An On-Line Hierarchical Decomposition Based Bayesian Model for Quality Prediction during Hot Strip Rolling

Kuldeep AGARWAL* and Rajiv SHIVPURI

Department of Integrated Systems Engineering, 210 Baker Systems Bldg, 1971 Neil Avenue, The Ohio State University, Columbus, OH 43210 USA. E-mail: shivpuri.1@osu.edu

(Received on February 28, 2012; accepted on May 29, 2012)

Mathematical models have been widely used for the prediction of the microstructure and mechanical properties in hot rolling of strip. However, their accuracy is insufficient for quality control purposes. To accurately predict these characteristics, it is necessary to create models which can replicate the thermo-mechanical state of the material and its evolution during processing. In addition, these models should be able to capture the uncertainties introduced in the processing by the dynamics of the casting process and the subsequent rolling. These uncertainties lead to considerable variations in the material and mechanical state of the rolled strip. This paper presents the development of a hybrid model (MICROL) which uses the mills setting and the real time plant data such as chemical composition; forces and temperatures; and integrates them a Bayesian format to predict the desired quality attributes as well as microstructural features. This information is combined into Bayesian Hierarchical models to create an on-line tool that predicts the properties of each individual rolled coil, as well as provide information on the batch-to-batch and heat-to-heat variations. Case study from a steel Plant is presented which illustrates the implementation, calibration and validation of this model across different materials grades. Model results are found to be within the 5% tolerance of the measured values for many steel grades and rolling conditions.

KEY WORDS: hot strip rolling; mechanical properties; bayesian hierarchical model; data mining; microstructural features; phase transformation.

1. Introduction

The hot strip mill (HSM) represents a complex engineered system that through a series of processing steps converts the material and mechanical state of the cast slab into that of the hot rolled steel coils. For example, in the hot rolling of steel, steel is melted with different alloying elements like Si, V, Cr and Mo, and poured into a continuous caster with multiple strands. The slabs produced by the caster then go through a series of roughing passes, intermediate passes, finishing passes and run-out-table through a hot rolling mill before being coiled. The rolled strips are sent to the customer for further processing into sheets for autobodies, sheets and piling for railways, heavy electrical winding, transformer cores, etc.

The properties of rolled steel products used in the various applications depend upon the composition of the material, deformation history in the rolling mill and the transformations after rolling. It is very important to accurately predict these mechanical properties during hot rolling so that the process can be controlled, testing can be minimized and quality can be improved.

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. Development of a comprehensive hot rolling model therefore requires an integrated approach to modeling metal flow, temperature distribution, microstructural evolution and phase transformation.

Microstructure modeling in hot strip mills began in the late 1970s pioneered by Sellars and Whitteman1 and empirical equations have been developed by many researchers for various processes thereafter. Most of the work leading to development of models for direct industrial application started in early 1990s. In 1991, Laasraoui and Jonas2 reported microstructure evolution model for hot rolling of steel with empirical relationships for flow stress, static recrystallization, dynamic recrystallization and austenite grain size. In 1992, a review paper of Kwon3 described a series of empirical equations developed by Sellars (at University of Sheffield), Esaka and Yada (NSC), Kwon (POSCO), Choque (IRSID), Roberts (Inst. for Metall.) and Hodgson (BHP) for kinetics of static recrystallization, gamma-alpha phase transformation and structure-property correlation. Beynon and Sellars4 described details of a SLIMMER (Sheffield Leicester Integrated Model for Microstructural Evolution in Rolling) which had been validated not only with the data of C–Mn grade of steel, but also with data of Nb-bearing microalloyed steel.
Yoshie et al.\(^5\) of Nippon Steel developed a mathematical model for predicting grain size of thermostatic Control Process (TMCP). Watanabe et al.\(^6\) of Nippon Steel developed an integrated model for the prediction of microstructural evolution and mechanical properties of the steel plates manufactured by TMCP by linking the metallurgical model and the process models. Hodgson & Gibbs\(^7\) developed mathematical models for each of the microstructural events that occur during the hot rolling of a range of commercial steels.

Major advances have been made recently in developing computational models of the metal flow and microstructural evaluation in multi-pass bar and sheet rolling. For example, Shivpuri et al.\(^8\) 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, a model for the prediction of microstructure and mechanical properties during the rolling of sheets was developed by AIIST.\(^9\) These models are offline, computationally very expensive, need to be tuned for each different mill and are deterministic in nature. They do not take into account the variations occurring in actual mills. Hence their use is limited to initial design.

The mathematical models try to use laboratory experiments and the models developed there in the actual mills. This results in poor predictions (with errors up to ±20% in some cases). To reduce these errors, researchers are trying to introduce more complexity into the models by adding more variables like chemistry, transformation temperatures, precipitation kinetics etc. Although this results in slight improvement of predictions (the errors are still very high), but the models now become very complicated. Another shortcoming of this modeling approach is that one parameter is changed at a time during the experimentation and its effect is looked at the final properties (for example, effect of alloying element like silicon, effect of cooling rate in ROT etc.). The interactions between the different processing steps are ignored in the experimentation and this causes the errors in the predictions. Due to lack of understanding of these interactions, no decision about the controls and design can be made. It is important to note that the empirical relationships derived from experiments are just statistical fits to the data for the particular material and conditions for which the experiment was done. It does not reflect the true behavior of the material under the actual rolling conditions encountered in mills.

