IDENTIFICATION OF IMPACTING FACTORS OF SURFACE DEFECTS IN HOT ROLLING PROCESSES USING MULTI-LEVEL REGRESSION ANALYSIS

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ABSTRACT
Severe competition in US steel industry urges quality improvements in hot rolling processes. Surface defects have been a long-standing troubling issue in hot rolling processes due to the ineffectiveness of existing detection methods. This paper presents an advanced statistical analysis method to identify the impacting factors in surface defects of hot rolling processes. The surface defects on the steel is measured by a new sensing system, the “HotEye” imaging system. The process variables considered in this paper include the heat number, strand number, and billet-location. Due to the structural characteristic of the data, multilevel analysis is presented to help identify the relationships between the process variables and the number of surface defects. A detailed case study is presented to illustrate the effectiveness of this method. The result obtained can provide guidelines for root cause identification and quality improvement of hot rolling processes.

INRODUCTION
Due to economic globalization, the US steel industry is facing severe competition from foreign competitors. To succeed in this environment, the American steel industry must significantly improve productivity and quality, and reduce scrap and waste during production. In addition to economic considerations, the environmental concerns and energy consumption requirements also strongly drive the steel industry toward that direction. Therefore, there is an urgent need from steel industry for efficient process quality control.

Hot rolling is among the key processes that convert cast or semi-finished steel into finished products. Since the rolling operation is often the last process step, the scrap at rolling stage is very costly and hence the quality control of rolling process is very important. Among all the quality concerns, the surface integrity is an extremely important quality characteristic of the hot rolled products. Surface defects remain as a weakness or stress concentration site of the bulk material and hence could cause catastrophic failure when the rolled product is in use. Products with severe surface defects have to be scrapped. Therefore, it is highly desired to detect, reduce, and eventually eliminate the surface defects if possible. Unfortunately, the surface defects remain as the most troubling problems in the hot rolling process. Major challenges in the surface quality control fall into the following two aspects.

(1) Effective surface sensing system to measure the surface condition in real-time during production environments (high temperature, high speed, noise, and dirty conditions) is not available.
(2) The root causes of surface defects in hot rolling processes are very complicated. Surface defects could be originated from multiple sources. For example, the nonmetallic impurities in the billet

during solidification as well as the mechanical failures in the rolling mills are all important potential sources of surface defects. The current knowledge of the root causes of surface defects in hot rolling process is very limited.

Due to the aforementioned challenges, although the dimensional dynamic control of rolling processes is well-developed (Ginzburg 1993, Lenard and Pietrzyk 1999), current quality control of surface defects in hot rolling process is very primitive. The understanding of the physics of the root causes of the surface defects is very limited. This makes surface defects the leading dragging issues in the improvement of quality and productivity in steel manufacturing processes.

There are very few attempts on the analysis of the surface defects. Eddy-current based sensing system is widely used in industry for non-destructive testing (Collins et al. 1996) of imperfections in hot rolling process. However, it must be very close to the hot surface (typically less than 2.5 mm). The testing result is not quantitative, and it cannot detect certain types of defects (Judd, 1996). Some other surface inspection systems tried to utilize high power radiant light sources (Rinn and Thompson, 2000) to overpower the self-emitting radiation of hot steel. However, the working temperature of these systems is limited to several hundreds Celsius degree. Sugimoto and Kawaguchi (1998) developed a surface inspection system using the self-radiant light from the hot steel. This system senses the temperature deviations caused by the surface defects. It will be difficult to detect very thin surface defects such as seams on the surface. Due to the insufficient inspection capability, little research has been done on the root cause analysis of surface defects. The British Iron and Steel Research Association (Ingot Surface Defects Sub-committee, 1955) and the American Iron and Steel Institute (AISI) (AISI, 1996) provided a qualitative classification of the surface defects of the hot rolled surfaces. Only some preliminary research on automatic classification of surface defects on the hot rolled steel is reported (Caleb and Steuer, 2000, Simonis and Rinn, 1998, and Vascotto, 1996). The developed algorithms often need intensive training. These technologies are not well adopted in practice. No systematic quantitative research on the relationships among the process variables and product surface quality has been reported. In many situations, the defects were unknown to the steel maker until they receive complains or stock returns from the end users. A vast amount waste, in material, energy, and transportation, has occurred. The quick hot surface defects detection and root cause identification has been identified as one of the major research thrusts by AISI (AISI 2001).

Recently, the development of an image inspection system, the so-called "HotEye" technology, provides a reliable, accurate on-line surface measurement technology for hot rolling processes. The system can give a sharp image of the hot surface up to 1550°C (Fig. 1). The measurement resolution can be up to 0.02mm and the measurement speed can be up to 100m/s rolled billet surface.

