, is known as the metallurgical length.

Literature overview

Casting defects

There are several defects that occur when continuous casting is applied. Any defects in a solidifying strand are primarily caused by the mould[23]. The secondary cooling zone can only compound the defect, not eradicate it.

The primary control problem in continuous casting is the level of steel in the mould. The level of steel in the mould should remain as constant as possible. The mould level control problem is the main problem that is addressed by control system researchers in the field of continuous casting (see e.g. De Keyser[24]). Mould level oscillations tend to cause depressed regions filled with solidified mould powders, resulting in surface defects. Until now, researchers have not been able to agree on the causes of mould level oscillation, though many theories exist[25].

Some of the metallurgical and mechanical problems that arise in continuous casting are summarized by Brimacombe and Samarasekera[26]:

➤ Cleanliness of the steel can be affected e.g. there can be
   • oxidation of steel with oxygen from air or refractories,
   • pickup of exogenous inclusions from ladle and tundish refractories and mould powders,
   • poor control of fluid flow in the tundish so that inclusions do not float out,
   • poor mould powder and startup/shutdown procedures, causing break-outs.
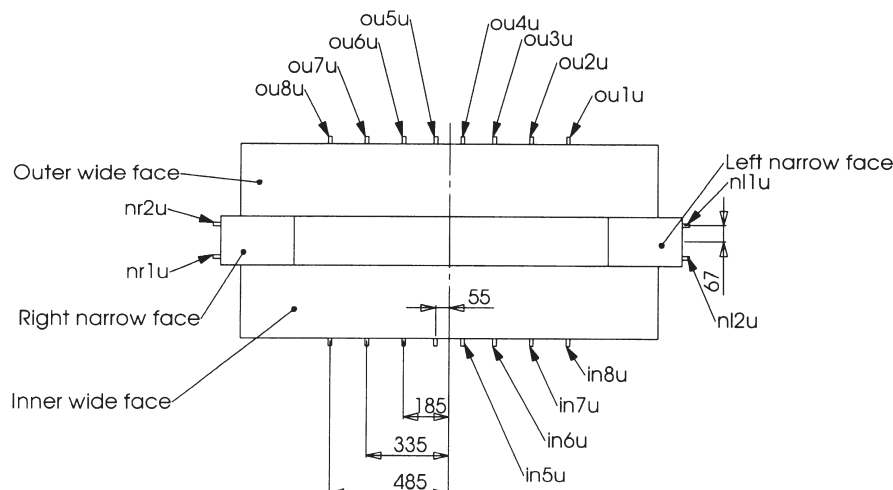

Figure 3—Top view of the mould depicting location and naming conventions of the thermocouples. Note that in this view, the thermocouples shown are the top row of thermocouples. The thermocouples in the bottom row have names 'ou8*l*', 'nr1*l*', etc.

➤ Cracks occurring in, or on the steel such as
  • surface cracks, which are a serious quality problem because the cracks oxidize and give rise to oxide-rich seams in the rolled product or, to an even greater extent, cause the strand to be scrapped due to extremely deep longitudinal cracks, and
  • internal cracks, which can also be a problem, particularly if during rolling they do not close, leaving voids in the steel product.

➤ As the strand moves from one cooling zone to the next, changes in heat extraction cause 1) shifts in thermal gradients through the solidifying shell and 2) stress generation resulting from differential expansion or contraction.

➤ Macro-segregation. There are higher concentrations of certain elements in certain regions of the strand, possibly causing cracks during rolling.

➤ Cross-sectional or transverse shape. Deviations from the specified shape due to non-homogeneous cooling in the mould require excessive reworking.

Defect summary

Table I shows a summary of the general causes of defects based on the literature found about the subject.

It is interesting to note that most authors do not explicitly link mould level to defects, with only longitudinal cracking and inclusions being explicitly mentioned. Contrary to this, researchers address the mould level control problem as the most important single factor that contributes to surface defects.

However, every considered defect is linked by the literature to some variable in the mould. The mould is therefore quintessential in the formation of defects.

Another important point to note from the table is that strand temperature plays a role in all the defects except inclusions and stopmarks. This suggests that temperature is a very valuable variable to use in any type of defect predictor.

Mould powder and mould friction are very closely related and are difficult to measure on-line, as is the taper of the mould[27].

Composition is a factor that does not change dynamically during casting. However, the composition of some steels is a factor that is influential in the formation of certain defects.

Measurement of inclusion outflow in the tundish is also difficult to quantify on-line and superheat is generally not measured at regular intervals (see e.g. Ozgu[27]).

Data

This section describes the mould variable data and defect data. The data were gathered at a South African steel manufacturer over a period of six months from May to September, 1999. A validation set of data was gathered in June, 2002. The data can be categorized by the inputs, which are the mould variables such as casting speed, thermocouple temperatures etc. and the outputs, which are defect data such as transversal cracks, inclusions, depressions etc.

These data are required to derive a model to predict the occurrence of defects based on variation of parameters in the mould.

Mould variable data

There are numerous variables (see e.g. Fisher and Mesic[28] for a description of the database structures at a continuous casting plant) that are measured within the mould. The data are gathered on the level 1 system (PLCs etc.), and stored on the level 2 system (database, SCADA etc.). Altogether 800 slabs were inspected for defects over the 6 month period, but data for only about 500 slabs were available for processing due to errors in the data gathering system, which was caused by down-time or maintenance of the system. This is a small percentage of actual cast product because slab inspection of every slab that was cast was not possible because of man-power constraints. About 3.3 GB of mould variable data were collected.

Defect data

Defect measurement

The cost of an automatic electronic defect measurement system is extremely high, and hence they are very rarely found in practice (see e.g. Mayos et al.[29], Knox[30] and Foster[31]). Therefore, another method to gather defect data from cast slabs has to be found. For this a Human

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Table I

Summary of causes of defect occurrence based on literature. A • indicates that the variable in question has an influence on the defect. Bold variables can be measured. The parenthesized texts indicate the numbering scheme that was used to identify each defect

	Transversal cracking (1a)	Longitudinal cracking (1b)	Inclusions (2a and 2b)	Bleeders (4)	Oscillation marks (5a and 5b)	Stopmarks (6)	Depressions (8)
Mould level		•	•				
Mould powder	•	•	•		•		•
Mould friction	•						
Mould taper	•	•					•
Mould oscillation	•	•	•		•		
Casting speed	•	•	•		•	•	
Temperature	•	•		•	•		•
Composition	•	•					•
Tundish		•			•		
Superheat				•			
Bending	•						

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Measurement System (HMS) was used (see Hague and Parlington[32] for a similar idea). Three grinding plant operators with many years of experience on defects were instructed to investigate the slabs for defects during their (separate) shifts. (The operators inspect the slabs and mark defects that have to be ground as part of the grinding process.) The idea is simple. Human operators use a schematic representation of the slabs (slab inspection report, see Figure 4) to indicate positions where specific defects occur. In the example of Figure 4, an inclusion occurred 3 metres from the top of the slab on the left portion of the slab with medium (m) severity. After grinding, the defect was still present, but now only had a severity of 'very slight'. A longitudinal crack also formed on the bottom part of the slab at the centre location. The defect severity was bad (b). After grinding the defect was removed.