As more and more automation is done at the plants, there is a need for online models which can predict the properties of coils as they being rolled so that corrective actions can be taken immediately. These models rely on the data generated during the rolling process to find the relationship between processing history and properties. Statistical techniques and machine learning methods are commonly used to build these methods. With the advancement in statistical analysis and data mining tools, a lot of newer models have tried to use different statistical techniques in developing models for hot rolling. These include models like neural networks,\(^10\) fuzzy logic and logistic regression. These models need a lot of data during the training phase and are not adaptable to changes in the mill setup. Hence they are not suited for on-line predictions. Recently, hybrid models which combine the usefulness of both the statistical and FEM models have been developed for the prediction of properties of hot rolling.\(^11\) Notable among these is the model by Danieli Automation called DANIELI – CQE\(^12\) which is an online model for prediction of UTS, YS and elongation. This model is proprietary software which is not portable to different mills and needs to be based on strict hardware requirements.

Empirical models, although, have a better prediction than the mathematical models, but is really black-box in nature. The models based mainly on neural network type non linear regression give no idea about the interactions between the different processes and chemistry. It is almost impossible to control or suggest design changes to improve the mechanical properties. These models require huge amounts of data for training and predictions. Moreover, every time there is a slight change in the mill setup (new machines, machines degrading over time), the models need to be reformulated for the predictions.

2. Hierarchical Decomposition

To overcome the main disadvantages of the physical and statistical models and to design the sheet rolling process for enhanced mechanical properties, a novel decomposition technique was developed. In this methodology, the mechanical properties are decomposed into the different kinds: yield strength (YS), ultimate tensile strength (UTS) and elongation. These are then decomposed into the physical quantities affecting them (e.g. stress, strain etc.). The physical quantities are decomposed into the design parameters on the rolling mill which are connected to the individual sub-processes (Fig. 1).

To achieve the above mentioned decomposition, Bayesian Hierarchical Modeling is used. Let \([X]\) represent a probability distribution for a random variable \(X\); \([X \mid Y]\) represents the conditional probability distribution of \(X\) given \(Y\). Bayes’s theorem provides a mechanism for updating our prior distribution \([X]\) based on data, say, \(Y\). That is, the posterior distribution \((i.e., \text{after observing the data})\) is

\[
[X \mid Y] = [Y \mid X] [X]/[Y]...................... (1)
\]

where, for a continuous variable \(X, [Y] = \int [Y \mid X][X]dX\). The basic concept of hierarchical modeling is the notion of conditional thinking. The joint probability distribution of a collection of random variables \(X_1, \ldots, X_k\) can be represented as a product of conditional distributions:

\[
[X_1, \ldots, X_k] = [X_1 \mid X_2, \ldots, X_k][X_2 \mid X_3, \ldots, X_k][X_k]...
\]

(2)

In any process, we are interested in finding the output given

\[\text{Fig. 1. Hierarchical Decomposition of the Sheet Manufacturing.}\]
the input and observables (prediction) and also the inverse (design). In both the cases we need the joint probability distribution of all the variables. Let us denote the data by D and the process by P.

We assume that there are statistical parameters $\Theta$ (typically error variance, but possibly parameters accounting for factors other than variability) and physical parameters $\eta$. We apply Bayes’ theorem to model the joint uncertainty of all the quantities involved, making some assumptions along the way, which are related to the physical process. Thus,

$$[P, D, \Theta, \eta] = [D | P, \Theta, \eta] [P | \Theta, \eta] [\Theta, \eta]$$ (3)

The first term is the data model, the second term is a prior physical process model and the last term is a prior model for the statistical and physical parameters, called the prior parameters model. This formulation has been used extensively in the modeling of geophysical systems\(^{13,14}\) and has later been adapted by researchers in fields like climate modeling and personal exposures,\(^{15,16}\) but has not been used in the manufacturing domain. This has the advantage that all the unknowns are treated as random and more complicated models can be easily incorporated in the same setup. The methodology and the model formulation does not change as more and more data becomes available and new knowledge about the process can also be incorporated in the physical process model at any point of time.

3. Hierarchical Decomposition of Sheet Rolling Process

After the above mentioned decomposition is done, it is necessary to convert it into the Bayesian Hierarchical Model. Let us denote the different levels in the decomposition as follows:

- M: Mechanical Properties in general ($M_{YS}$, $M_{UTS}$, $M_e$ to represent them individually)
- I: State variables affecting the surface defects (Stress, Strain, etc.)
- F: Process Parameters (Roll Loads, Temperature, Speeds etc.)

