Continuous cast width control using a data mining approach

P. G. de Beer and K. J. Craig*

Twelve per cent chrome ferritic (non-stabilised) stainless steel cast at the continuous caster at Columbus Stainless exhibited notable differences in the width change between consecutive heats. The reason for these differences is related to the fact that the steel is in a dual phase region between austenite and ferrite during the solidification stages of the continuous casting process. A model was developed and is currently used as a production tool to predict the width change of a 12% chrome ferritic heat before it is cast based on heat composition. The strand width is altered based on the model predictions by changing the secondary cooling pattern. It was uncertain if the current model is the best suited for this application and a study was carried out using different but more advanced data mining techniques in an attempt to improve the existing model. It was found that advanced data mining techniques could not improve the original rule based model.

Keywords: Continuous casting, Rule based, Strand width control, Statistical regression, Decision tree, Fuzzy logic

Introduction

Continuous cast width control is important because it affects the material yield and can also lead to material being allocated away from the original order, leading to increased lead time, production time losses and overdue orders that all contribute to increased costs for the steel producer. The continuous caster at Columbus Stainless casts slabs of constant thickness but with variable widths. This study describes a variable that was found to be important for 12% chrome non-stabilised ferritic stainless steels (hereafter referred to as 12% chrome steel) that influenced the cast width. Chemistry variations influencing the phase fractions between austenite and ferrite in the temperature range 1200 to 850°C (secondary cooling temperature range in the continuous caster) were found to play an important role in the final cast width. Research[1,2] on the transformation behaviour and hot strength of a 12% chrome ferritic stainless steel (non-stabilised) has indicated that as long as the ratio of austenite and ferrite keeps on fluctuating, the width change variation will persist. A rule based model was successfully implemented initially[3] indicating the potential for predicting the cast width change of a 12% chrome heat before it is cast based purely on the composition. The uncertainty whether the modelling approach used in the implemented model is the most suited for this application, culminated in further study. More specifically, alternative, more advanced modelling techniques than the rule based approach were investigated. The three techniques used are statistical regression, decision trees and fuzzy logic. As the accuracy of the models is of paramount importance due to the fact that incorrect predictions can be very expensive, a thorough data mining exercise was done to test the models against each other in order to determine the best solution for this specific application.

The next section describes the theoretical aspects concerning the relationship between the cast width and heat composition, after which the development and results of the different data mining techniques are presented. Some operational results of the rule based model are also discussed.

Cast width modelling

Most of the literature deals with techniques that were successfully implemented to improve cast width change. The techniques range from simple monitoring techniques to theoretical prediction models. Evans et al.[4] achieved improved width change results by better slab width verification techniques. Nakamura et al.[5] implemented a slab width model that controls the width of the strand by changing the mould dimensions using a mould that can continuously adjust its dimensions. Assar et al.[6] attribute the widening of the slabs during casting to the ferrostatic pressure and shell malleability. They found the widening of the slabs to be directly correlated to the casting speed and to depend on both the strand width and steel grade. They developed a prediction model based upon casting speed, mould width and steel grade. Kocatulum et al.[7] studied the causes of width change using physical devices to measure slab width and also developed a statistical slab width prediction incorporating the mould width and the residence time in the upper sections of the secondary cooling zone. Mostert and Brockhoff[8] developed a slab width prediction model based on theoretical principles. They determined an equation for the shrinkage factor and stated that the

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final cold width of a slab is influenced by thermal shrinkage and contraction counteracted by expansion. They expressed the shrinkage factor as the ratio of mould width and cold slab width and stated that the expansion of the shell depends on the thickness and temperature of the shell combined with ferrostatic pressure. The relationship between the spray cooling, ferrostatic pressure, casting speed, shell thickness and shell temperature was studied. They concluded that the expansion depends on the ferrostatic pressure, spray cooling and casting speed. The factors that affect the width change according to literature are, therefore, mould set-up practises, secondary cooling in the casting machine, cast speed and steel type. Only Kocatulum et al.[7] touched on the subject of relating compositional changes within a certain steel grade to the cast width change. They found it to be negligible and did not pursue it further. This study indicates that for the special case of 12% chrome stainless steels, the compositional variation between heats has a significant effect on the width change. This is indicated by the fact that a model was successfully implemented in the plant as a production tool to predict the width change of a 12% chrome heat before it is cast purely based on the composition.

