DATA CLASSIFICATION IN TEMPERATURE MODELLING OF LD-KG CONVERTER

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Abstract: In this paper a temperature model for an LD-KG-converter is presented. Especially the classification of the variables into groups is discussed. In the steel plant there was a need to develop models for predicting the temperature at the end of the blow, using the dropping sensor measurement. Large databases from the steel plant were used in modelling. The expert knowledge from the personnel in the steel plant was utilised during the project. In off-line test runs 75 – 80 % of the blows were predicted within the target window, ±10°C. The developed temperature model is in the use on the three 120 tonnes LD-KG-converters in Ruukki Production, Raahe Steel Works.

Keywords: LD-KG converter, data classification, temperature control, steel making

1. INTRODUCTION

The control of steel making converters can be based on different static or/and dynamic models. In the static models parameters (for example the amount of the charge materials and blowing practice) are chosen in advance using material and energy balances. The static models can be corrected or adjusted during the blow with the help of dynamic models so that for example the target carbon content and temperature of steel are achieved as exactly as possible. The dynamic model uses real time process measurements from the converter, for example the off-gas temperature and the temperature, level, carbon and oxygen contents of the molten steel, to adjust the static model. These static and dynamic models are based on the exact information of raw materials and they work best if the successive blows are repeated as similarly as possible. There are, however, several error sources that make the control of the steel converter challenging. The quantity and quality of the scrap is difficult to define. Also for example the slag from the hot metal mixer and different types of dust- and splash losses cause unpredictable errors. Because of these random errors both static and dynamic models must be adaptable. A lot of statistics and data are needed to maintain these models.

Four dynamic control systems for converters used in steel making were found in the literature. MEFCON (MEFOSNews, 2000), the off-gas analysis-based system for prediction of metal component concentrations and temperature has been used for the two LBE converters at SSAB Tunnplåt AB in Luleå. In DYNACON (VAI Technology News, 1999) the calculation principle is based on the reaction kinetics between steel and slag components, the trend behaviour prediction of the off-gas composition in the last minutes of blowing and on heat and material balances. BloCon (Grethe, *et al.,* 1996) is a system for dynamic control developed by Mannesmann Demag. Many different materials can be taken into account in calculations, but the system has to be tuned into the parameters of any converter on which it is implemented. VAI-CON Temp (Schwelberger, *et al.*, 1999) is used to measure the temperature of the melt in an AOD-converter through a submerged tuyere.

In this paper the data classification in temperature modelling of LD-KG –converter is presented. The temperature model was developed in the Control Engineering Laboratory of the University of Oulu in co-operation with the personnel of Rautaruukki Oyj, Ruukki Production, Raahe Steel Works. TEKES (the National Technology Agency) and Rautaruukki Oyj financed the project. Rautaruukki Oyj is the largest steel company in the Scandinavia and the leading producer of flat rolled products in the region. Raahe Steel Works produces rolled plate, sheet and coil, at an annual production rate of 2.8 million tonnes of slabs.

2. PROCESS DESCRIPTION

2.1 Steel Converter Process (Heikkinen et al, 1999)

The task of the steel converter is to lower carbon content (about 4.5%) of hot metal to target carbon content of steel (about 0.05%). Other tasks are to heat the melt enough for further processing, to remove impurities (for example sulphur and phosporus) and to melt the charged scrap. Blowing pure oxygen into hot metal decarburizes the melt. Oxygen reacts with carbon generating mainly carbon monoxide. LD-KG-converter (Linz-Donawiz Kawasaki Gas) (Fig 1) is a combined blowing BOF-converter with inert gas stirring, which is achieved through multi-hole nozzle bricks in the bottom. Stirring is used to keep the melt homogeneous and to lower the oxygen level in relation to carbon content at the end blow.

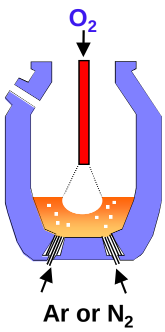

Fig. 1. LD-KG-converter.

The raw materials of the converter process are hot metal coming from the blast furnace, oxygen blown through the lance, inert gas blown from the bottom, steel scrap, slag formers and fluxes.

Normal amount of scrap is about 15 - 20 % of the charge. Besides being important raw material, scrap can be used to control the temperature of the melt at the end of the blow.