The joint PDF of these variables can be written as:

$$[M, I, F] = [M | I, F] [I | F] [F]$$ (4)

Our aim is to find this joint distribution based on the observed data D. However, we would like to use the Bayesian framework to learn about the underlying variables and parameters. Using the likelihood and the prior distribution on process parameters F, the posterior distribution is given by:

$$[M, I, F | D] \propto [D | M, I, F] [M, I, F]$$ (5)

Here, $[D | M, I, F]$ is the data model and $[M, I, F]$ is the process model.

Section 4 discusses the data collection and integration necessary for creating a data model. This section describes how the data was collected for calibrating and validating the model and methods to convert this raw data into a usable format through data mining. Section 5 describes the data collected and processed on the rolling mill involving the temperature, roll loads, roll speeds etc. This corresponds to the Level 4 in the decomposition.

Section 6 describes the process modeling methodology which was used for creating the process model (Level 3 in decomposition). Section 7 outlines how the data from sections 4–6 was used for creating the Bayesian Hierarchical model.

4. Data Collection and Integration

The framework described in this study was developed at a hot strip mill. This is a 2 000 mm (78.74") wide continuous mill that 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 (RM) has one vertical stand for slab control and sizing, one 2-high stand and four 4-high universal stands with edger and roller tables with hydraulically operated side guards. The Finishing Mill (FM) has seven stands in tandem with hydraulic AGC in the last 4 stands.

A modern hot strip mill has multiple sensors and data acquisition systems installed for monitoring and control. These are the chemical sensors measuring the chemical composition of steel, thermocouples and pyrometers measuring the temperatures at different stages, load cells measuring the roll loads and torques and optical gages measuring the thicknesses and width along the rolling process (Fig. 2).

This recorded data is then transferred to a central computer which stores it in a database format. The format of this data varies from mill to mill based on the automation system, but the basic features remain the same. Different parts of the mill generally use different databases to store this information. For example, in the steel melting shop the chemical composition is usually stored in a heat by heat manner. On the other hand, in the rolling mill the information is stored on a coil by coil basis. It is therefore necessary to combine all the information from these various sources into a common format which can be used for the development of the framework. In the previous work done by researchers using plant data, they have pre-selected some of these variables in their prediction models. This practice introduces bias in the modeling and we can miss some of the important interactions between the different process parameters. Therefore, in this study we collected all the available data from the mill before starting any model building activity.

All the data available from the sensor fusion was transferred in a text file. Each row of the text file represented one coil and the different columns represented the different pro-
cess settings and variables. In total there were 150 variables in the file including:
1. Chemistry (Percentage of C, Mn, Si, S, P, Nb, Ti, V, Al, Cr, Mo, Ni, Cu)
2. Heat Number for that coil
3. Temperature setting of the furnace
4. Rolling speeds, load and torque at each stand of the finishing mill
5. Entry and exit thicknesses at each stand of the finishing mill
6. Temperatures at the front and tail of the coil at each finishing stand
7. Temperature at the entry and exit of run out table
8. Coiling temperature
9. Measured UTS, YS and Elongation

A sample file is shown in Table 1. Note that the temperatures, loads etc. were averaged by the data acquisition system before storing in the database. Hence, within coil distribution of these variables was not obtained.

5. Data Mining

Data over a period of 2 years for many different materials was collected. Since the data set obtained was large enough for analysis, it was decided to remove all the coils which either had missing data value or had a data value which was an outlier. All these two cleaning steps were completed; three materials having the most information were selected for further analysis and study. Two of these materials were C–Mn steels and one was microalloyed steel. The chemistry of these materials is given in Table 2.

5.1. Exploratory Data Analysis

Before any model is built, it is necessary to look at the data to see the kind of distribution it follows. The first analysis which was done was to look at the distribution of different alloying elements in the different heats of Material A. The summary statistics are shown in Table 3.

Next, the mechanical properties for the different sheets were explored and their variation was looked into. The summary statistics for the mechanical properties for Material A are shown in Table 4. The histograms and the density curves for UTS and YS are shown in Fig. 3. This figure shows that the properties follow close to a Gaussian distribution.

6. Process Modeling

Before the hierarchical model can be built, it is necessary to convert the process parameters into process related variables which can be interpreted by engineers. To accomplish this, empirical models of the sheet rolling process were used.

To study the sheet manufacturing process empirically, the following assumptions are made:

- Workpiece does not spread laterally (plane strain)

Table 3. Summary statistics for alloying elements in Material A.

| Allying Element | Mn. 1st Quantile | Median | Mean | 3rd Quantile | Max. |
|-----------------|-----------------|--------|------|-------------|------|
| C               | 0.08            | 0.13   | 0.1343 | 0.16        | 0.18 |
| Mn              | 0.39            | 0.84   | 0.8346 | 1.04        | 1.04 |
| Si              | 0.045           | 0.1095 | 0.1149 | 0.16        | 0.183 |
| P               | 0.013           | 0.021  | 0.0208 | 0.025       | 0.026 |
| S               | 0.003           | 0.12   | 0.0136 | 0.0215      | 0.031 |
| Al              | 0.019           | 0.037  | 0.0344 | 0.042       | 0.069 |
| Cr              | 0.007           | 0.01   | 0.0085 | 0.011       | 0.011 |
| Cu              | 0.001           | 0.0078 | 0.0078 | 0.0087      | 0.011 |
| Ni              | 0               | 0.0017 | 0.006  | 0.0087      | 0.011 |
| Mo              | 0               | 0.0017 | 0.0074 | 0.0117      | 0.012 |