Theoretical influence of heat composition variations on continuous cast strand width change of 12% chrome stainless steels

The main reason why 12% chrome steel would exhibit a relationship between the heat composition and cast width change is because the shell is in a dual phase region between austenite and ferrite at temperatures typically between 850 and 1250°C. The creep, hot strength and volume of austenite and ferrite are different which causes strand width variations when the ratio between austenite and ferrite changes.

Dual phase characteristic of solidified shell

The dual phase characteristic is evident from the iron–chromium binary phase diagram (Fig. 1a). The dual phase temperature range corresponds to the temperature range between mould exit and continuous casting machine exit. Variations in the austenite and ferrite stabilisers between different heats result in the 'gamma loop' changing between these heats resulting in a different phase ratio between heats. Rowlands[9] also indicate that the 12% chromium content places it at the critical boundary of the gamma loop and therefore austenite or ferrite stabilisers (formers) can change the structure of the steel at elevated temperatures. Elements that are important ferrite stabilisers in stainless steels are chromium, titanium and molybdenum. Important austenite stabilisers are carbon, nickel, nitrogen and manganese. Small changes in any of these elements can change the austenite to ferrite ratio in a 12% chrome steel. Figure 1b indicates for example the effect of the austenite stabiliser carbon on the 'gamma loop'. It is clear that the carbon expands the austenite region to higher chrome levels and lower temperatures. The other austenite stabilisers have a similar effect.

Hot strength of austenite and ferrite

The hot strength of austenite at elevated temperatures is larger than that of ferrite at elevated temperatures. The
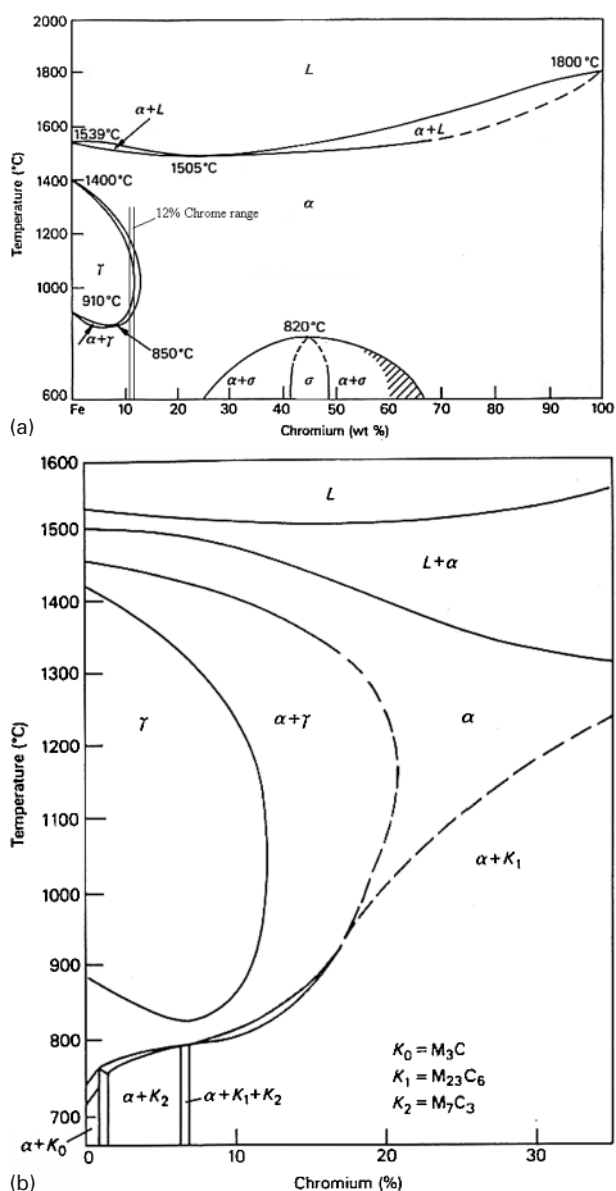
1 *a* Fe–Cr binary phase diagram indicating dual phase region[10] and *b* effect of carbon content on austenite/ferrite region[15]

more the phase ratio favours austenite, the stronger the shell will tend to be and vice versa. A stronger shell will be able to contend more effectively with any forces that will attempt to deform it (ferrostatic pressure for example). An important factor considering the phase ratio is the transformation rate of austenite to ferrite. If the transformation rate from austenite to ferrite is high (under constant cooling) then the austenite fraction of the structure will decrease (transform to ferrite) quickly and relatively high up in the casting machine bow. This will leave room for a weaker shell that might be prone to deformation.