HotEye provides a unique opportunity to develop a quantitative real-time in-process surface quality inspection and diagnosis system for the hot rolling process. In this paper, we focus on the study on the quantitative relationship between the process parameters and the number of surface defects based on systematic statistical analysis. With this quantitative relationship, we can provide guidelines on the identification and elimination of root causes of the surface defects.

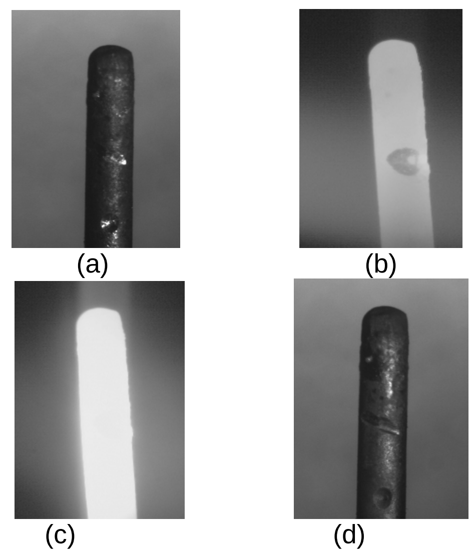

FIGURE 1. DIFFERENCE OF HOTEYE AND A REGULAR CCD CAMERA. (a) A thermal couple tip, with artificial marks, at room temperature (regular CCD); (b) Same tip, at 1,100°C (regular CCD); (c) Same tip, at 1,350°C (regular CCD); (d) Same tip, at 1,375°C (Image by HotEye technology).

This paper is organized as follows. The layout of a typical rolling process and the corresponding sensing system are introduced in Section 2. The quantitative relationship between process parameters and product quality is investigated in Section 3 using multi-level regression technique. Concluding remarks and future works are discussed in the last section.

INTRODUCTION TO THE SENSING SYSTEM FOR HOT ROLLING PROCESSES

Hot rolling process is a very complicated process. Figure 2 illustrates a layout of a sensing system of a hot rolling process. The whole process can be classified as two sub-processes: casting process and progressive rolling process.

The purpose of casting process is to produce billets for later-on progressive rolling process. In the casting process, ingots and scraps are charged into a bowl-shaped ladle and heated in the furnace. The melted steel is then poured into a tundish and ready for continuous casting. Four strands of steel simultaneously come out of the tundish (to be brief, only one strand is illustrated in Figure 2). Each strand has a separate mold for continuous casting. Usually, steels that come out from the same furnace at the same time are grouped as a heat. A whole heat can be further classified into four strands according to the strand where the steels are molded. Steels from each strand will be cut to 10~12 billets by scorch. The sequence of a billet that comes out from a strand is denoted as billet-location. Thus we can refer to a specific billet according to a triplet < heat number, strand number, billet-location >. For example, < 123000, 2, 5 > represents a billet that comes from heat 123000, and it is the fifth billet molded by second strand.

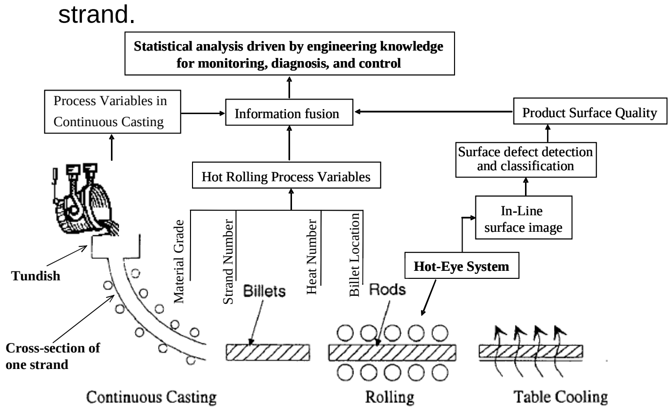

FIGURE 2. LAYOUT OF A HOT ROLLING PROCESS.

Progressive rolling process is committed consecutively at several (14~48) stands. The diameter of the billet is reduced every time it passes through a stand. At the end of the progressive rolling process, the billet is coiled for shipping.

HotEye is located at the last few stands of the progressive rolling process to measure the possible defects on the billet surface. The defects captured by HotEye can be taken as a quality measurement of product surface quality. Based on the process sensing information and surface quality information, statistical analysis driven by engineering knowledge for monitoring, diagnosis, and control can thus be implemented to identify the relationship between process variables and product surface quality.

Figure 3 is a seam picture detected by “HotEye” system. The brighter band in the center is the surface of the steel. In addition, the sharply contrasted, slim, dark line within the brighter band is a captured seam. Based on the information provided by “HotEye”, we may know how many seams there are on a billet surface and where the seam is located. Moreover, we can roughly estimate the overall length of seams on one billet to rate the severity of the defects.