Table 4. Summary statistics for mechanical properties of Material A.

| Property   | Mn. 1st Quantile | Median | Mean | 3rd Quantile | Max. |
|------------|-----------------|--------|------|-------------|------|
| YS (Mpa)   | 265             | 337    | 341  | 355         | 433  |
| UTS (Mpa)  | 421             | 496.4  | 514  | 550         |
| Elongation | 24              | 30     | 30.09| 32          | 36   |

Table 2. Chemistry of the three materials in this study (percentage by volume).

|         | C     | Mn    | Si    | P     | Al    | Nb    | Ti    | V     | Cr    | Cu    |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Material A | 0.05–0.23 | 0.3–1.5 | 0.1–0.40 | 0.01–0.05 | 0.01–0.07 | Trace | Trace | Trace | 0.005–0.015 | 0.01–0.02 |
| Material B | 0.05–0.16 | 0.1–0.3 | 0.05–0.25 | 0.01–0.03 | 0.02–0.4 | Trace | Trace | Trace | 0.005–0.015 | 0.01–0.02 |
| Material C | 0.1–0.25 | 0.5–1.5 | 0.1–0.2 | 0.01–0.04 | 0.01–0.05 | 0.01–0.2 | 0.01–0.1 | 0.01–0.1 | 0.005–0.015 | 0.01–0.02 |

Fig. 3. Histograms and density curves of mechanical properties for Material A.
The equations used to calculate these are accomplished by the following components:

- Roll flattening does not occur in the arc of contact (rolls can be assumed to be rigid).
- Peripheral velocity of the rolls is constant.
- Material does not undergo work-hardening during its passage between the rolls.
- Vertical component of the frictional force is negligible.
- Material does not undergo deformation heating and the roll chilling, while most of the heat loss occurs between the head and tail of the sheet. Similar trends were observed during the roughing passes. Hence the primary mechanism of heat transfer during the roughing and finishing passes is the laminar cooling due to water channels.

Heat transfer plays a significant role in the hot rolling process as the temperature affects both the sheet and the rolls. The two areas during sheet manufacturing where heat transfer occurs are the rolling (roughing and finishing) and the run out table. The different mechanisms by which heat transfer occurs during these processes are:

- Heat transfer due to convection
- Heat transfer due to radiation
- Heat generation due to deformation
- Heat transfer due to roll chill
- Heat transfer due to water cooling

To understand and decompose these mechanisms, the temperature history of the sheet was explored. The median temperatures at the head and tail of the sheet during the finishing passes (both at entry to a pass and its exit) are shown in Fig. 5. This plot shows that there is little temperature drop during the rolling process itself due to an offset between the deformation heating and the roll chilling, while most of the heat loss occurs between the head and tail of the sheet. Similar trends were observed during the roughing passes. Hence the primary mechanism of heat transfer during the roughing and finishing passes is the laminar cooling due to water channels.

This heat transfer in 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. Moreover, the settings on the mill usually remain constant and hence if an estimate of the heat transfer coefficient can be found, that can be used for the model building. The most common form

Rolling load for different Thicknesses

Rolling Torque for different thicknesses

| Material Constants |
|---------------------|
| C       | α       | n       |
| Material A | 3.85 × 10^2 (1.12 × 10^2) | 0.015 (0.001) | 2.85 (0.14) |
| Material B | 2.89 × 10^2 (2.25 × 10^2) | 0.018 (0.0015) | 2.68 (0.16) |
| Material C | 3.23 × 10^2 (1.8 × 10^2) | 0.016 (0.0012) | 2.77 (0.11) |

Fig. 4. Variation in roll loads and torque in the finishing mill due to the variation in chemistry and the resulting flow stress for material A are shown in Fig. 4. Two different sheet thicknesses of 5 mm and 16 mm are shown to illustrate the difference in variability with the thickness too. Using Eq. (13), 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. The constants determined from these equations are shown in Table 5. The values in parenthesis for the constants represent their standard errors. The variation in the material constants is due to the variation in the chemical composition occurring during the melting.

Using Eq. (13), 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. The constants determined from these equations are shown in Table 5. The values in parenthesis for the constants represent their standard errors. The variation in the material constants is due to the variation in the chemical composition occurring during the melting.