Volume difference between austenite and ferrite

The lattice structure of austenite is face centred cubic (FCC) and the lattice structure of ferrite is body centred cubic (BCC). The BCC structure occupies a higher volume than the FCC structure and therefore changes in the ratio of austenite to ferrite will be accompanied by a change in the volume that will translate into a change to the cast width.[1]

Creep properties of austenite and ferrite

The inherent resistance to creep of austenite is more than that of ferrite,[11] hence changes in the phase ratio between austenite and ferrite affects the creep characteristics of the strand. Creep becomes evident typically above $0.4\ T_m$ where T_m is the absolute melting point.[12] If a continuous casting process is considered, then typically the strand is at a temperature $>0.4\ T_m$ for the whole of the secondary cooling stage and is therefore prone to undergo creep at high temperature. Temperature plays a major role in the creep rate with a higher creep rate experienced at a higher temperature.[12,13] The creep resistance of austenitic stainless steels is increased by the following elements: carbon, nitrogen, chromium, molybdenum, tungsten, vanadium, boron, titanium and niobium.[11] According to Austin *et al.*[13] the following elements have an influence on the creep properties of ferrite (ferrite itself does not have a high resistance to creep at elevated temperatures) nickel, silicon and cobalt only increase the creep resistance at elevated temperatures marginally while carbon, chromium, manganese and molybdenum increase the resistance to creep markedly. Owing to the fact that these elements influence the creep properties of austenite and ferrite it follows that variations in these elements translate into different creep rates between heats.

Selection of input variables for modelling width change

In order to quantify and calculate the constitution and transformation properties of 12% chrome steels, the Columbus Stainless research and development department has developed a model to calculate the phase fractions and transformation rate of 12% chrome steels given the composition. The model is called MEDUSA[14] (Mathematical evaluation of dilatometry using statistical analysis). The following parameters are calculated (among others) by the MEDUSA model and are of value in the present work:

(i)   gamma max. (Gmax) (%): this is the amount of austenite present at 1100°C in ferritic stainless steels

(ii)   AC1 temperature (°C): this is the temperature at which austenite begins to form when ferritic stainless steel is heated at 1°C min^{-1}

(iii)   CR95 (°C min^{-1}): cooling rate at which 95% of the austenite present at 1000°C transforms to ferrite

(iv) A_{max} (Austenite potential): this is the percentage austenite present in ferritic stainless steels at 1000°C and approximates to the maximum austenite potential of the steel.

The input variables used for the more advanced data mining techniques were the same as the input parameters currently used by the rule based model that is implemented in the plant. The initial input parameters were decided after an investigation to determine the influence of the chemistry on the width error. Apart from the MEDUSA calculated parameters, two additional parameters were added as input to the model; the Kaltenhausen ferrite factor (FF) and the addition of the absolute carbon and nitrogen (C+N) chemical analysis. The Kaltenhauser ferrite factor[1] is an empirical expression that is used to predict the microstructure (ferrite volume fraction at 1000°C)

$$FF = Cr + 6Si + 8Ti + 4Mo + 2Al + 40(C+N) - 2Mn - 4Ni \qquad (1)$$

Three different data mining approaches were followed. A suitable model would be able to predict the expected width error of a specific heat before it is cast. The three modelling approaches used were:

(i)   statistical regression

(ii)   regression decision tree

(iii)   fuzzy logic.

Two independent data sets were used during this study that consisted of the six input parameters and associated width change. One data set was used for training the different models and consisted of 249 heats with associated width change. A validation data set was used to test the accuracy of the models and consisted of 129 heats with associated width change. The dependent variable that was modelled is termed the 'width error'. The width error is defined as the difference between the actual cold width of a slab and the aim cold width (width error = actual cold width–aim cold width) and is expressed in millimetres.