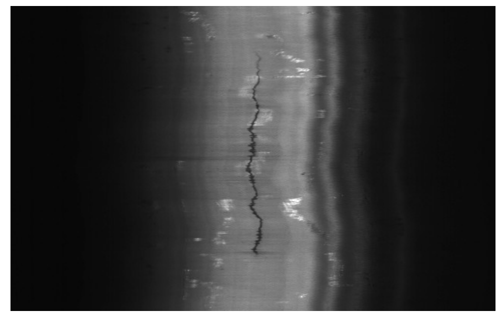

FIGURE 3. SAMPLE IMAGE OF SEAM DEFECT DETECTED BY HOTEYE.

Huge amount of sensing information data is available because of the highly modernized rolling control process. Among them, three fields (heat, strand, and billet-location) might be the most important causes of the large variation in the hot rolling process. Some physical interpretations support the hypothesis. Considering the complexity of casting process, a large amount of uncertainties may exist in the material component. Billets from the same heat are highly likely to have similar physical properties. Many control parameters (such as mold temperature, oil moisture, spray system parameters, etc.) are involved with the strand number (range from 1 to 4). During the continuous casting, it is very likely that the billets molded at the same strand tend to have the same effects on the number of defects per billet. Billet-location (range from 1 to 12) where a billet is sequenced within all the billets that passed the same strand might also play an important roll since it is very likely that the billets sequenced at the same location might have experienced the similar working environment and thus might have the similar behaviors.

Table 1 is an abbreviated portion of the sensing information table (Some listed data are modified due to privacy consideration). Here we will only show and briefly introduce the fields that will be used for data analysis later in this paper. “Billet ID” is a unique ID assigned to a given billet; “Heat” and “Strand” are the heat number and strand number of a billet which may date back where the billet comes from; “Billet Speed” is the average speed that a billet passed through where the “HotEye” system is located. “Billet Grade” is a material grade assigned to a specific chemical component of the steel. The steels with the same “Billet Grade” share the same chemical and carbon component and thus tend to have similar physical properties. “Defects Per Billet” is the number of defects on the billet surface that is captured by “HotEye”. Many other important physical parameters of the rolling process (e.g., temperature at each stand, tundish temperature, nozzle size, etc.) are also available. We did not put those data here since this paper will only demonstrate the relationship of the number of defects with heat number (material grade), strand number, and billet-location.

Many typical surface defects can be found in the rolling process. According to the A.I.S.I technical report (AISI, 1996), the typical defects are overfill, scratches, gorges, seams, laps, etc. Among them, seams are rated as the most important defects in rolling industry because seams are frequently generated in the final product and have detrimental impact on the physical properties of the steel. Hence, we will focus on the analysis of seam defects in this paper.

TABLE 1. DATA FROM HOT ROLLING PROCESS.

Billet ID	Heat	Strand	Billet Location	Billet Speed	Billet Grade	Defects Per Billet	…
121752800	123000	1	2	18.43	4140	1	…
123757000	123002	2	3	18.418	4140	5	…
127763100	123003	3	10	18.406	4140	1	…
129753900	123004	4	7	18.411	4140	3	…
…	…	…	…	…	…	…	…

In summary, we will study the relationship between the response variable (i.e., the number of seams per billet) and the process variables (i.e., heat, strand, and billet-location). Because the rolling speed will also influence the number of seams from previous experience, the speed factor is also included in the study as a process variable. The dataset used in our paper include three-month HotEye measurements of a hot rolling process. Billets from 270 different heats are monitored during this period. Strand numbers for individual billet cover from 1 to 4 and billet-locations for individual billet range from 1 to 12. An important characteristic of the HotEye data is the significant unbalance of our dataset. Different sample sizes (number of billets per heat) are found for different heats in the existing HotEye data, which may vary from two to 46 billets per heat.

MULTILEVEL ANALYSIS OF HOTEYE DATA

The purpose of the data analysis is to identify the impacts of the process factors such as heat, strand, and billet-location. In another word, we want to identify the variation due to heat factor, the variation due to strand factor, and the variation due to billet-location factor among the overall variations of the number of defects per billet. There are some special characteristics of this dataset: (i) The data structure is not “flat”, i.e., there are clustered groups in this dataset. For example, the characteristics of the number of surface defects tend to be similar for the same heat. We want to identify not only the within-heat variation, but also between-heat variation. (ii) A nested structure exists in the dataset: To locate a billet, first, heat needs to be determined; then, the strand and billet-location need to be determined within the heat. To analyze the impacts of these different factors with group and nested structure, we introduce the multilevel analysis technique.