They also award—based on their experience—a fuzzy value of the severity of the defect (see e.g. Brockhoff *et al.*[33] for an index describing the severity of some defects). These fuzzy values are termed as follows.

➤ None i.e. no defect occurred
➤ Very slight i.e. the defect is very slight in the opinion of the operator
➤ Slight
➤ Medium i.e. the defect is considered to be a standard severity of the occurring defect
➤ Bad
➤ Very bad.
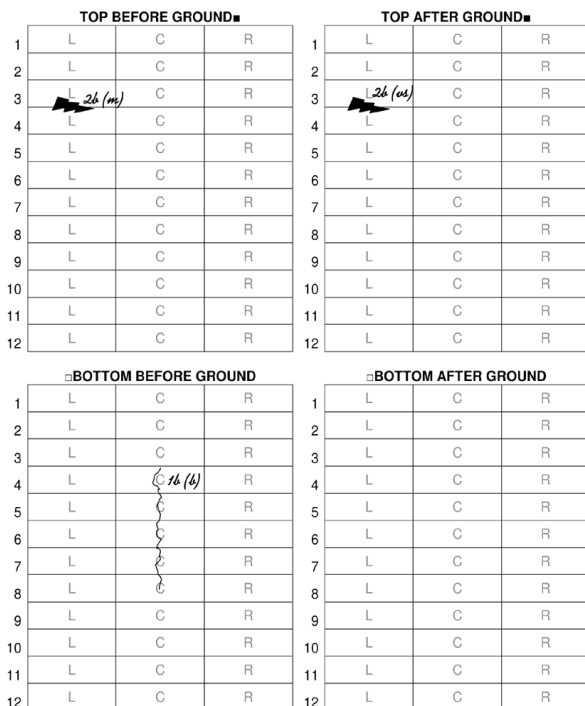
The date, slab number, grade (type), width, and length are also indicated on the slab inspection report. Each slab inspection report has four slab faces depicted on it. They are for slabs that are inspected before grinding and after grinding (with about 3 mm taken off) and for the top and the bottom of the slab.

Each slab on the slab inspection report is divided (in length) into one metre intervals. This means that the average distance within which the operator would be able to precisely indicate a defect would be 1/2 metre because the operator can indicate a defect on the separating line or on the space between two separating lines. Each slab depiction is further divided into three segments along the transversal axis, i.e. a left side, right side, and the centre. This further restricts the area within which the operator can indicate the defect.

Once all the slab inspection reports had been gathered, the data had to be converted into electronic format for manipulation on a personal computer.

Defuzzyfication

The data are then accordingly read into a file for computer use. Since the slab was divided into 1/2 m segments, the defect files are said to be sampled at 1/2 intervals. The fuzzy levels of severity of each defect are then quantified into discrete numerical values, and this was done as follows.

➤ None: 0
➤ Very slight: 1
➤ Slight: 2
➤ Medium: 3
➤ Bad: 4.
➤ Very bad: 5.

Measurement problems

There are several problems associated with this method of defect measurement. Firstly, there may be noise on the measurements because the value systems of the different operators were different i.e. a very slight defect may be considered to be a slight defect by one operator and a medium defect by another. Secondly, the data are not necessarily ordinal, i.e. the distance between 1 and 2 is not necessarily the same as the distance between 2 and 3. This is a consequence of the value system of the different instruments (humans) in the HMS. The third problem is that the defect may not be seen by the operator, and the fourth problem is that the defects are only measured several hours after they actually occurred, because the slab must cool down substantially before grinding can take place and before the operator can inspect the slab. Lastly, not all slabs can be inspected.

With this new data in hand, the variables were investigated and models were trained to predict the occurrence of defects.

Statistical analysis

This section describes the use of statistical analysis to determine which inputs affect the defects and which input variables are closely correlated.

Statistical tests

The use of statistical methods, to determine the influence of input variables on output variables, are useful when many

Figure 4—Slab inspection report (SIR)

different input variables exist. The main idea is to determine whether there are *significant* differences between the inputs of slabs that exhibit a particular defect and those which do not exhibit the particular defect. This is done in terms of the mean and variance of the inputs of the system. Higher order moments can also be used, but were unnecessary for this system. The reasoning behind this is that a change of input variables from the regular mean value indicates a change in the equilibrium of the system. Generally, all variables should remain constant for steady-state operation (see e.g. Pinger[34]).

By examining the means of a specific input variable of all the slabs which do not have a particular defect contained on the slab (good slabs), and comparing these distributions of means with the distributions of means on slabs what do contain the specific defect (bad slabs), some conclusions can be drawn about the effect of a specific variable on the defect. The same reasoning follows for the variances/standard deviations. This is useful to indicate which variables change when defects occur.

Figure 5 shows the concept of means and variances of good slabs versus means and variances of bad slabs for any particular input variable.

In this case, many good slabs are used to form the theoretical distribution of a particular variable. Few data exist for the bad slabs (3 in Figure 5). From the histogram of the bad slabs, it is clear that the observations for both means and variances fall within the distributions of good slabs. This implies that the mean and variance for the particular mould variable are not unique when defects occur.

Kolmogorov-Smirnov and Anderson-Darling tests[35] were performed for each defect and the corresponding input variables.

The means and variances for the good slabs were taken as the 'theoretical' distribution, since more than enough data were available to define the cumulative density function of the variable. The means and variances of the bad slabs were taken as the 'empirical' distribution since not many defects were present for all types of defects. The standard deviations were corrected by a factor $\sqrt{n}$, according to the central limit theorem to account for the small size of the standard deviation sample for bad slabs[35].

Summarized result

Thermocouple temperatures play an important role in the detection or control of casting defects, since their means and variances are considerably different for bad slabs compared to good slabs. All nine defects continually show that there are differences between good and bad slabs. Casting speed seems to differ from the good slabs only in three cases using the Kolmogorov-Smirnov test and in 5 cases using the Anderson-Darling test. The mould controller status, which describes whether a mould controller was used during operation, is influential only for bleeders using the Kolmogorov-Smirnov test; but is influential in all defects, except transversal cracks, using the Anderson-Darling test.