Width change modelling using different data mining techniques

Statistical regression

Response surface methodology (RSM) is a tool for understanding the quantitative relationship between multiple input variables and one output variable. A quadratic response surface was used to model the width error using the mentioned input parameters. The statistical toolbox in Matlab was used to derive the RSM models. The general equation describing the quadratic response surface of an input vector **x** and response vector **y** has the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_n x_n$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(linear)}$$
$$+ \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \ldots\ldots + \beta_{1n} x_1 x_n + \ldots +$$
$$\beta_{(n-1)n} x_{(n-1)} x_n \ldots \text{(interaction)}$$
$$+ \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \ldots\ldots + \beta_{nn} x_n^2$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(quadratic)} \qquad (2)$$

The 'rstool' in Matlab was used to derive the quadratic response surfaces used in this section. The 'rstool' has the functionality of deriving separate response surface models including the linear section alone, linear and quadratic alone and linear and interaction terms separately and a response surface including the linear, interaction and quadratic terms. In total, four response surface models were developed, one model representing each of the before mentioned models. The results were evaluated by dividing the width error range into three groups. The groups were chosen based on when a width error would be problematic on the narrow or wide side. All results from the different models will be given based on their performance on the training data set and validation data set. The definition of 'correct' in the tables is the percentage of records in each group where the model predicted the width error correctly.
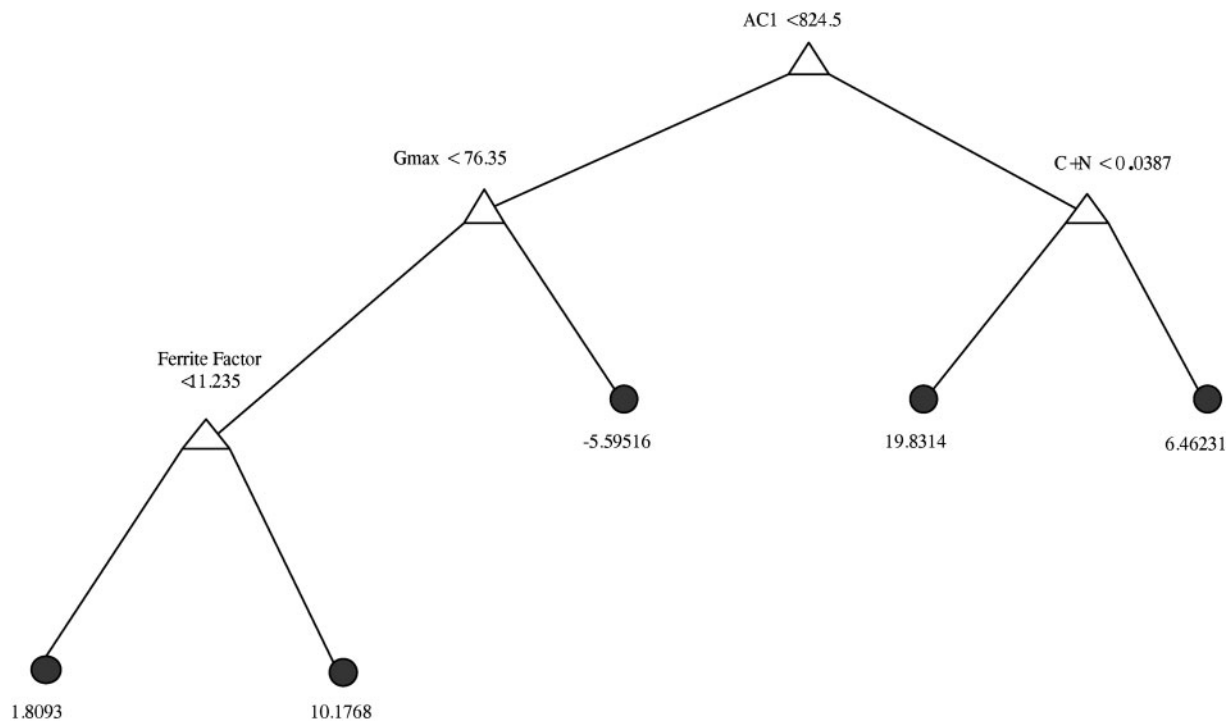
2   Pruned version of decision tree

Table 1 indicates that the response surface models give results that are very close to each other. The overall accuracy ranges from 54 to 52% correct, which indicates no significant difference between the different models. All the models indicated the best results in group 2.

From Table 2, it can be seen that all the models are accurate in the width error range represented by group 2, but all the models perform very poorly in the width error ranges represented by group 1 and group 3. The accuracy in group 2 is not thought to be due to the models being accurate in that range, but rather due to the fact that most of the actual width errors and predicted width errors fall in the range of group 2.