The plots depicting the variation in loads and torque in the finishing mill due to the variation in chemistry and the resulting flow stress for material A are shown in Fig. 4. Two different sheet thicknesses of 5 mm and 16 mm are shown to illustrate the difference in variability with the thickness too. Heat transfer plays a significant role in the hot rolling process as the temperature affects both the sheet and the rolls. The two areas during sheet manufacturing where heat transfer occurs are the rolling (roughing and finishing) and the run out table. The different mechanisms by which heat transfer occurs during these processes are:

- a) Heat transfer due to convection
- b) Heat transfer due to radiation
- c) Heat generation due to deformation
- d) Heat transfer due to roll chill
- e) Heat transfer due to water cooling

To understand and decompose these mechanisms, the temperature history of the sheet was explored. The median temperatures at the head and tail of the sheet during the finishing passes (both at entry to a pass and its exit) are shown in Fig. 5. This plot shows that there is little temperature drop during the rolling process itself due to an offset between the deformation heating and the roll chilling, while most of the heat loss occurs between the head and tail of the sheet. Similar trends were observed during the roughing passes. Hence the primary mechanism of heat transfer during the roughing and finishing passes is the laminar cooling due to water channels.

This heat transfer in 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. Moreover, the settings on the mill usually remain constant and hence if an estimate of the heat transfer coefficient can be found, that can be used for the model building. The most common form
Hence it can also be combined with the constant K. Also, the strip speed remains the same for a particular thickness.

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,

$$h = K v^a t^b (T_1 - T_2)^c Q^d$$

This equation was used for the different materials and the constants K, b and c were determined. The assumption made here is that this heat transfer coefficient is same for all the passes.

7. Bayesian Hierarchical Model for Mechanical Properties

Based on the hierarchical decomposition shown in Fig. 1, the posterior distribution identified in Eq. (1) and the data available from both the plant and the process models (sections 4–6), the joint PDF for the mechanical properties model is written as:

1) M: MYS, MUTS, ME: Mechanical Properties of each coil
2) I: Strain (ε), strain rate (ε′) and Heat Transfer (h) for each pass i = 1, 2, ..., 8, Furnace (f), ROT Cooling (R)
3) F: Chemistry (C, Mn, P, Sul, Si, V), Temperature of furnace (TF), Roll Load (L), Roll Speed (RS), Roll Torque (RT), Temperature at each stand (T1, T2, ..., T8), ROT Temperature (TROT), Coiling Temperature (TCOIL)
4) The data D has the following components:
   a) DYS, DUTS, D: Data on furnace and ROT Cooling
   b) Df, DRS, D: Data on furnace, ROT Cooling, load, roll speed, roll torque, ROT Temperature and Coiling Temperature (Either for each pass, i = 1, 2, ..., 8 or one value)
   c) Dc, Dn, Dp, Ds, Dv: Data on the elemental composition of the material

7.1. Data Model

The data model for each of the mechanical properties can be built separately. The data model for YS is:

$$[DYS_i, D_{ΔS_i}, D_{ΔS_i}, D_{Δr_i}, D_{ΔL_i}, D_{ΔR_i}, D_{ΔT_i}, D_{ΔC}, D_{Δn}, D_{Δp}, D_{Δs}, D_{Δv}]$$

We will try to simplify the conditional structure in the above equation based on process knowledge.

1. First assumption we make is that the data on the strain given the strain rate is conditionally independent of the other process variables. The relationship of strain data to other process variables like strain rate, temperature comes from the process model and not the data itself.
2. The data on the process parameters given the parameter itself is conditionally independent of other process variables. Thus the data on rolling speed given the rolling speed process is conditionally independent of the data on rolling torque and so on.

Based on the abovementioned assumptions, the data model is rewritten as:

$$[DYS_i, D_{ΔS_i}, D_{ΔS_i}, D_{Δr_i}, D_{ΔL_i}, D_{ΔR_i}, D_{ΔT_i}, D_{ΔC}, D_{Δn}, D_{Δp}, D_{Δs}, D_{Δv} | MYS, ε, ε′, h, f, T, L, RS, RT, T1, C, Mn, P, Sul, Si, V]$$

From the exploratory data analysis, these different data variables look normal distributed in nature. Hence, we assume a prior distribution which is normal for each of these conditionally independent subsets.

$$[DYS | MYS] ~ N (MYS, σ^2YS).................. (18)$$

$$[D_{ΔS_i} | ε_{ΔS_i}] ~ N (ε_{ΔS_i}, σ^2ε_{ΔS_i})................. (19)$$

$$[D_{Δr_i} | ε_{Δr_i}] ~ N (ε_{Δr_i}, σ^2ε_{Δr_i})................. (20)$$

And so on.

Here i = 1, 2, ..., 8 because there are eight passes in the rolling mill and k = 1, 2, ..., N represents the number of coils in the database

Also, N represents Normal distribution and its probability distribution functions (pdf) is:

$$N (μ, σ^2) = \frac{1}{\sqrt{2πσ^2}} \exp \left( -\frac{(x - μ)^2}{2σ^2} \right)$$

The data model captures the uncertainty inherent in the observation of processes imperfectly (measurement error, location error, sampling error etc.). The variance in each of these distributions represents these uncertainties for each of the variables. For example, $σ^2YS$ is the error in the testing of the coupons to obtain the yield strength and $σ^2ε_{ΔS_i}$ is the error in the measurement of strain by physical models.
7.2. Process Model

We can create the process models in two different ways. In one method we can consider all the properties together and then create a common process model containing all the different properties. In another method, we can select each of the properties one by one and then create process models for them individually. The second method is simpler and can be understood in a slightly easy manner, hence in this section we will build the process model individually for each property.