Water inlet temperature is influential in three defects, and the water flow rates have an influence in 5 defects using the Kolmogorov-Smirnov test and 4 defects using the Anderson-Darling tests. The temperature differences are influential in 4 defects, and the oscillation frequency varies between 4 and 5 defects for the respective tests.

Drive current affects 3 and 4 defects respectively for the tests, and the heat fluxes influence 4 of the defects. The longitudinal temperature differences affect all defects except longitudinal cracks, as tested by the Kolmogorov-Smirnov test.

The results indicate that thermocouples are heavily influential in the detection or control of the defects, with some other variables, such as casting speed, oscillation frequency, flow rates, temperature differences, drive currents and heat fluxes, not far behind.

Correlation

This section describes the use of correlation theory to determine whether there is linear dependence between variables so that some variables can be dropped from possible modelling strategies.

The following important observations are made based on the correlation table:

➤ The correlation parameter between casting speed and oscillation frequency is one. This indicates that oscillation frequency is linearly dependent on casting speed. This relationship is commonly found in practice[36]. Because of this, oscillation frequency does not provide additional information and can be excluded from the model.
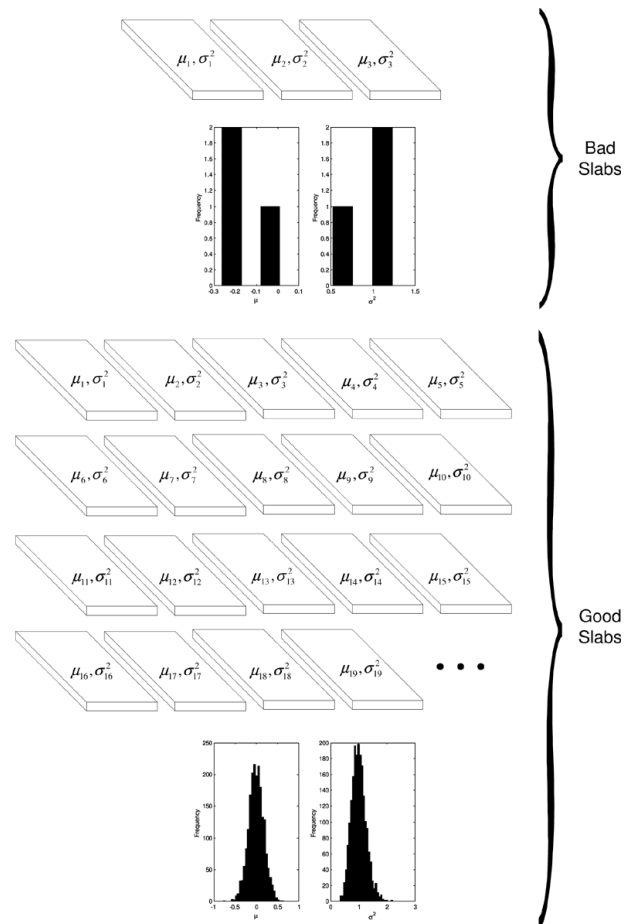

Figure 5—Depiction of the distributions of means and variances of bad slabs versus distributions of means and variances of good slabs for a specific input variable

➤ As expected for a constant water flow-rate, the heat fluxes in the four mould walls are perfectly positively correlated with the average temperature differences in the four walls of the mould. This implies that the heat fluxes can be excluded from the model.

➤ The thermocouple temperatures, in turn, have medium ($0.5 < \rho \le 0.75$) to strong ($0.75 < \rho \le 1$) correlation to the average temperature differences, which indicates that the temperature differences are also computed from thermocouple temperatures. This was also validated with plant personnel* and thus the temperature differences should also be excluded from the model.

➤ The temperature differences between the top and bottom thermocouple rows also correlate well with the thermocouple temperatures**. Therefore they should also be ignored.

➤ The drive current is not related to the mould section of the system and can also therefore be neglected from a model. This is underlined by the fact that correlation with other input variables is weak.

➤ The water flow rates are weakly correlated ($0 < \rho \le 0.25$) with all other input variables. This is probably because the flow rates are usually maintained at a constant maximum value (maximum change of about 1.5 per cent) implying that they have no effect on the output. The flow rates should therefore also be dropped from the model.

➤ The water inlet temperature has a weak to medium correlation with the thermocouple temperatures. It is also very weakly correlated with casting speed. The inlet temperature has a medium correlation to mould level, which is probably due to the stochastic nature of mould level.

➤ Mould level is weakly correlated with the thermocouple temperatures. There exists a medium correlation between casting speed and mould level. This could also be due to the stochastic nature of mould level or because there may be some output feedback, i.e. as the speed increases, the mould level should drop momentarily. Note, however, that mould level is controlled at this plant with a slide gate. The effect of mould level may not be linear on other variables, but may have some non-linear effect or a delay may be present. Since it is considered to be an important variable to control, mould level will not be excluded from any model.

➤ Mould controller on/off status only takes on values of zero or one and can therefore not be included in the linear model.

➤ Casting speed has medium to strong correlation with the thermocouple temperatures and should therefore be included in the model as a manipulated variable.

Model separation

Based on the above correlations, and the results of the previous section, the following conclusions can be drawn about the model structure. Due to the strong variation when defects occur compared to the case when defects do not occur, (as indicated by the goodness-of-fit-tests), the thermocouple temperatures are influential (and/or carry much information) in the detection of defects. Note, however, that this does not imply that mould temperature is necessarily a cause of all the defects. The mould temperature may be influential in the formation of some defects, as the literature shows, but the formation of the defects can be detected from temperature readings.

The strong correlation of casting speed with temperature gives an indication that casting speed can be used as a manipulated variable to control temperature (see Langer and Moll[37], Lally et al.[38] and Lally et al.[39] for optimal steady casting speed design to improve quality). This is also intuitive because a basic energy, mass and momentum balance of the system given by $\frac{\partial H}{\partial t} + v \frac{\partial H}{\partial z} + \rho v \frac{\partial v}{\partial t} = \nabla \cdot K \nabla T$ shows that an increase in casting speed must be balanced by an increase in temperature[40].

Lastly, measured disturbances that have an impact on the mould temperature are inlet temperature and mould level. These are the only variables that were not excluded as a result of the correlation tests. These will then be used as measured disturbances because they should remain constant and can therefore not be controlled. All other variables are left out because they are either non-influential on the defects or they are strongly correlated to the thermocouple temperatures.

It is proposed that the model structure be broken down into two sub-models[41]. The first sub-model is called the manipulated variable (MV) to intermediate variable (IV) model, and the second sub-model is called the intermediate variable (IV) to output variable (OV) model. The (only) MV is casting speed and the IVs are the thermocouple temperatures. The OVs are defects. The structure is depicted in Figure 6.