Regression decision tree

The statistics toolbox in Matlab was used to derive two decision trees from the training data set. The two decision trees are the basic complete decision tree as derived from the training data and the second tree is the pruned version. The unpruned tree consisted of 41 levels.

Pruning can be done to the basic tree to optimise the structure. With a tree having many branches, there is a danger that it fits the current data set well, but would not do a good job at predicting new values. Some of its lower branches might be strongly affected by outliers and other artefacts of the training data set. The second decision tree was found by pruning the first tree using cross validation. Figure 2 indicates the structure of the pruned decision tree obtained from the training data set.

The best pruning level was determined as level 37 of the original 41 of the unpruned tree. The results are given in Table 3.
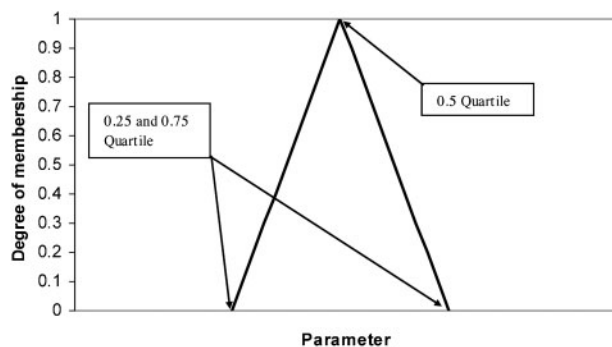
In terms of the training data set, it can be seen that the model is more accurate on the extremes of the width error range than the RSM models. The accuracy obtained of 78% overall is acceptable. If one considers the results obtained from the validation data set then the performance is poor with a 42% accuracy rate. It can also be seen that the model is very inaccurate on the narrow distribution in group 1 and performing slightly

Table 1   Results from response surface models as applied to training data set

Group	Width error range, mm	No. of records	Linear % correct	Linear + interaction % correct	Linear + quadratic % correct	Full quadratic response surface correct
1	<0	79	30%	30%	26%	30%
2	0–15	65	75%	72%	74%	71%
3	>15	105	59%	59%	63%	57%
		249	54%	53%	54%	52%

Table 2   Summary of accuracy obtained with surface response models as applied to validation data set

Group	Width error range, mm	No. of records	Linear % correct	Full quadratic % correct	Linear + quadratic % correct	Linear + interaction % correct
1	<0	38	3%	8%	3%	8%
2	0–15	76	87%	88%	92%	91%
3	>15	12	42%	0%	0%	0%
			57%	55%	56%	57%

3 Typical membership allocation using triangular membership functions

4 Typical membership functions as defined across parameter range

better in group 2. The overall accuracy rate of 42% is however not acceptable.

Fuzzy Logic

Two types of fuzzy logic models were developed. One with triangular membership functions and one with polynomial membership functions.

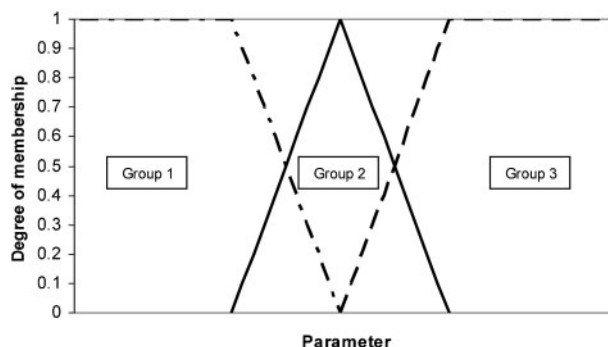### *Fuzzy logic model based on triangular membership functions*

The aim was to categorise the input parameters into one of three predefined groups. The groups are defined in terms of the width error. Group one is defined as heats with negative width error (i.e. narrow from aim), group two is defined as those having acceptable width error and group three is defined as those heats with large positive width errors (i.e. wide from aim). The fuzzy logic membership functions were defined as straight lines using equations of type

$$y = mx + c \qquad (3)$$

Each parameter was viewed separately and divided into the three groups according to the width error. The 0·25, 0·5 and 0·75 quartiles were determined for each subgroup in each parameter. The 0·5 quartile for each subgroup was chosen to have a membership of one and then the 0·25 and 0·75 quartiles were chosen as having zero membership to the specific subgroup (*see* Fig. 3).