The slag is very important for the converter process. The slag former (typically CaO) is needed to form slag quickly on the surface of molten iron. Slag collects impurities coming from hot metal and scrap. At the end of the blow the slag consists of components oxidized during blowing (for example SiO_2, MnO, P_2O_5), oxides coming from scrap (for example CaO, FeO, Al_2O_3, MgO), slag formers, fluxes and oxides dissolved from lining.

2.2 Automated Drop in Sensor System (Laine, 1998)

Raahe Steel Works has installed the Automated Drop In Sensor System (ADSS) on all three converters. The ADSS comprises three fundamental parts: expendable sensors, instrumentation for signal interpretation and display, and an automatic manipulator to drop the sensors into the vessel during and/or after the oxygen blow cycle. The manipulator and sensors are designed to obtain fast and reliable measurements of bath temperature and oxygen activity to provide the process operator with control data. During the blow, measurements can be obtained as late as 30 seconds before the programmed endpoint of the heat. The ADSS enables automated measurements to be made from the operating console.

3. TEMPERATURE MODEL

3.1 Basic structure of temperature model

The aim was to keep the temperature model as simple as possible, because the calculation had to be kept to a minimum. The alternatives were a linear model, in which the slope changes during the blow, or a linear model, where the slope is defined based only on the initial values of the blow. Because the time available to calculate the change in temperature is short, it was decided to search for the constant slope, defined from the initial values of the blow. The calculation was easier to carry out and it was assumed to provide as good results as calculations using the changing slope. Before this model development there was a constant value in use: 0.54°C per second is added to the temperature measured with the dropping sensor.

The calculation of the slope is carried out according to the following equation:

$$S = \frac{T_f - T_s}{t_b - t_s}, \qquad (1)$$

where T_f is the measured end temperature, T_s is the temperature of the dropping sensor, t_b is total duration of the blow and t_s is the blowing time elapsed when the dropping sensor is used.

3.2 Data used in modelling

The data, process measurements and analyses, were collected into the database from the plant automation system, information being collected from May –00 to September –02. In total, thirty-six measurements were collected from over fifty one thousand blows. The validation of the measurements was carried out in co-operation with the steel plant personnel.

From the following figure (Fig. 2) can be seen that data has large distribution and it needs to be well pre-processed before being used in modelling.

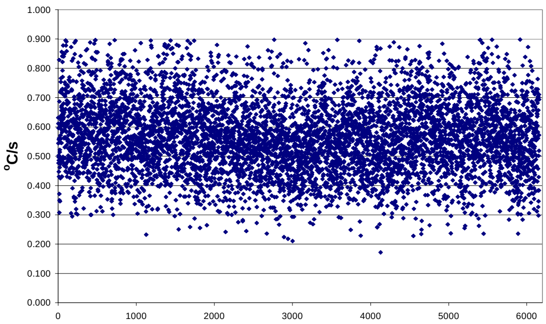

Fig. 2. Distribution of temperature slope in data.

3.3 Data Classification into groups

The data pre-processing and preliminary modelling are reported in Ruuska *et al*, 2003. Theory about variable selection and classification can be found from several handbooks, for example about variable selection in Weiss, Indurkhya, 1998, and about classification in Michie, 1994. However in this case variable selection and classification is done in co-operation with the steel plant personnel.

Preliminary models were formed as follows: first all blows not having all the required measurements were omitted → kk-ka –model; then blows that weren't possible physically and for example small heat sizes were omitted → kk-ka mod –model. Next, the blows, where the increase in the temperature was over 20°C after the dropping sensor were included in mod>20 –model and the blows with under 20°C increase in mod<20 -model. To show that preliminary modelling was done in the correct directions, statistical parameters are introduced in Table 1. It can be seen that the standard deviation decreases while moving towards the best model of these four preliminary models, mod>20 –model.

Table 1. Statistics of preliminary modelling

	kk-ka	kk-ka mod	mod>20	mod<20
Average	0.37	0.50	0.54	0.32
Std dev.	1.301	0.174	0.138	0.186
# of blows	3787	3341	2700	641

The tree-like structure in Fig.3 shows, how the data is divided into different groups. The limits between different groups of variables are presented in Table 2. Variables are the converter number, heat size, carbon content, end temperature and remaining time after the dropping sensor measurement.

