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Process-structure-microstructure relationship in hot strip rolling of steels using statistical data mining

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Abstract

Mathematical models have been widely used for prediction of microstructure and mechanical properties in hot rolling of strip. To accurately predict these characteristics, it is necessary to create models that can replicate thermomechanical state of material and its evolution during processing. This paper presents development of a hybrid model that uses mills setting and real time plant data such as chemical composition; forces and temperatures; and integrates them with empirical relationships of material evolution to predict quality attributes. This information is combined with non-linear statistical data mining models to create on-line tool that predicts properties of individual coil. Case study from Steel Plant is presented that illustrates implementation, calibration and validation of this model across different materials grades.

Keywords: Hot rolling; Strips; Material evolution; Statistical data mining; Microstructure

1. Introduction

Manufacturing processes like hot rolling of coils represent a complex engineered system as they involve a series of steps through different machines which the material has to undergo before it is converted into a final product. For example, in hot rolling of steel, steel is melted with different alloying elements like Si, V, Cr, Mo etc. and

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poured into a continuous caster which has different strands and is formed into a slab. This slab then goes through a series of roughing passes, intermediate passes and finishing passes through a hot rolling mill.

Accurate prediction of dimensions and material properties in the hot rolled steel product requires modeling of the mechanical behavior of the material during rolling, microstructural evolution in the roll bite and in the inter stand region, and phase transformation during controlled cooling after rolling.

With significant progress been made in recent years in modeling of microstructural evolution, mathematical models are gaining acceptance as powerful tools for conducting off-line analysis of metal flow and metallurgical changes during rolling. For example, Shivpuri et al. (1997, 1999) developed an integrated framework for hot rolling of bars (ROLPAS) which can predict the microstructural evolution during the rolling and also the profile of the bar being rolled. Similarly, AIST (Integ) developed model for prediction of microstructure and mechanical properties during the rolling of sheets. These models are off-line, computationally very expensive, need to be tuned for different mill and are deterministic in nature.

Recently, hybrid models that combine the usefulness of both the statistical and FEM models are being tried in the prediction of properties of hot rolling (Kusiak, 2002; Hodgson, 1992; Yoshie, 1992). Notable among these is the model by Danieli Automation called DANIELI – CQE (Mukhopadhyay, 2010) that is an online model for prediction of UTS, YS and elongation.

The aim of this research is to come up with a model that not only takes the metal flow, temperature distribution, microstructural evolution etc. into account, but also the actual variation in the hot rolling mill. Such a model should be able to calculate the properties of the rolled coils in real time and be able to tune itself as the rolling process continues. This paper presents the development of such a hybrid model (MICROL) that uses the real time plant data such as chemical composition; forces and temperatures from HSM; reduction schedule etc; and integrates them with the empirical relationships to predict the quality attributes as well as microstructural features.

Nomenclature

h_2	exit thickness at a given pass
h_1	entry thickness of the strip
R	roll radius
N	roll peripheral speed, rpm
Q	activation energy for plastic deformation determined by experiments for different materials
R	universal gas constant, 8.314 J/mole/K
T	temperature in K
C, α, n	Material constants
K	curve fit constant
v	strip speed
T_1, T_2	strip surface temperature between the cooling
a, b	exponent of strip speed and thickness
c, d	exponent of surface temperature and flow rate.
t	reheat time (s),
D^m	Grain size at time t
D_0	Initial Grain size.

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2. Background

The hybrid mode MICROL described in this study was developed for a steel plant. This is a 2000 mm (78.74") wide continuous mill. It has three 100 ton/hr continuous pusher type reheat furnaces, five 4-high roughing stands, seven 4-high finishing stands and three pneumatic coilers. The roughing mill has one vertical stand for slab control and sizing, one 2-high stand and four 4-high universal stands with edgers and roller tables with hydraulically operated side guards. The finishing mill has seven stands in tandem with hydraulic automatic gauge control in the last 4 stands.