The measured disturbances in the MV to IV model are mould level and inlet temperature, and the unmeasured disturbances are, amongst others, superheat, mould powder addition and flow-rate of steel into the mould etc.

Inlet (water) temperature was chosen to form part of the MV to IV model because a change in the inlet temperature has a direct effect on the thermocouple temperatures, as the correlation showed. However, the variable could also have been made part of the IV to OV model, if desired, but this would be unwise since the variable has an influence on the thermocouple temperatures, and repetition of information could result. The mould level forms part of the MV to IV model because it is also already a controlled variable. Placing it in as part of the IV to OV model defeats the purpose because the inputs to the IV to OV model must ideally be changeable, and change in the mould level set-point is usually undesired.

The usefulness of this separation of the model into two sub-models is that the delay that occurs before the defects are measured is outside the feedback control loop. The IV to OV model can be used to find an optimal set-point for the

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*The dependence is not necessarily linear

**these were in fact computed by the author from the thermocouple temperatures with the top row values delayed by the same amount of time as it would take a narrow strip of steel to move from the top row to the bottom row. The correlation with the top row was always strong

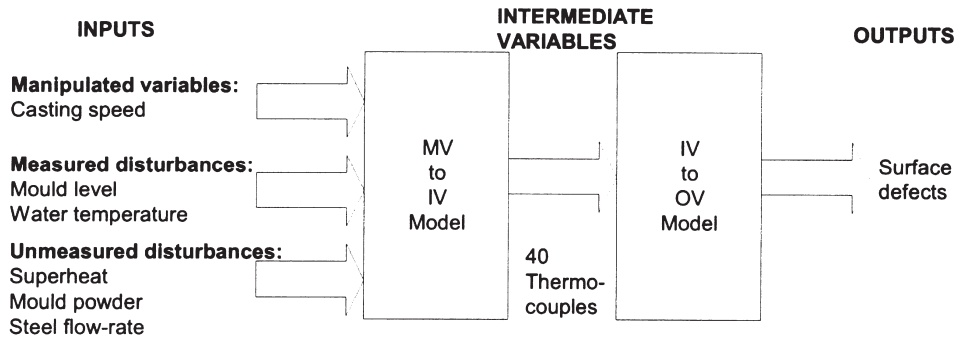# Quality prediction in continuous casting of stainless steel slabs

Figure 6—Separation of system into two models, manipulated variable to intermediate variable and intermediate variable to output variable
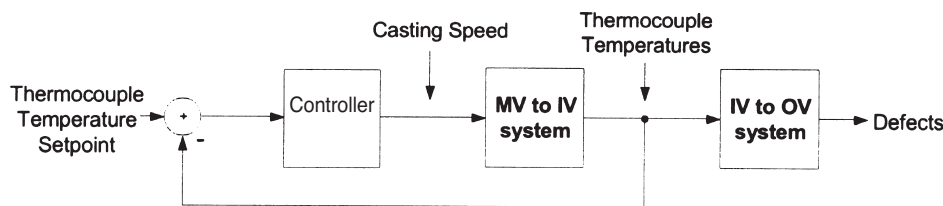

Figure 7—Block diagram description of the separation for control systems purposes

temperatures and the MV to IV model can be used to design a controller to follow the temperature set-points so that the effect that temperature variation has on the formation of defects is negated. A block diagram of the structure for control is given in Figure 7.

The temperatures are measured instantaneously, thus eliminating the delay caused by measuring the defects. The temperature measurements are fed back and casting speed is used as the input to control the desired temperature set-point. The IV to MV model is used to infer the occurrence of defects. The next two sections describe the derivation of the MV to IV and IV to OV models.

Intermediate variables to output variables (IVOV) model

The IV to OV model has two purposes. The first is to predict when a defect will occur, and the second is that it can be used to determine ideal temperature set-points so that no defects will occur. These temperature set-points can then be used to design a controller using the MV to IV model. The ARX system identification procedure was used[42,43].

Derivation of the IVOV model

IVOV model set-up

For the IV to OV model, 38 inputs (thermocouple temper-atures) and 108 defect outputs are available. The 108 defects are grouped as follows: 9 defects × 2 (top or bottom) × 3 (left, right or centre) × 2 (before or after grinding) = 108. This grouping was necessary because the defects roughly correspond to the location of the thermocouples. Therefore m = 38 (number of inputs) and p = 108 (number of outputs).

Figure 8 depicts a block diagram of the IV to OV model.

$y(t) \in \Re^{38}$ are the thermocouple temperatures as inputs and $p(t) \in \Re^{108}$ are the defects as outputs. The disturbances may include the spray pattern in the secondary cooling (see e.g. Barozzi et al.[44]), the bulging effect of the rollers on the strand *etc*. $G(t) \in \Re^{108 \times 38}$ is the transfer of the inputs (thermo-couple temperatures) to the outputs (defects) in $p(t) = G(t) * y(t)$.

Though 108 defects can theoretically be expected, only 70 defects actually occurred during the data gathering period. The defects that did occur and their positions are indicated with a ● in Table II.

Naturally, if defects do not occur, they cannot be detected in the regression and hence do not form part of the model. However, because the structure can later be extended to included defects at all locations, it was assumed that there are 108 possible defects present for the model structure definition.

IVOV structure selection

Table III shows the mean least squares (as an example) for the longitudinal crack defect (which shows up on the top left portion of the slab only after grinding) with different values for n_a (number of output regressors) and n_b (number of input regressors).

A more accurate fit was obtained as the structure size was increased. Based on this result and the fits of the other defects, the optimal choice for the structure was $n_a = 5$ and $n_b = 4$. This model structure contains enough information to detect the defects, and is not too large to handle during training and simulation.