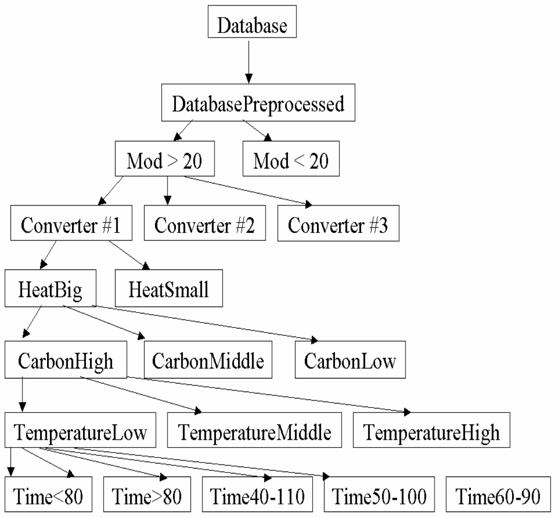

Fig.3. Data classification tree

Table 2. Classes of different variables

Group	Range
HeatBig	>= 120 t hot metal
HeatSmall	< 120 t hot metal
CarbonHigh (C3)	0.045 <= C-% < 0.08
CarbonMiddle (C2)	0.035 <= C-% < 0.045
CarbonLow (C1)	< 0.035 C-%
TemperatureLow (T1)	< 1660°C
TemperatureMiddle (T2)	1660 <= °C <= 1700
TemperatureHigh (T3)	> 1700°C
Time<80 (t1)	< 80 s
Time>80 (t2)	> 80 s
Time40-110 (t3)	40 - 110 s
Time50-100 (t4)	50 - 100 s
Time60-90 (t5)	60 - 90 s

As an example of the complexity even after the classification, the distribution of the temperature slope versus the carbon percentage is shown in Fig. 4. As the trend line is set into the figure, it can be seen that when the carbon percentage increases, the value of the slope decreases. This trend is in correct direction because as steel is blown to a smaller carbon percentage the rate of temperature increase grows. From the figure it can also be seen that the scattering is huge.

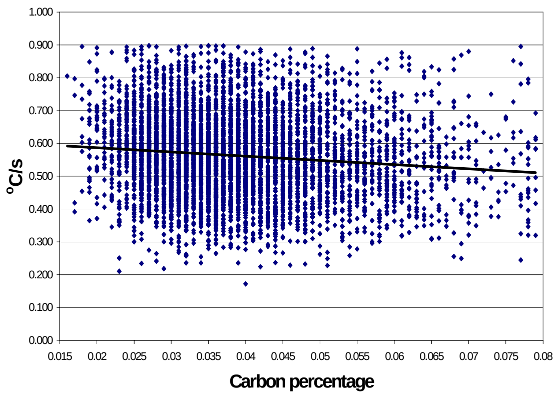

Fig. 4. Distribution of slope vs. carbon percentage.

More detailed info on modelling procedure can be found from Ruuska *et al*, 2003. After discussing with the personnel of the steel plant, the end temperature was left out from the variable list. The remaining time after the dropping sensor measurement was left out from the variable list as well. It was omitted because using different time ranges did not have a very big effect on the value of the slope or on the standard deviation of the slope. In the following table (Table 3.) slopes for groups of big heat size and low carbon percentage for converter #3 are shown as example.

Table 3. Slopes of groups

Converter #3 HeatBig CarbonLow (C1)

	Group				
	C1	C1T1	C1T2	C1T3	
Average	0.57	0.47	0.58	0.65	
Std dev.	0.116	0.096	0.108	0.126	
# of heats	284	32	223	29	
	C1t1	C1t2	C1t3	C1t4	C1t5
Average	0.58	0.56	0.56	0.57	0.56
Std dev.	0.134	0.1	0.119	0.117	0.12
# of heats	124	160	185	229	130

4. PRACTICAL CONSIDERATIONS

4.1 Need for Adaptivity

There is a periodic variation in the slope. The variation correlates to the time the converter has been in use after relining. The variation is caused because the heat losses to the environment are different during the campaign. The variation of over three hundred and fifty slopes is presented (moving average of thirty blows and no filtering) in Fig 5. From the figure, it can be observed that there were periodic variations. It was recognised that adaptivity was needed; meaning that instead of constant slopes the slope is allowed to follow the variation over the lining campaign.