3. MICROL – framework

The main framework of MICROL is illustrated in Figure 1. In this framework, thermo-mechanical parameters of the system for the coil being rolled are acquitted in real time using the Level -3 control system implemented on the mill. These parameters include the system parameters for the melt processes (such as the steel grade, steel chemistry and casting conditions), the preheating furnace, the descalers, rolling stands, the laminar cooling system and the coilers. Some of the parameters important for determining the mechanical and material state are shown in Figure 1. The MICROL system acquires these parameters from the mill system and uses different mathematical modules to calculate the mechanical and microstructural state of the rolled coil. In addition to this deterministic calculation, the MICROL system also assesses the process uncertainties inherent to the mill and using the theory of statistical inference compensates for these production variances. Therefore, it is able in its predictions not only to include the steady state conditions of production but also the non-steady state conditions that influence the system responses.
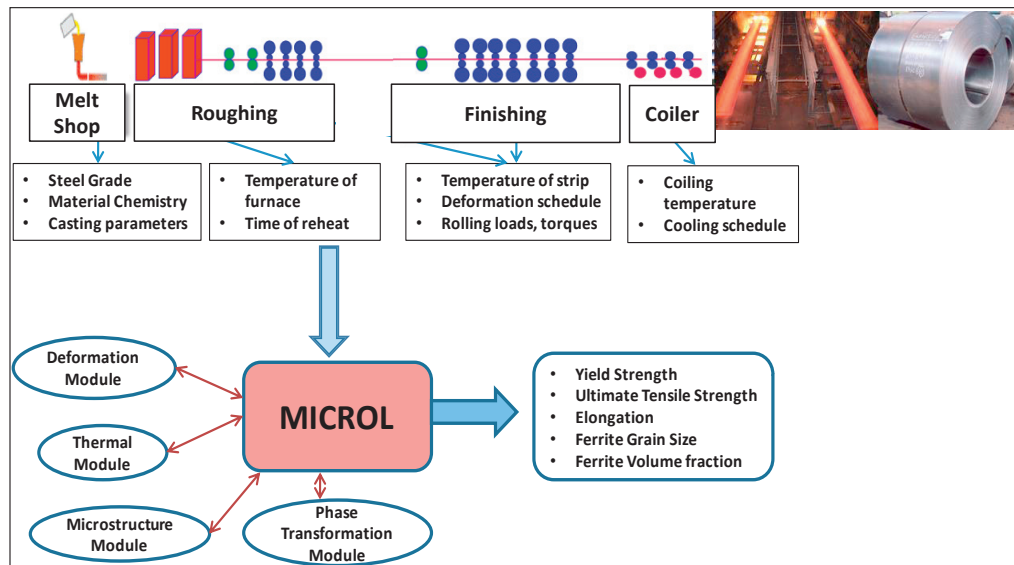

Fig. 1. Framework of the integrated model.

After the model is run, the output is stored in another file that contains the input parameters along with the predictions. A report file containing the description of all the predicted coils is also updated at each run.

4. MICROL – modules

4.1. Deformation module

To accurately predict the grain size, phase transformation and mechanical properties during the flat rolling process, the two most important parameters to be calculated during the rolling are the strains and strain rate at each pass. The calculation of these is accomplished by the following equations:

$$Strain(\ ) = \ln(h_2 / h_1), \tag{1}$$

$$\text{Strain rate}\,(\xi) = \frac{\pi N}{30}\sqrt{\frac{R}{h_1}}\frac{h_2}{(1-h_2)}\,. \tag{2}$$

The strain rate is related to the Zener – Holloman parameter *Z*, where

$$Z = \exp(Q/RT) = C\sinh(\quad)^n. \tag{3}$$

There is no direct way to measure the parameter *Z*. Hence an indirect method is used to calculate this.

$$Z = C\sinh\left(\frac{P^2}{MQ_p}\ddagger\right)^n \tag{4}$$

Using Eqn. 4, legacy data is used to find the constants *C*, *α* and *n* for different materials using least square regression and *Z* is then calculated as each coil is rolled.