If the membership functions are combined then the result is a distribution with triangular sets. Figure 4 indicates the combined membership functions as applied across a typical parameter range.

The membership functions were determined using the training data set. Each parameter was used separately to determine the membership equations across the parameter range. The values of each parameter were then fuzzified using the specific membership functions. The defuzzification was done using a centre average approach. Each parameter gave an individual prediction of which width group the heat belongs to, selected from the three predefined width groups. The average of the

six predictions was then used to determine the final prediction of the width group.

The results from the model (see table 4), indicates good results in group 1 and group 2 on the training set, but these results are not repeated on the validation set. The overall accuracy obtained on the validation set of 48% is considered to be poor.

Fuzzy logic model based on polynomial membership functions

The basis of this model is to use a polynomial for each parameter to predict a width error separately. The final width error is then taken as the average of the predictions resulting from the six polynomials derived from the six input parameters. The optimum order of the polynomial was found for each parameter by deriving six polynomials for each parameter ranging from pure linear to a polynomial of the 6th order. The optimum degree of the polynomial was chosen as the one with the best correlation to the actual width error. The polynomials used for the six input parameters are given in equations (4)–(9). It can be seen that the order of the polynomials ranges from 2 to 5

$$WE = \text{width error}$$

$$WE = -4 \cdot 724(AC1)^3 + 8 \cdot 012(AC1)^2 - 2 \cdot 9784AC1 + 0 \cdot 5078 \qquad (4)$$

$$WE = 2 \cdot 9147(Amax)^3 - 5 \cdot 5702(Amax)^2 + 2 \cdot 4045Amax + 0 \cdot 4055 \qquad (5)$$

$$WE = 1 \cdot 3266(CR95)^3 - 2 \cdot 7794(CR95)^2 + 2 \cdot 0942CR95 + 0 \cdot 1805 \qquad (6)$$

$$WE = 4 \cdot 2285(Gmax)^3 - 6 \cdot 1782(Gmax)^2 + 1 \cdot 4921Gmax + 0 \cdot 6988 \qquad (7)$$

Table 3   Results obtained from pruned decision tree as applied to training and validation data sets

Group	Width error range, mm	Training data set		Validation data set	
		No. of records	% correct	No. of records	% correct
1	<0	79	81%	38	7%
2	0–15	65	71%	76	59%
3	>15	105	80%	12	50%
		249	78%	126	42%

$$WE = 0 \cdot 6271(FF)^2 + 0 \cdot 2055FF + 0 \cdot 0753 \qquad (8)$$

$$WE = 34 \cdot 3452(C+N)^5 - 94 \cdot 048(C+N)^4 +$$
$$92 \cdot 8363(C+N)^3 - 39 \cdot 1632(C+N)^2 + 5 \cdot 8697(C+N) +$$
$$0 \cdot 4508 \qquad (9)$$

The results obtained by applying the polynomial fuzzy logic model to the training and validation data set are given in Table 5.

The overall accuracy of 58% on the validation data set is reasonable, considering the results obtained with the other models. One positive about this model, is that it seems to be fairly accurate in group 1 and group 2 but unfortunately not in group 3.

Rule based model

The model that is used in the production environment is a rule based model derived from a different training set than the previous models due to the fact that it was created some time before the other models.[1] The rules give the freedom of not having to use all the input parameters. The set of rules was generated from historical data. The width change was divided into three groups (narrow from aim, acceptable and wide from aim) and the combination of the parameters that resulted in the width error falling into one of the three groups was determined. The combination of parameters is expressed in terms of rules. The amount of parameters per rule can range from 1 to 6. The model therefore consists out of a mixture of rules all having the form of if–then statements. A typical example of a rule incorporating four parameters is illustrated below

if $AC1 < x$ and $Gmax > y$ and $CR95 < z$

and $(C+N) > zz$ then ...