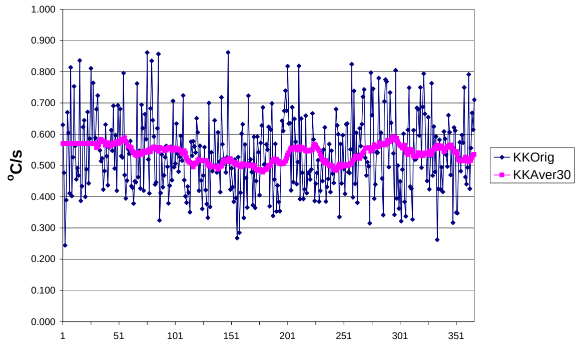

Fig. 5. The variation of the slope (moving average of thirty blows and no filtering).

Theory about adaptation can be found from several textbooks, for example from Åström, 1989. In this case simple filtering with moving average within different groups was effective enough.

The effect of adaptation was tested by using normal slope and adapted slopes in calculating the end temperatures. The test showed, how well the calculated temperature predicted the measured temperature at the end of the blow within the target window, ±10°C. It showed that the performance of the model increased from 67 % to 70 % as filtering was used. Median filtering was not used as it requires more calculation and it was observed that it doesn't give any benefit against average filtering. Those blows that weren't within the target window had some unexpected randomness. This kind of adaptivity is implemented in the automation system in Ruukki Production, Raahe Steel Works.

4.2 Test results

The performance of the temperature model was tested with data from all three converters. The test shows, how well the calculated temperature predicts the measured temperature at the end of the blow within the target window, ±10°C. All blows based on the time of the dropping sensor were accepted. However there were still blows, which do not fit into the temperature target window. The main reasons for this were the measurement error of the dropping sensor and the fact that the measured temperature does not always represent the temperature of the whole melt. In addition to this, there is a random, unexpected variation in all process conditions. This leads to the fact that the slope for the molten steel temperature can differ considerably from the average. The difference of the slope for two similar blows can be 0.4°C/s and thus if the remaining blowing time is quite long, for example one hundred seconds, the difference in the measured temperature can be as much as 40°C. In cases such as this there is a special need for the expertise of the operators in the control room. They need to be able to recognise that for some reason the temperature growth in the blow is not normal. The test results are presented in Table 4.

The following equations are needed in validating the success of the classification of data. The end temperature was calculated according to equation 2, by adding the difference of the total duration of the blow and the dropping time of the dropping sensor multiplied with the slope to the temperature obtained by the dropping sensor according to equation 2. The error was calculated as the difference of calculated temperature and the measured end temperature according to equation 3.

$$T_c = T_s + S(t_b - t_s)\,, \qquad (2)$$

where T_s is the temperature obtained by the dropping sensor, S (slope) is the growth in temperature per second, t_b is the total duration of the blow and t_s is the blowing time elapsed when the dropping sensor is used.

$$e = T_c - T_f\,, \qquad (3)$$

where T_c is the calculated temperature and T_f is the measured end temperature.

Table 4. The testing results with different converters

Converter #1	Converter #2	Converter #3
HeatBig	HeatBig	HeatBig
C1	C1	C1
274(356)->77.0%	313(399)->78.4%	246(367)->67.0%
C2	C2	C2
582(743)->78.3%	453(579)->78.2%	250(361)->69.3%
C3	C3	C3
596(782)->76.2%	588(741)->79.4%	219(287)->76.3%
HeatSmall	HeatSmall	HeatSmall
C1&C2	C1&C2	C1&C2
31(41)->75.6%	24(27)->88.9%	16(20)->80.0%
C3	C3	C3
165(212)->77.8%	93(132)->70.4%	34(51)->66.7%

The testing for the blows, which had less than 20°C rise in temperature, was done for converters #1 & 2. If the slope found for under 20°C rise in the temperature was used instead of the average group, the slope performance was much better. Of the blows, 70 – 80% were within the target window, ±10°C, instead of the previous 40 – 60%. This grouping cannot be used in the final automation system; however, as if the operator decides to blow for example 20°C over the target temperature for some reason, the growth in the temperature would be normal. Instructions regarding this issue need to be given to the operators. They need to recognise that if the temperature is already near the target temperature as measured with the dropping sensor, the rise in temperature will be slower. This lower rise in the molten steel temperature is the result of a "hot spot", from which the dropping sensor measures the temperature. So the dropping sensor measurement and the temperature measurement at the end of the blow are not directly comparable.