No real difference could be detected between the types of steels cast and the widths of the slabs that were cast during the study. Therefore, only one model was derived for all widths and types of steel. A model was, however, derived for

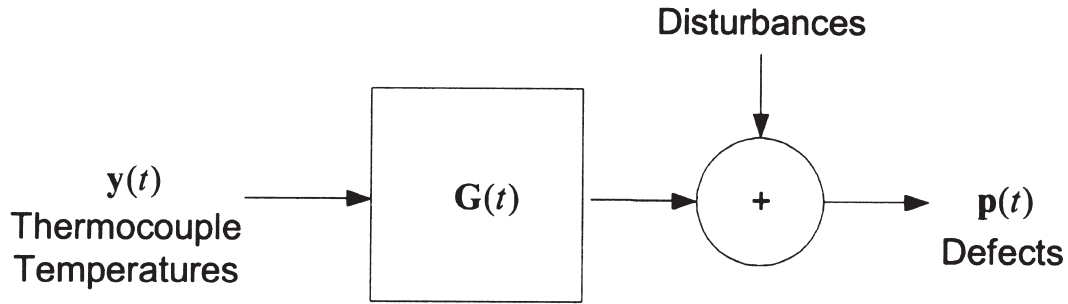# Quality prediction in continuous casting of stainless steel slabs

Figure 8—Block diagram depiction of the IV to OV model with thermocouple temperatures as inputs and defects as outputs

Table II

Locations of the specific defects of the gathered data. T=Top and B=Bottom as first letter. B=Before and A=After as second letter. L=Left, C=Centre and R=Right as third letter

	1a	1b	2a	2b	4	5a	5b	6	8
TBL			●	●	●	●	●	●	●
TBC			●	●	●	●	●	●	●
TBR			●	●	●	●	●	●	●
BBL				●		●	●	●	●
BBC				●		●	●	●	●
BBR				●		●	●	●	●
TAL	●			●		●	●	●	●
TAC	●	●		●		●	●	●	●
TAR				●		●	●	●	●
BAL				●		●	●	●	●
BAC			●	●		●	●	●	●
BAR				●		●	●	●	●

Table III

Comparison of mean least squares for different ARX structures for the IVOV model for longitudinal cracks

	n_b=1	2	3	4	5	6
n_a=1	0.466					
2	0.446	0.458				
3	0.434	0.446	0.431			
4	0.428	0.443	0.429	0.421		
5	0.425	0.442	0.428	0.420	0.417	
6	0.423	0.442	0.428	0.420	0.416	0.414

each specific defect, to lessen the burden on the processing machine*. Data of slabs that have a specific defect and data of slabs with similar characteristics (i.e. widths and types), but without defects, were included in the training set. This was to ensure that the model is also derived from data in which no defects occur.

*Training was done on a 256 MB RAM, 1 GHz Pentium III machine, with typical training times of about 30 minutes

IVOV time domain results

The training procedure of the IVOV model gave satisfactory results on the training data with the structure defined above. Figure 9 shows the model vs. plant output for a transversal crack occurring on the top left location after grinding has taken place.

Though the estimate does not follow the defect output perfectly, a clear increase in the model output is observed when a defect occurs. This non-perfect following is probably due to the fact that the defect measurements are taken by humans and that the severity scale is not ordinal. Figure 10 shows the model and plant output for casting powder entrapment at the bottom centre location after grinding.

This result is also adequate with a substantial increase in the model output when a defect occurs. Figure 11 shows the model and plant outputs for the 'other inclusions' defect at the top left location before grinding.

The figure clearly shows that the 'other inclusions' defects are detected (see e.g. t=1.025e5, t=1.125e5, t=1.2e5 and 1.42e5 seconds). There are certain instances where there are false alarms (see e.g. t=1.175e5 and t=1.275e5 seconds). These could be due to measurement inaccuracies on the part of the human (i.e. the person did not see the defect) or it could be an error in the predictor. Figure 12 shows the predictor performance for deep oscillation marks at the top right position before grinding.
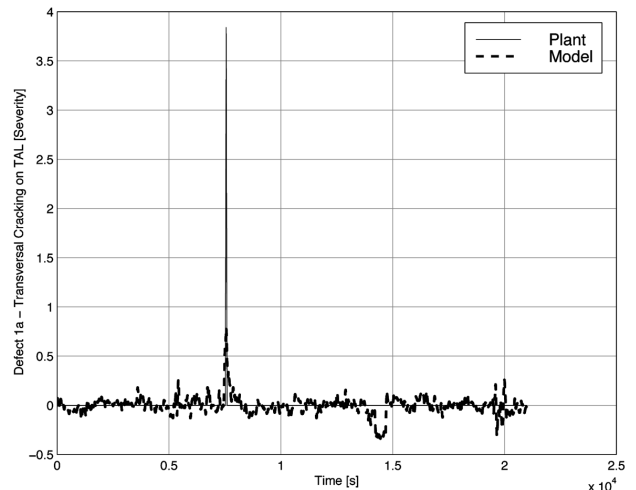

Figure 9—Comparison of model output and plant output for defect 1a (transversal crack) at the TAL location
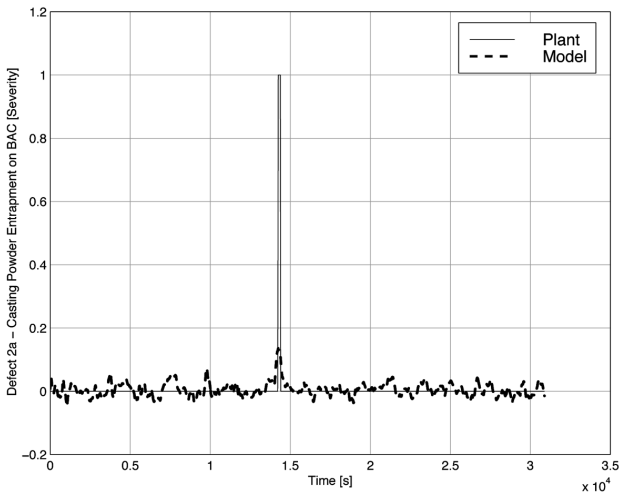
Figure 10—Comparison of model output and plant output for defect 2a (casting powder entrapment) at the BAC location

The two defects that occur (see $t \approx 3e4$ and $t \approx 12e4$) are detected, and some possible false alarms occur (see e.g. $t \approx 0$, $t \approx 1.5e4$, and $t \approx 9e4$ seconds). Figure 13 shows the model output for stopmarks at the bottom centre location before grinding. Figure 14 shows the predictor output for depressions at the top left location before grinding has taken place.

IVOV model threshold

The behaviour that is observed in the predictor output is probably due to the fact that the relation between thermocouple temperatures and the defects is non-linear. The human measurement system also gives an estimate of the severity of the defects based on individual knowledge of defects. Furthermore, the HMS may make errors in the observation of the defects i.e. it may not detect a defect that is truly present or it may detect something that looks like a defect but is in actual fact not a defect. The defect output cannot be less than zero, since this has no physical meaning.