7.2.1. Process Model for YS

Using the hierarchical decomposition, the process model for YS can be written as:

\[
[M, I, F] = [M | I, F] [I | F] [F] \quad \text{Or, } \quad [MYS, I, F] = [MYS | I, F] [I | F] [F] \quad \text{............... (21)}
\]

\[
[MYS, I, F] = [MYS | I, F] [I | F] [F] \quad \text{............... (22)}
\]

\[
[MYS, I, F] = [MYS | I, F] [I | F] [F] \quad \text{............... (23)}
\]

\[
[MYS, I, F] = [MYS | I, F] [I | F] [F] \quad \text{............... (24)}
\]

\[
[MYS, I, F] = [MYS | I, F] [I | F] [F] \quad \text{............... (25)}
\]

We make the following simplifying assumptions in this case:

1) The physical mechanism which determines the YS is the heat transfer, strain, strain rate, furnace and the ROT during the rolling. This is relevant based on previous observations by researchers.

2) The heat transfer, strain, strain rate, furnace and the ROT are conditionally independent. The strain and strain rate depend on the rolling schedule and the speed and not on chemistry or temperature. Hence, they are conditionally independent given these parameters.

Therefore,

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (26)}
\]

3) Given the chemistry, speed, load, torque and the temperatures; the strain, strain rates, heat transfer, furnace and ROT are conditionally independent. The strain and strain rate depend on the rolling schedule and the speed and not on chemistry or temperature. Hence, they are conditionally independent given these parameters.

Therefore,

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (27)}
\]

4) The roll load, torque and temperature are conditionally independent of each other given the roll speed. The roll load depends on the strain and strain rate which are dependent on the speed and rolling schedule. The temperature of the furnace is also independent of all other quantities. The chemistry is independent of everything else as it is dependent on the continuous casting process and not the rolling process.

Therefore,

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (28)}
\]

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (29)}
\]

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (30)}
\]

\[
[MYS, I, F] = [MYS | \varepsilon, \dot{\varepsilon}, h, f | R] [\varepsilon, \dot{\varepsilon}, h, f | R | TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] [TF, L, RS, RT, T1, ..., T8, C, Mn, P, Sul, Si, V] \quad \text{............... (31)}
\]

We now assume linear relationships between the different response variables and the exploratory variables of each of these subsets. Thus:

\[
\begin{align*}
[MYS_{ik}, f], \dot{\varepsilon}_k, h_k, f_k, R_k] \sim N\left(\mu_{YS} + \sum_{m=1}^{8} \beta_{m0} \varepsilon_k^m + \sum_{m=1}^{8} \beta_{m1} \dot{\varepsilon}_k^m + \sum_{m=1}^{8} \beta_{m2} h_k^m + \beta_{m3} f_k + \beta_{m4} R_k, \sigma^2_{MYS} \right) \quad \text{............... (26)}
\end{align*}
\]

\[
\begin{align*}
[h_k | RS_k, RT_k, L_k] \sim N\left(\mu_h + \sum_{m=1}^{8} \beta_{m0} RS_k^m + \sum_{m=1}^{8} \beta_{m1} RT_k^m + \sum_{m=1}^{8} \beta_{m2} L_k^m, \sigma^2_{MR} \right) \quad \text{............... (27)}
\end{align*}
\]

7.3. Model Building

The above specified model was created in R.\(^{17}\) Models were created for different mechanical properties and different materials and the data from the empirical relationships and the plant were used as inputs to the models. The most common means of specifying the hierarchical model is through Markov Chain Monte Carlo (MCMC) algorithm. This algorithm allows the calculation of parameters at each stage iteratively. WinBugs follows the MCMC simulations based on the general idea presented by Gelfand and Smith.\(^{18}\) The data was randomized and 80% of the data was used for model building and the remaining 20% was left for model validation. Two different sets of initial values of parameters were chosen. These are called 2 chains of MCMC simulation. These values were chosen to represent 2 ends of a possible spectrum to check if the algorithm converges to the same level in both cases. 5 000 iterations were done for the simulation and the first 1 000 were discarded to take the values only after the simulation had converged. The procedure for calculating the values of parameters is given in Appendix.

The results of the MCMC simulations for various parameters of the model described above for the YS for Material A are shown in Fig. 6.

7.4. Model Validation

The model was developed in section 5 with 80% data and
the remaining 20% of the data was used for model validation. The data set for each material had around 5,000 coils. The result of model validation for Material B for the different mechanical properties is shown in Fig. 7.

8. Bayesian Networks for Mechanical Properties

Based on the Bayesian Hierarchical models developed in section 7, a simplified directed acyclic graph is drawn for the different materials and mechanical properties. The arrows represent the conditional independence structure of the model and the values represent the median with the 95% credible intervals for the parameters linking the variables. The regression parameters are normalized between (0, 1) for ease of comparison.