The distribution of the error within the test run is shown in Fig 6. It can be seen that the error is distributed quite equally on both sides of zero. The range being about 50°C indicates that there are big random changes between the heats belonging to the same group according to their initial values.

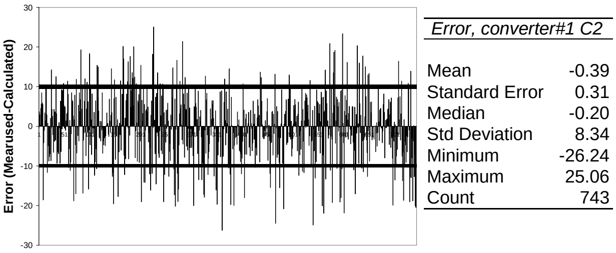

Fig. 6. Typical error distribution in test run.

The target window was set to be ±10°C by the personnel of steel plant, but just for curiosity another target window was tested. Because it isn't so harmful if the temperature is higher than the target temperature, target window of -10 - +25°C was used. Having too high temperature isn't so harmful as further processing is also done in molten phase. If temperature is too low, however, there is risk of interrupted casting at the continuous casting process. The test results are presented in Table 5.

Table 5. The testing results with different converters

Converter #1	Converter #2	Converter #3
HeatBig	HeatBig	HeatBig
C1	C1	C1
314(356)->90.8%	350(399)->87.7%	275(367)->74.9%
C2	C2	C2
651(743)->87.6%	498(579)->86.0%	279(361)->77.3%
C3	C3	C3
678(782)->86.7%	642(741)->86.6%	255(287)->88.9%

5. CONCLUSION

In this study it was found that the increase in the metal temperature after the dropping sensor measurement is a complex function of several variables. This increase rate may be considerably different, even for blows, which in the light of the initial values would appear to be identical. All the variables affecting the rise in temperature and their magnitudes cannot be modelled and so statistical modelling based on historical data was the natural choice. The blows were divided into classes based on the converter number, heat size and target carbon percentage. Also dividing by end temperature and remaining time after the dropping sensor measurement were used as variables, but they were omitted later. It was observed that use of the correct variables and the correct limits between the groups of the variables is essential in order to get good results. When the data was divided as mentioned above, 75 –

80% of the blows were within the target window of ±10°C in the testing of the models. As always in the modelling based on historical data, good quality of the training data is extremely important. First of all, data pre-processing needs to be done very carefully, so we don't remove too much data, but also that we need to remove false data or data which doesn't have all the measurements needed. In addition two groups of blows were removed from training set: the blows with reblow, and the blows, where the additional material was added less than two hundred seconds before the dropping sensor measurement. The latter group was removed, because any effect of the additional material should not still be in progress as the dropping sensor is used. Also the blows, where the additional material was used after the dropping sensor measurement, were removed. The last group of blows was used in developing the models for the additional materials. The model for the additional materials has been presented in Ruuska et al (2004).

Following conclusions can be drawn concerning the reliability of the temperature model:

- Variation of the temperature slope within the converter campaign leads to the need for adaptivity.
- The converter's "hot spot" (temperature has a local maximum).
- The temperature model was developed using two different kinds of measurements, the dropping sensor and manual measurement. The temperatures obtained from these measurements were not fully comparable.
- In the temperature model there were only two groups based on the heat size. The temperature rise can be assumed to be different in the edge zones of these groups, but it was assumed that this difference was small compared to other variations.
- When the carbon percentage of the heat was very low the temperature rise was quicker because of additional energy from iron oxidation.
- As the temperature is being measured there may be for example scrap that has not melted or some other material addition close to the measurement spot, and which can cause a local, sometimes even big, temperature gradient.
- General reliability of the temperature measurement; single temperature measurement represent only one spot of the melt and there was no information about possible temperature gradients.

The temperature model introduced in this paper and the model for the additional material have been implemented into the automation system along with other models developed during the plant's own project. Along with the models introduced in the paper the knowledge about the issues effecting the temperature growth in the molten steel has increased. Still there were several cases with an abnormal difference in the temperature rise compared to the average. The heterogeneous raw materials are likely to be the biggest reason for this variation. Steel converter process is very complex process and there is a great need for further research both on metallurgical and automation side. Also we need to try to find new methods for measurements and if possible, even direct measurements, to get to know more about the reactions taking place inside the converter.

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