Each rule categorises a heat according to the groups described in the previous sections. A chemistry sample is taken at the end of the process at the rinsing station (ABS–Argon Bubbling Station). There is approximately a 10–15 min gap between the end of the rinsing station process and the start of the casting operation. After the chemistry sample has been taken, it is sent to the laboratory for analysis. The chemical composition results are sent to the computer system of the continuous caster. The width model is situated in the caster level two computer system. Once the chemical analysis has been received, the relevant parameters are calculated and sent to the model as input parameters. The input parameters are checked by the model by fitting each rule in sequential order to the input parameters. The individual rules are checked until a rule becomes active. When all the rules have been checked and none fits, the default/standard secondary cooling practice is used. If one of the rules becomes active, the secondary cooling practice is changed to either a more aggressive or a less aggressive secondary cooling practice, based on the result of the specific active rule. Table 6 indicates the results obtained by applying the rule based model to the same validation data set as the other models in the previous sections. The 'correct' column indicates the amount of correct decisions where the model was able to make a decision. The percentage 'no decision' is the percentage of material where no rules became active and no decision was made by the model.

The percentage of 'no decision' is relatively high at 54%, and this material should be viewed as lost opportunities where a change could have been implemented, to improve the width error. The 54% also indicates that the model can be improved to be able to recognise more problematic material. Table 6 also indicates that where decisions were made by the model, it was 73% correct with very good results in groups 1

Table 4   Results across width error range from fuzzy logic model

Group	Width error range, mm	Training set		Validation set	
		No. of records	% correct	No. of records	% correct
1	<0	79	56%	38	32%
2	0–15	65	40%	76	57%
3	>15	105	74%	12	50%
		249	59%	126	48%

Table 5   Results from polynomial fuzzy logic model

Group	Width error range, mm	Training set		Validation set	
		No. of records	% correct	No. of records	% correct
1	<0	79	25%	38	52%
2	0–15	65	80%	76	67%
3	>15	105	49%	12	16%
		249	49%	126	58%

Table 6   Results of current model as applied to validation set

Group	Width error range, mm	No. of records	% correct	% no decision
1	<0	38	88%	58%
2	0–15	76	67%	N/A
3	>15	12	71%	42%
		126	73%	54%

Long term width error trend of material on which width prediction model was activated
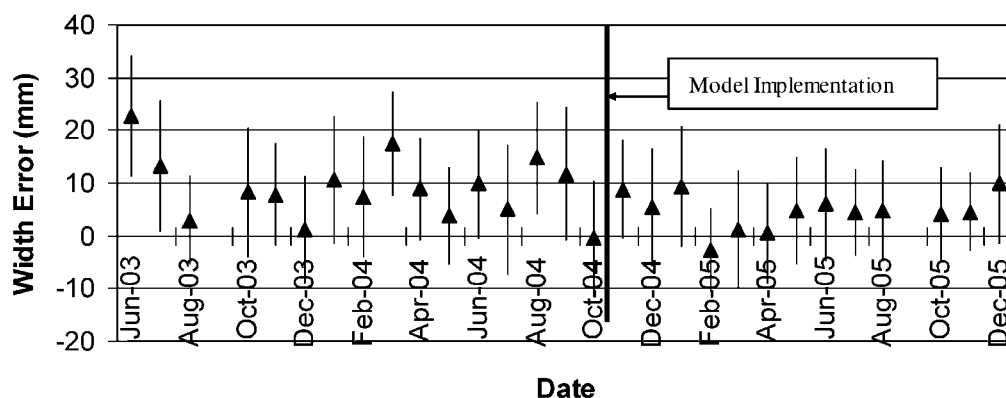
5   Long term width error trend of 12% chrome non-stabilised ferritic stainless steel

and 3. The accuracy of 73% is considered to be excellent if it is compared to the other models derived and tested in the previous sections. The rule based model that was running 'live' in the plant exhibited the best results on the validation data set and was chosen as the best model for this application.

Plant results of rule based model implemented in production environment

The rule based model was implemented in the production environment in November 2004. Figure 5 indicates the long term width control achieved on 12% chrome ferritic non-stabilised material cast at the caster at Columbus Stainless. The trend is divided into a population 'before' the model and 'after' the model. It can be seen that the width error stabilised after the implementation of the model. The width error also seems to be lower on average. A more stable width error on average per month means that the control on the strand width improved because the width error for each month is in a similar region. This was not the case before the model was implemented. Before the model was implemented it is clear that each month had a different average width error indicating poor width control.

The model results were further evaluated by comparing them to a population where the model was not in operation. The reference population chosen was all 12% chrome non-stabilised ferritic material that ware cast between July 2003 and November 2004.The population where the model was in operation (November 2004 to December 2005) was split into two populations. This was necessary because the secondary cooling practice

used for the heats with large positive width errors was changed in May 2005 to a less aggressive pattern, after it was suspected that the high cooling intensity resulted in some slabs cracking. The relationship between the cracked slabs and the secondary cooling practice was not confirmed. Table 7 gives a summary of the three populations.