For the sake of simplicity, only the variables for which the parameters do not contain a 0 in their credible intervals are shown in these graphs. A representative graph is shown in Fig. 8.

The following interpretations can be made from the graph:
1) The YS for Material A is influenced by all the major variables – strain, strain rate, heat transfer, furnace and the run out table.
2) The influence of heat transfer on the YS seems to be the most as it has the maximum coefficient of linear relationship.
3) The strain in the first and second stand and the strain rate in the second and fifth stand affect the YS.

Similar graph was created for Material B which is shown in Fig. 9. Yield Strength for material B is affected by only the strain, strain rate and the furnace. Heat Transfer during the finish rolling, ROT, coiling and the chemistry do not affect the YS directly.

9. Microl – Installation & Calibration

After the model was built, it was converted into a portable format through programming in Java with the following design features:
- Open Architecture: The source code for MICROL is written in JAVA (JDK 1.6) so that it can be run on any
PC without the need of installing any software. JDK 1.6 is an open source software and freely available from Sun Microsystem’s website. Any PC running Windows OS is capable of running MICROL.

- Scalability: MICROL is designed to have open menu design. This will enable changes to be made without any difficulty in future.
- Portability: MICROL is designed to read in material data and mill data from external text files. This way any new material can be added without changing the source code itself.
- Ease of Use: MICROL is designed to be used both by engineers and also by plant personnel. This way, the predictions can be seen on line during the coiling operation itself.

This open source platform was installed in Level 3 automation room, the operator console at Finishing mill and the personnel at Quality Control. The issues which were encountered during the installation included configuration with the ERP, read/write access to personnel at different stations and the display of results. Once these issues were sorted, calibration of MICROL was done.

MICROL was calibrated for three different materials (two representing C–Mn steels and one representing Microalloyed steel) over a period of 5 days. A total of 450 coils were used for the calibration. After calibration, the errors in the prediction and the tested values were looked into. These errors were within a ±5% range for all the mechanical properties (UTS, YS and Elongation) and all the three materials. Operators in Level 3 automation room, QC lab and Finishing mill were trained in the use of the system. Thus, MICROL was deemed to be successful in installation.

10. 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. Another aspect which we wanted to investigate at his time was the importance of considering the variance in the system by the model (use of data from each coil versus data averaged over a day for the same material). 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 which was 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.) into account
2) When the model does not take the variance into account.

The results of the validation for both these conditions are shown in Fig. 10. This shows the following:

a) The errors of the model when the variance is considered and when the 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%.
11. Conclusions

The quality of steel rolled in hot strip mills is determined by their microstructural characteristics and mechanical properties like YS and UTS. Due to variation in process parameters and material state in melting, continuous casting, furnace reheating, rolling and coiling, there is significant variation observed in these attributes. To accurately predict these parameters it is necessary to create models which can replicate the mechanical deformation, microstructural evolution and phase transformation occurring during the hot rolling process and capture the variability of the production process. This paper presents the development of such a model (MICROL) which 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. This information is combined in a novel Bayesian Hierarchical 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. The errors for the mechanical 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.

Acknowledgements

The authors would like to thank SAIL-RDCMS management and personnel involved in the data collection and implementation at Steel Plant. We would also like to thank the Steel Development Fund (SDF) for providing financial support to develop this model. The Bayesian formulation was supported under grant from NSF CMMI Engineering Design and Innovation Group. (Grant #1000330). We would also like to thank Transvalor S.A for providing FORGE software for metal flow analysis.

REFERENCES

1) C. M Sellars and J. A. Whiteman: Met. Sci., 13 (1979), 187.
2) A. Laasraoui and J. J. Jonas: ISIJ Int., 31 (1991), 95.
3) O. Kwon: ISIJ Int., 32 (1992), 350.
4) J. H. Beynon and C. M. Sellars: ISIJ Int., 32 (1992), 359.
5) A. Yoshie, M. Fujioka, Y. Watanabe, K. Nishioka and H. Morikawa: ISIJ Int., 32 (1992), 395.
6) Y. Watanabe, S. Shimomura, K. Funato, K. Nishioka, A. Yoshie and M. Fujioka: ISIJ Int., 32 (1992), 405.
7) P. D. Hodgson and R. K. Gibbs: ISIJ Int., 32 (1992), 1329.
8) P. Pauskar and R. Shivpuri: CIRP Annals, 48 (1999), 191.
9) www.integpg.com/hsmm/files/HSMM_Overview_Rel_2_0.pdf.
10) M. B. Esfahani, M. R. Toroghinejad and S. Abbasi: ISIJ Int., 52 (2012), No. 10 471.
11) C. J. Park, S. H. Han, D. M. Lee and W. H. Kwon: ISIJ Int., 47 (2007), 1583.
12) A. Mukhopadhyay, A. Polo and F. Perotti: Proc. of Int. Conf. on Thermomechanical Simulation and Processing of Steel, SimPro, Ranchi, India, (2008), 265.
13) L. M. Berlinger, R. F. Milliff and C. K. Wickle: J. Geo. Res., 108 (D24), (2003).
14) E. M. Berlinger: Maximum Entropy and Bayesian Methods, Kluwer Acad., Norwell, Mass, (1996), 15.
15) N. Cressie, B. E. Buxton, C. A. Calder, P. F. Craigmile, C. Dong, N. J. McMillan, M. Morara, T. J. Santner, K. Wang, G. Young and J. Zhang: J. Stat. Plan. , 137 (2007), 3361.
16) T. J. Santner, P. F. Craigmile, C. A. Calder and R. Paul: Envi. Sci. Tech., 42 (2008), 5607.
17) R Development Core Team: R Foundation for Stat. Compt., Vienna, Austria, (2008).
18) A. E. Gelfand and A. F. M. Smith: Comm. Stat., 20 (1990), 1747.