Figure 11—Comparison of a portion of the model output and plant output for defect 2b (other inclusions) at the TBL location

Figure 13—Comparison of a portion of the model output and plant output for defect 6 (stopmarks) at the BBC location

Figure 12—Comparison of the model output and plant output for defect 5b (deep oscillation marks) at the TBR location

Figure 14—Comparison of a portion of the model output and plant output for defect 8 (depression) at the TBL location

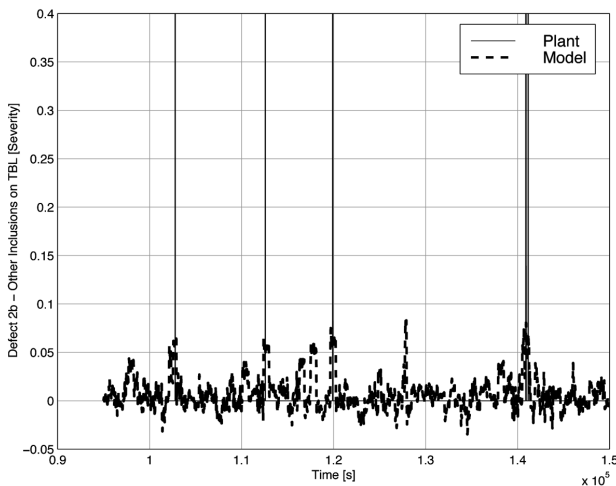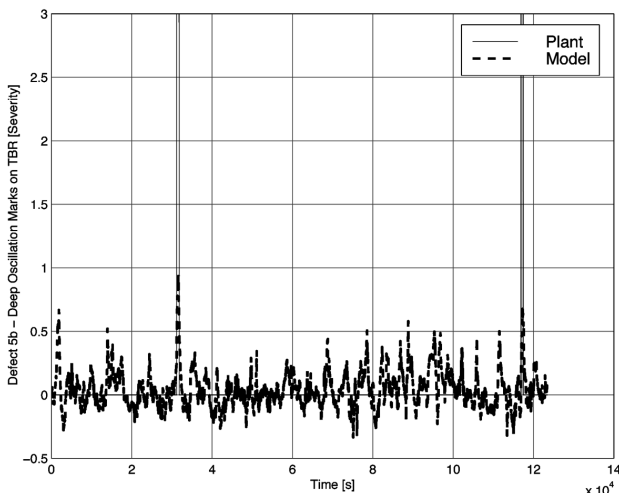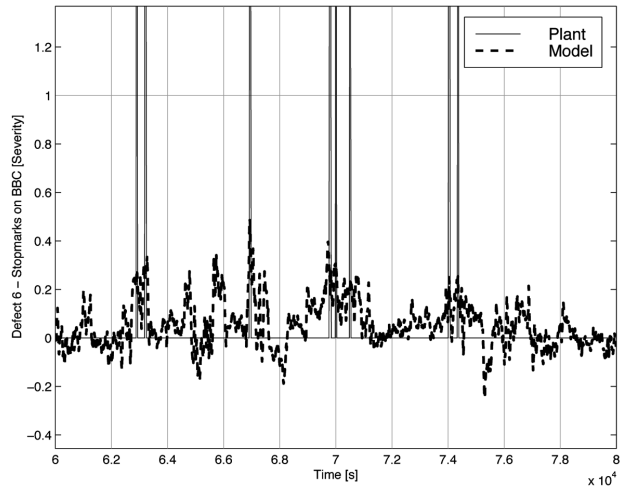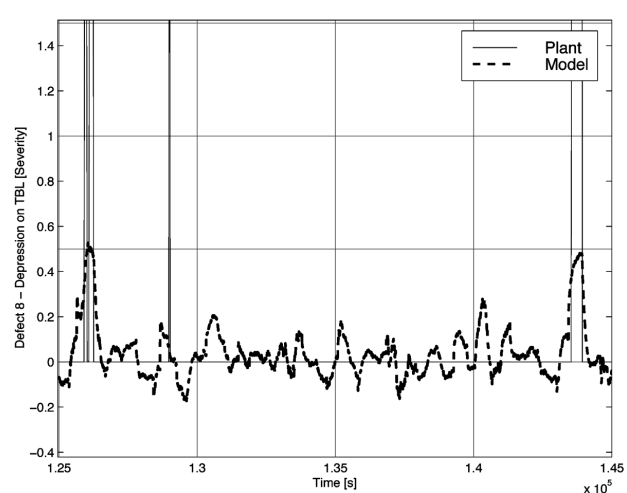# Quality prediction in continuous casting of stainless steel slabs

For these reasons, the accuracy of the predictor can be improved by supplying the detection algorithm with a threshold. The threshold is defined as follows: if the predictor output is above the threshold value, then the defect is said to be present and if the predictor is below the threshold, the defect is said not to occur.

To determine the threshold for each defect, a simple statistical approach was followed. Define A as the event that a defect occurs over time and B as the event that a defect is predicted. Then $\bar{A}$ is the event that a defect does not occur and $\bar{B}$ is the event that a defect was not predicted. Then the probability of a prediction error occurring is given by

$$P(E) = P\left[\left(\bar{A}/B\right) \cup \left(A/\bar{B}\right)\right]$$

$P(E)$ is the probability that a defect is predicted but did not occur or the defect was not predicted but did occur. The respective probabilities, $P(\bar{A}|B)$ and $P(A|\bar{B})$ can also be weighted if either error is more important (e.g. it may be more important to detect a defect that is truly present even if a false alarm could result or it may be more important to have fewer false alarms even if a defect may not be predicted) but in this work both errors carry the same weight. A suitable error is 5 per cent i.e. errors are made less than five per cent of the time. Note that an error of 0 per cent is infeasible because the threshold will then be set above any output of the predictor. The threshold is calculated within a minimization algorithm to determine the threshold that gives the predictor an accuracy of 95 per cent (i.e. $P(E)$ =5 per cent).

IVOV model defected slabs ratios

A comparison of the number of defected slabs that should be sent for direct rolling, and the number of slabs that were predicted to have defects after the threshold has been applied is also informative. Table IV shows the number of slabs that would have been falsely sent for grinding based on the output of the predictor for each defect and defect location. N is the number of slabs that were used in the training of the IVOV model.

These values are somewhat conservative, since they are linked to a specific defect and location so that repetition could have occurred because the same slab may have been sent for

grinding based on the outcome of the predictor for two or more defects or defect locations. For transversal cracks (1a), the ratio of false alarm slabs to cast slabs (N) is 0 per cent. For longitudinal cracks (1b) it is 5.6 per cent, and for casting powder entrapment it has a mean value of 7.1 per cent*. One of the worst performing defects is other inclusions (2b) with a ratio of 16.5 per cent, i.e. the conservative estimate of slabs with inclusions that should not have been sent for processing is 16.5 per cent. For bleeders the figure is 0.43 per cent and for deep oscillation marks (5a) it is, on average, 6.8 per cent. For uneven oscillation marks (5b) the ratio is 2.9 per cent, noting that the number of false alarms increases for predictions below surface (after grinding on the top of the slabs). For stopmarks the average value for the ratio is 24.6 per cent and for depressions it is 15.6 per cent.