The three means were tested against each other using the Student t-test with a 95% confidence interval and all three means were found to be significantly different from each other. It is evident that the mean of the reference population is higher than the two means of the populations where the model was active. The reason for this is that in September 2004 by management decision, the preferred range for the caster to supply ferritic slabs to the Hot mill was changed to 7·5 mm narrower. This resulted in a general width error population shift with a larger percentage of the material falling in group one of the width error definition (<0 mm width error). It can also be seen that the standard deviation for the June 2005–December 2005 population is significantly less than the other populations. This is an indication of improved width control. Further analysis was performed to determine how much material was cast with modified secondary cooling practices and the comparison of these data with standard cooling practices. Table 8 gives a summary of the results.

The means of the two populations of the material between November 2004 and May 2005 are significantly different (Student t-test 95% confidence interval). This can be attributed to the fact that the majority of the water patterns that were modified were changed to the

Table 7   Summary of reference population and model active population

	Reference population (before model)	Model active population (November 2004–May 2005)	Model active population (June 2005–December 2005)
No. of heats	420	242	141
No. of slabs	1637	866	541
Tons	46 200	26 620	15 510
Mean*	9·27 mm	3·29 mm	5·68 mm
Standard deviation*	10·46 mm	10·42 mm	8·33 mm
Range* (max.–min.)	54	55	44

*Based on heats.

Table 8   Summary of populations with and without secondary cooling modifications

	November 2004– May 2005 Standard water pattern	November 2004– May 2005 Modified water pattern	June 2005– December 2005 Standard water pattern	June 2005– December 2005 Modified water pattern
No. of slabs	352 of 818 total slabs	466 of 818 total slabs	157 of 529 total slabs	372 of 529 total slabs
'Wide' cooling practice	52% of 818 slabs		68% of 529 slabs	
'Narrow' cooling practice	4·5% of 818 slabs		1·89% of 529 slabs	
Mean*	7·21 mm	0·24 mm	5·41 mm	6·46 mm
Standard deviation*	11·42 mm	9·31 mm	9·1 mm	9·3 mm
Range*	56 mm	57 mm	49 mm	54 mm

'wide' pattern. The compensation achieved with the modified secondary cooling was too much and the mean of 0·24 mm with a standard deviation of 9·3 mm means that some material was cast too narrow and could have caused processing problems downstream. The 7·5 mm set-up change of September 2004 exaggerated this result. This caused problems with the model compensation, because the data used for training the model, and to derive the secondary cooling pattern were based on a population with an average width error of 7·5 mm wider. The population of June 2005 to December 2005 is relatively smaller than the population of the first part of 2005 because of lower production volumes due to market conditions. The means of the two populations of the material from June 2005 to December 2005 are not significantly different (Student *t*-test, 95% confidence interval). This result indicates that the model changed material that would have been problematic to be within the range achieved with the standard cooling practice, resulting in an improved (reduced) width error distribution during the time period June 2005 to December 2005. On the population from November 2004 to May 2005 the model changed 56·5% of the material cast to more suitable secondary cooling practices. On the population from June 2005 to December 2005 the model changed nearly 70% of the material cast to more suitable secondary cooling patterns with a vast majority being changed to the 'wide' cooling practice. This means that a majority of the material was predicted to be problematic (too wide) and a more aggressive cooling pattern was used to force them to be narrower.

Conclusions

1. This study used parameters that describe the dual phase characteristic of the solidified shell to predict the expected width change of a heat based on the composition before the heat is cast.

2. In this paper, three different data mining approaches were used to model the relationship between the heat composition and cast width error. The models included statistical regression, regression decision trees and fuzzy logic. The accuracy of the derived models was tested against the accuracy of the model currently in use. The model currently in use outperformed the newly derived models in terms of accuracy on the same validation data set. The current rule based model was therefore proven to be the best suited for this specific application.

3. The model currently implemented in the plant has resulted in a notable improvement in the strand width control of 12% chrome ferritic (non-stabilised) stainless steel cast at the continuous caster at Columbus Stainless.

4. The project suggests that a good engineering understanding of the width change governing phenomena coupled with a simple data mining technique performs better than the more advanced data mining techniques.

Acknowledgement

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