Appendix: Gibbs Sampling in Hierarchical Model

To estimate all the unknown parameters and hyperparameters in the hierarchical model, Bayesian approach requires some assumptions about the prior distribution. The model described in Section 7 is said to be normal hierarchical model and a general representation of the model is shown below:

\[ y_{ijk} | \theta_{jk}, \sigma^2_{jk} \sim N (\theta_{jk}, \sigma^2_{jk}) \]

\[ \theta_{jk} | \mu_k, \sigma^2_k \sim N (\mu_k, \sigma^2_k) \]

\[ \mu_k | \alpha, m^2 \sim N (\alpha, m^2) \]

\[ \alpha \sim N (\mu_0, \nu_0^2) \]

\[ \sigma^2_{jk} \sim IG(a_{jk}, b_{jk}) \] for all j, k combinations

\[ \tau_{jk} \sim IG(a_{jk}, b_{jk}) \] for all k

\[ m^2 \sim IG(a_{jk}, b_{jk}) \]

As discussed by Gelfand and Smith[10] the full conditional posterior distributions can be derived as follows:

\[ P(\alpha | y_{ijk}, \theta_{jk}, \mu_k, \sigma^2_{jk}, \tau_{jk}, m^2) = N \left( \frac{1}{m^2} \sum_{k=1}^{K} \mu_k + \frac{\mu_0}{\nu_0}, \frac{1}{m^2} \right) \]

\[ P(m^2 | y_{ijk}, \theta_{jk}, \mu_k, \sigma^2_{jk}, \tau_{jk}, \alpha) = IG(a_{jk}, K/2, b_{jk} + \frac{1}{2} \sum_{k=1}^{K} (\mu_k - \alpha) \]

\[ P(\tau_{jk} | y_{ijk}, \theta_{jk}, \mu_k, \sigma^2_{jk}, m^2, \alpha) = IG(a_{jk} + \frac{1}{2} \sum_{k=1}^{K} N_k, b_{jk} + \frac{1}{2} \sum_{k=1}^{K} (\theta_{jk} - \mu_k)^2 \]

\[ P(\theta_{jk} | y_{ijk}, \theta_{jk}, \mu_k, \sigma^2_{jk}, \tau_{jk}, m^2, \alpha) = N \left( \frac{N_{jk} \theta_{jk} + \mu_k}{\left( \frac{\sigma^2}{\tau^2} + \frac{1}{m^2} \right)}, \left( \frac{N_{jk} \theta_{jk} + \mu_k}{\left( \frac{\sigma^2}{\tau^2} + \frac{1}{m^2} \right)} \right) \]

Markov Chain Monte Carlo (MCMC) methods can be used to obtain the posterior distributions. One of the ways this can be effectively done is by using the Gibbs Sampler. In this method, we assume an set of starting values (\( \alpha^{(0)}, \mu_k^{(0)} \), ...) and iteratively solve the equations as:

\[ Draw \theta_{jk}^{(i)} \sim P(\theta_{jk} | y_{ijk}, \theta_{jk}^{(i-1)}, \mu_k^{(i-1)}, \sigma^2_{jk}^{(i-1)}, \tau_{jk}^{(i-1)}, m^{(i-1)}, \alpha^{(0)}) \]

\[ Draw \tau_{jk}^{(i)} \sim P(\tau_{jk} | y_{ijk}, \theta_{jk}^{(i)}, \mu_k^{(i)}, \sigma^2_{jk}^{(i)}, m^{(i)}, \alpha^{(0)}) \]

\[ Draw \sigma^2_{jk}^{(i)} \sim P(\sigma^2_{jk} | y_{ijk}, \theta_{jk}^{(i)}, \mu_k^{(i)}, \sigma^2_{jk}^{(i)}, m^{(i)}, \alpha^{(0)}) \]

\[ Draw \alpha^{(i)} \sim P(\alpha | y_{ijk}, \theta_{jk}^{(i)}, \mu_k^{(i)}, \sigma^2_{jk}^{(i)}, \tau_{jk}^{(i)}, m^{(i)}) \]