Table V shows the ratio of slabs that were predicted to have a specific defect at a specific location to the number of slabs that did have the defect present.

Note that these values are conservative because a slab that was not predicted to be defective on one defect and defect location may have been predicted to be defective based on another defect or defect location. Slabs with transversal cracks were identified perfectly, while prediction of longitudinal cracks has an accuracy of 33 per cent. Casting powder entrapments were predicted perfectly, while other inclusions had a success rate of only 30 per cent. Bleeders were predicted only 43 per cent of the time. Deep and uneven oscillation marks were predicted with a success rate of 54 and 88 per cent respectively on average, and stopmarks were predicted with an accuracy of 92 per cent. Depressions on slabs with predicted with 48 per cent accuracy.

Some of the 'other inclusions' were predicted poorly, probably due to a small defect passing between thermocouples (under-sampling of the thermocouples). The reason could also be that the operators were too conservative when making a measurement on other inclusions, thus including insignificant inclusions in the measurement. The inclusion

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*AV per cent denotes the average ratio of falsely predicted slabs to total slabs over all locations

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Table V

Number of slabs that should have been sent for processing based on the predictor where a slab was truly defected using the training data. In x|y, x is the number of slabs predicted to have the defect and y is the number of slabs that did have the defect present

	1a	1b	2a	2b	4	5a	5b	6	8
N	55	72	56	412	154	327	244	175	406
TBL	-	-	1|1	5|6	1|3	2|7	2|2	17|18	5|8
TBC	-	-	1|1	14|28	1|2	3|6	2|2	17|18	4|5
TBR	-	-	1|1	2|4	1|2	3|6	2|2	17|18	4|10
BBL	-	-	-	4|5	-	1|3	2|2	13|15	4|7
BBC	-	-	-	17|25	-	1|3	2|2	13|15	1|2
BBR	-	-	-	2|2	-	1|3	2|2	13|15	5|11
TAL	1|1	-	-	8|42	-	2|2	3|3	14|15	15|30
TAC	1|1	1|3	-	10|72	-	2|2	2|2	14|15	9|32
TAR	-	-	-	9|34	-	2|2	3|3	14|15	16|30
BAL	-	-	-	4|19	-	1|1	1|2	11|12	9|20
BAC	-	-	1|1	8|55	-	1|1	1|2	11|12	12|23
BAR	-	-	-	10|18	-	1|1	1|2	11|12	8|15
AV%	100	33	100	30	43	54	88	92	48

could also have formed after the mould and even outside the casting machine. An example of this is when a slab has to be spot ground because the slab was placed on a dirty floor, with the sheer weight of the slab making an impression of the dirt (resembling a 'cleaned out' inclusion) on its surface. Deep and uneven oscillation marks and stopmarks were predicted in batches of three at the top before, top after, bottom before and bottom after locations. This is because the defects usually affect the whole width of the slab. Depressions were also not predicted accurately because 1575 mm wide slabs are also included in the study, and thermocouples are not available near the off-corner of the slabs in this case, a location where the defect is predominant. Overall, a conservative average accuracy of about seventy per cent of all defects is achieved using the ARX technique as a predictor.

Also note in Table IV and Table V that, in some instances such as stopmarks, when the prediction accuracy is high, the false alarm rate is also high. This implies that the method for determining the threshold is of such a nature that the increase in defect prediction accuracy results in an increase in the occurrence of the false alarm. This implies that, if it is desirable to detect when defects occur and some false alarms are allowed, the accuracy of positive defect prediction will also increase. Though more slabs will then have to be inspected before direct rolling or hot charging, more slabs can be direct rolled or hot charged because the slabs do not have to be ground.

To ensure that the best possible result was obtained, the IVOV model was also trained using casting speed, mould level and inlet temperature as inputs. These results were, however, not an improvement on the current result. The reasons for not including the casting speed, mould level and inlet temperature in the IVOV model are described earlier in this paper.

Optimal set-points for IVOV system

With the IVOV model in hand, the next step is to determine which values for the thermocouple temperatures will yield the smallest number of defects. These values then become set-points for a defect controller based on the MVIV model. The procedure was to assume that the system is at steady-state and then to calculate the values for the thermocouples which will deliver the smallest number of defects. In the ARX formulation, the model is of the form*.

$$p[nT] + A_1 p[(n-1)T] + \cdots + A_5 p[(n-5)T] =$$
$$B_o y[nT] + B_1 y[(n-1)T] + B_2 y[(n-1)T] + B_3 y[(n-1)T]$$

At steady-state, all inputs and all outputs are steady, so that

$$p_{ss} = (I + A_1 + \cdots + A_5)^{-1} (B_o + B_1 + B_2 + B_3)$$

To find a non-trivial solution to the above problem (i.e. find the values of y_{ss} s.t. p_{ss} are at least below the threshold values) one can use a search algorithm together with a least squares error to determine the values for the set-points of the thermocouple temperatures to ensure that no errors occur.

This has been done for the four models involved, and the resulting set-points are shown graphically in Figure 15 (Table VI explains the thermocouple indexes).

The figure shows that there is a distinct cooling pattern from the top thermocouple row of the mould to the bottom row.

The variation between thermocouples, the non-symmetry (e.g. 'ou4u', 'ou5u', 'in4u' and 'in5u' are all symmetrically situated but do not have the same values) and the variation for different widths probably has to do with the contact that the thermocouple makes with the copper face. The set-points are based on a subset of the occurring defects, and may not include all defects that will be present in the process in the future. However, it is assumed that these set-points will define a scenario which, if followed, can be considered to be the best process set-points for the thermocouple temperatures. Using the above set-points, the MVIV model can be used to derive the optimal casting speed, mould level and inlet water temperature in a similar fashion as was followed using the IVOV model to derive the optimal temperature set-points.