4.2. Thermal module

To understand and decompose these mechanisms, the temperature history of the sheet was explored. It was found that the primary mechanism of heat transfer during the roughing and finishing passes is the laminar cooling due to water channels. This heat transfer is practice depends on the temperature of water being sprayed, the pressure at which it is being sprayed and the number of nozzles. However, to model these phenomena is a complex procedure. The most common form of calculating this heat transfer coefficient is given as:

$$h = Kv^a t^b (T_1 \quad T_2)^c Q^d. \tag{5}$$

The header flow rate and is assumed to be constant and hence can be combined with the coefficient *K*. Also, the strip speed remains the same for a particular thickness. Hence it can also be combined with the constant *K*. Therefore,

$$h = Kt^b (T_1 \quad T_2)^c. \tag{6}$$

The Eqn. 6 was used for the different materials and the constants *K*, *b* and *c* were determined.

4.3. Microstructure module

From a microstructural point of view, different stages in the processing of steel are 1) Austenite grain growth during reheating, 2) Dynamic recrystallisation during deformation and 3) Metadynamic and static recrystallisation during interpass time intervals. To model these different stages, it is necessary to calculate the grain size and phases at each of these stages. This is done by the following sub modules:

Reheating furnace module: Before the slab is sent for deformation in the rolling mill, it is subjected to high soaking temperatures. The austenite grain growth in the furnace is exponentially related to the soak temperature. An empirical relation connecting reheated grain size, D_0 in mm, with soak time and temperature is:

$$D_0 = K_1 t^{K2} \exp\left(\quad Q/RT\right). \tag{7}$$

Recrystallization module: Recrystallisation is divided into 3 categories: dynamic, metadynamic, and static. Static recrystallization occurs during the interpass time. If the applied strain exceeds the critical strain, the start of dynamic recrystallization is marked by the formation of new grains. Once the dynamic recrystallization starts, post-dynamic recrystallisation will continue even in absence of strain, as grains are already work hardened. The Johnson – Mehl – Avrami – Kolmogorov (JMAK) expression accounts for the fraction recrystallised and is given by

$$X = 1 - \exp\left(-0.693(t/t_{0.5})\right)^n. \tag{8}$$

Once the different values have been calculated, they are transferred to a CSV file and the statistical model is fit to them. The statistical model used is Multivariate Adaptive Regression Splines. It is a non-parametric regression technique and can be seen as an extension of linear models that automatically models non-linearities and interactions. It builds models of the form:

$$f(x) = \sum_{i=1}^{k} c_i B_i(x). \tag{9}$$

The model is a weighted sum of basis functions $B_i(x)$ and each c_i is a constant coefficient.

5. Installations and calibration

Data was collected for a period of 100 days and 3 materials were chosen for model building. The chemical compositions of the materials is given in Table 1.

Table 1. Chemical composition of materials (by %wt.)

	C	Mn	Si	P	S	Nb	Ti	V
Material A	0.05-0.23	0.3-1.5	0.1-0.40	0.01-0.05	0.01-0.05	Trace	Trace	Trace
Material B	0.05-0.16	0.1-0.3	0.05-0.25	0.01-0.03	0.01-0.03	Trace	Trace	Trace
Material C	0.1-0.25	0.5-1.5	0.1-0.2	0.01-0.04	0.01-0.04	0.01-0.2	0.01-0.1	0.01-0.1

To fit the MARS model, the package "earth" was used in *R*. The complete model was fit with degree=1 (no interaction) and degree=2 (one way interaction). There was no pruning done of the number of steps. The results compared on the models were training R^2 values; the prediction percent error mean, medians and standard errors; number of variables selected (simplicity of model). This is shown in Table 2.

The results show that degree=2 models have higher R^2 values but generally do very poorly on the predictions. The full model behaves as an average of the other models built individually. There are some variables that are common to all the models. Hence these variables can be treated as the most important ones and model can be fit with these variables only later on.

Table 2. Results from MARS models

Model	Training R^2	% Error mean	Error Median	No. of variables selected
Full Model Degree =1	0.831	8.054	0.3365	25
Full Model Degree =2	0.85	68.1	1.224	29
Material A Degree =1	0.765	-2.83	-1.91	18
Material A Degree =2	0.762	-0.91	-3.00	14
Material B Degree =1	0.678	-8.25	-1.38	31
Material B Degree =2	0.743	24.61	4.72	29
Material C Degree =1	0.585	-7.34	-7.58	4
Material C Degree =2	0.931	-3.67	-1.42	4

6. Validation and running

After the successful installation and calibration of MICROL, it was necessary to validate the model over a longer period of time and see if the operators are able to use the software effectively without any issues. For the validation of the model, the software MICROL was run for a period of 73 days. During this time, the data from the continuous casting, roughing mill, finishing mill, run out table etc. was transferred in a file that were used by MICROL for prediction. The predictions were stored in a report file. After the validation period was over, the predictions were transferred in another file and compared with the tested properties from the QC. The predictions were then compared for two different conditions:

1) When the model MICROL take the variance in the system (chemistry, loads, temperatures, speeds etc.)
2) When the model does not take the variance into account.