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*y are the thermocouple inputs (outputs of the MVIV model) and p are the defects (outputs of the IVOV model). Note that one sample delay has been incorporated into the inputs

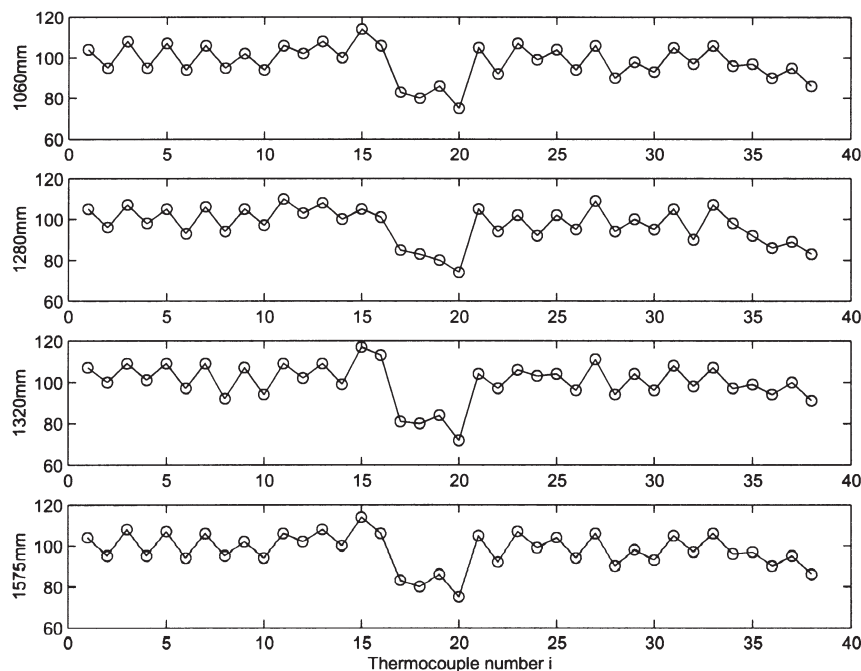# Quality prediction in continuous casting of stainless steel slabs

Figure 15—Graphical depiction of the optimal thermocouple temperature set-points (in ºC) for different slab widths

Table VI														
Indexes for each of the thermocouples used														
1	in1u	6	in3l	11	in6u	16	in8l	21	ou1u	26	ou3l	31	ou7u	36	nr1l
2	in1l	7	in4u	12	in6l	17	nl1u	22	ou1l	27	ou4u	32	ou7l	37	nr2u
3	in2u	8	in4l	13	in7u	18	nl1l	23	ou2u	28	ou4l	33	ou8u	38	nr2l
4	in2l	9	in5u	14	in7l	19	nl2u	24	ou2l	29	ou5u	34	ou8l		
5	in3u	10	in5l	15	in8u	20	nl2l	25	ou3u	30	ou5l	35	nr1u		

Comparative results

For comparison, the only paper found on the prediction of defects with quantified results is by Hunter *et al*.[10]. Table VII shows the results of the ARX predictor per defect using the training and validation sets together where available.

The calculation of the accuracy is based on predictions per sample point. The sensitivity is the proportion of correctly predicted sample points to all the sample points where a defect truly occurs. The specificity is the proportion of unpredicted defect points to the number of points where defects truly do not occur. The false alarms (FA) is the proportion of predicted defect points to the number of points where defects truly do not occur (FA=1-specificity). The positive predicted value (PPV) is the number of correct predictions of defects being present to the total number of predictions that the defects are present. The negative predicted value (NPV) is the number of correct predictions of defects not being present to the total number of predictions that defects are not present. N is the number of sample points used. Note that this method is conservative if the only consideration is whether a slab must be ground or not.

The result that is given in the paper of Hunter *et al*.[10] is that of the validation set for longitudinal cracking, where a neural network output generates a sensitivity of 61.5 per cent and specificity of 75 per cent. The table shows that the respective values using the ARX methods are 63.6 per cent and 93.5 per cent*. This implies that the ARX predictor is marginally more accurate than that published in terms of

Table VII					
Accuracy of the ARX predictor using sensitivity					
Defect	**Sensitivity**	**Specificity**	**FA**	**PPV**	**NPV**
Transversal cracks	73.4	99.5	0.5	51.7	99.8
Longitudinal cracks	63.6	93.5	6.5	16.3	99.2
Casting powder entrapment	8.8	98.6	1.4	4.9	99.3
Other inclusions	24.8	96.6	3.4	13.1	98.4
Bleeders	14.4	100.0	0.0	98.5	99.6
Deep oscillation marks	42.3	98.7	1.3	12.4	99.7
Uneven oscillation marks	66.3	99.4	0.6	43.0	99.8
Stopmarks	41.3	94.8	5.2	13.0	98.9
Depressions	44.8	96.3	3.7	13.7	99.3

*Note that the longitudinal values are based on the validation set for comparison. Transversal cracks and stopmarks are based on the training set because none of these defects occurred during the validation

Quality prediction in continuous casting of stainless steel slabs

correct predictions of defects. The specificity, however, shows that many false alarms occur in the results of the previous paper, while the ARX predictor has far fewer false alarms (0.5 per cent). An allowed decrease in specificity should also increase the sensitivity. This can be achieved by lowering the threshold. Transversal cracks have the best overall performance, with a sensitivity to predict a crack of 73.4 per cent. Casting powder entrapment fares the worst with a sensitivity of 8.8 per cent and a PPV of 4.9 per cent. There are, however, few false alarms (1.4 per cent). Other inclusions have a correct prediction when defects occur over the sample points of nearly 25 per cent. Bleeders have no false alarms, but have low sensitivity. Deep oscillation marks have a sensitivity of 42.3 per cent and very few false alarms (1.3 per cent). Uneven oscillation marks also have high sensitivity (66.3 per cent) and specificity (99.4 per cent). Stopmarks have a sensitivity of 41.3 per cent and 94.8 per cent specificity so the number of alarms is low. Depressions have similar sensitivity at 44.8 per cent and specificity of 96.3 per cent. Overall, the data show that the predictor has few false alarms, but is also not always very accurate. However, comparative results could not be found for other defects.

Conclusion

This work presented a model that can be used for prediction and control of defects in the continuous casting process.

The data gathering procedure of the mould variables (inputs) and the defects (outputs) was described. The inputs were obtained from the level 2 system of the plant of the industrial partner in real time, and the defects are measured by experienced operators several hours after the casting of a slab is completed. The procedure to extract the relevant data from the vast amount of data collected from the plant was also described.

Using statistical hypothesis testing and correlation analysis, it was found that the model can be divided into two sub-models. The first model, here called the MV to IV model, describes the dynamic effect of casting speed, as a manipulated variable, and mould level and inlet temperature as two possible disturbances, on the thermocouple temperatures as outputs. The second model is called the IV to OV model and uses the thermocouple temperatures as inputs and the defects as outputs. The IV to OV model is the predictor of the defects. This is convenient as feedback control can now be used because the time delay caused between measurement of the defect and the actual occurrence of the defect is outside the control loop.

The training of the IVOV models was also presented. The model tracks the true plant outputs well. System identification techniques in the form of linear auto-regression with exogenous input was found to be suitable to model the process. The IV to OV model could not determine the severity of the defects, but the use of a threshold improved the predictor to the extent that it could tell when and where a defect occurs and which defect was present, with relatively high accuracy. Validation data for the IVOV model were not available, due to the comparatively few defects that occurred. Data collected three years later were used to validate the IV to OV model, and the obtained results compare favourably to published results for longitudinal cracking.

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