The results of the validation for both these conditions are shown in Figure 2. This shows the following:

a) Errors of the model when variance is considered and when variance is not considered are quite different.
b) When the variance of the system is captured and included in model development and running, the errors in the prediction of the mechanical properties are within ± 5%.
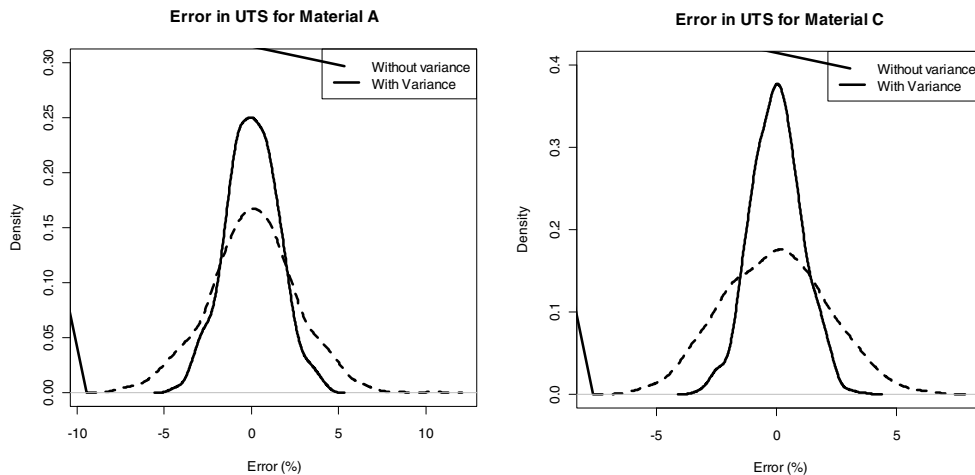

Fig. 2. Errors from MICROL when the variance in system is considered and when it is ignored.

7. Conclusions

This paper presents the development of a hybrid model (MICROL) that uses the real time plant data such as chemical composition; forces and temperatures from HSM; and integrates them with the empirical relationships to predict the quality attributes as well as microstructural features. This information is combined with a non-linear statistical model to create an on-line tool that predicts the properties as soon as the coil is rolled. Case study from a Steel Plant is presented which illustrates the implementation, calibration and validation of this model across different materials grades. The predicted results from the model agree very well with the legacy plant data.

References

Shivpuri, R., Pauskar, P., Cho, H. and Kim, N., 1997. An FEM Based Model of Metal Flow and Microstructure Evolution in Continuous Hot Rolling, Transactions of the Society of Manufacturing Engineers, XXV.

Shivpuri, R., Pauskar, P. "Microstructure and Mechanics Interaction in the Modeling of Hot Rolling of Rods", Annals of CIRP, 48, 191-194 . www.integpg.com/hsmm/files/HSMM_Overview_Rel_2_0.pdf.

J. Kusiak, R. Kuziak, 2002. Modelling of Microstructure and Mechanical Properties of Steel using the Artificial Neural Network, Journal of Material Processing Technology, 127, 115-121.

P.D. Hodgson, R.K. Gibbs, 1992. A Mathematical Model to Predict the Mechanical Properties of Hot Rolled C-Mn and Microalloyed Steels, ISIJ Int. 32, 1329-1338.

Yoshie, A., et. al., 1992. Modeling of microstructural evolution and mechanical properties of steel plates produced by thermo-mechanical control process, ISIJ International, 395- 404.

A. Mukhopadhyay et al, 2010. DANIELI-CQE: System for controlling Mechanical Properties of Hot-Rolled Coils, Materials and Manufacturing Processes, 25, 76-84.