Introduction of Multilevel Analysis

Two methods are widely used to compare the importance of different group effects. The first method is Moment Method. The whole dataset is pre-sorted into different groups manually. Moments of different groups are calculated and compared with each other to show the relative importance of different group effects. Usually first and second order moments (mean and variance) are the two most frequently used moments. Occasionally the third and fourth order moment applications might also be found. For the HotEye data, average number of defects per strand can be viewed as a preliminary index of relative number of defects occurred at different strands while the variance of the number of defects per strand shows how much the actual number of defects per strand at different time deviates from its average value. The same rough estimation can also be applied to billet-location and heat groups. The advantage of this method is that it is easy to understand and use. However, moment method is a very rough estimation and is very sensitive to the sample uncertainty.

The second method is linear regression method. Linear regression methods propose a linear relationship between the response variable and the predicator variables and build up models to fit the actual dataset. Systematic theory and many statistical inferences are available to quantify the goodness-of-fit of the model, i.e., how well the model fits the actual data. Hence, regression method becomes more and more widely used in estimating relationships among factors. Most of the regression models used in engineering area is ordinary linear regression model, which always assumes independent residual errors with constant variance among all the individuals, regardless of the possibility that individuals from the same groups tend to have more similar variation than individuals from different groups. For example, given the simplest ordinary regression model $Y = C \times X + \xi$ (Y is the response variable, C is a constant, X is predictor variable, ξ is residual error), it cannot compare group effects at all since there is no group defined in this model. A common technique of comparing different group effects in the ordinary linear regression model is to predefine a set of dummy variables to classify the dataset into different groups. Assume we want to test two groups: $X > 0$ and $X \le 0$, two dummy variables I_1 and I_2 are defined to group the original dataset: $I_1 = \begin{cases} 1, & if \quad X > 0 \\ 0, & else \end{cases}$ and $I_2 = \begin{cases} 1, & if \quad X \le 0 \\ 0, & else \end{cases}$. Our new regression model now can be represented as $Y = C_1 \times X \times I_1 + C_2 \times X \times I_2 + \xi$. Hypothesis tests on the coefficients C_1 and C_2 will show if these two groups are significantly different from statistical point of view. However, this method is not efficient for the cases with large number of groups, which is true in the HotEye data. In our dataset, the billets are chosen from 270 different heats. Obviously, it is inefficient to classify all the heats into 270 different groups and estimate the effect of each heat individually even without considering the possible interaction effects between different groups. Also, if the dataset has higher-level nested structure, the "dummy variable" classification method does not work because it cannot represent both the group variation and sub-group variation at the same time. Unlike the ordinary regression that focuses too much on the individual and too little on the group effect in which individuals are located, multilevel regression balanced this problem by considering both effects.

Multilevel Regression Analysis, sometimes called Random Coefficient Analysis, has important applications in social science research area. Many significant statistical results have been achieved in this area since the past decade (Hox, 2002, Raudenbush and Bryk, 1992).

A traditional example in multilevel regression model is presented by Raudenbush and Bryk (1992). We will use this example to show the basic principles of multilevel regression model. In the example, the relationship between a single predictor variable (SocioEconomic Status [SES]) and one response variable (Mathematics Achievement) within a population of schools is studied. The dataset can be grouped as two levels: student is level-1 and school is level-2. Suppose that we have a random sample of *J* schools from a population (*J* is a large number), then we can represent the relationship within any school *j* by the equation

$$Y_{ij} = \alpha_{0j} + \alpha_{1j} X_{ij} + U_{ij}, \; U_{ij} \sim N(0, \sigma^2) \qquad (1)$$

where $\alpha_{0j} = \beta_{00} + r_{0j}$ and $\alpha_{1j} = \beta_{10} + r_{1j}$. Y_{ij} is the reported achievement for student *i* in school *j*. U_{ij} is the level-1 error and assumed to be zero mean and variance σ^2. α_{0j} is the true mean of achievement in school *j*. α_{1j} is the true Achievement-SES slope for school *j*. β_{00} is the average achievement across the schools. β_{10} is the average Achievement-SES slope across the schools. r_{0j} is the level-2 error associated with mean of achievement for school *j* and is assumed to have a mean of 0 and variance u^2. r_{1j} is level-2 error associated with Achievement-SES slope for school *j* and is assumed to have a mean of 0 and variance v^2. Both r_{0j} and r_{1j} are called level-2 random effects.

From Equation 1, we notice that the random error in multilevel regression has a more complicated form, $r_{0j}+r_{1j}X_{ij}+U_{ij}$. The residual errors in this case are dependent since the components r_{0j} and r_{1j} have the same value for every student within school *j*. In addition, the variances of the residual errors are different since it depends on r_{0j} and r_{1j} as well, which are different for individual schools. Here we can clearly see that ordinary regression analysis is inappropriate because it fails to capture the variation between different groups.

We can get the combined model by substituting the expression of α_{0j} and α_{1j} into Equation (1),

$$Y_{ij} = \beta_{00} + \beta_{01} X_{ij} + r_{0j} + r_{1j} X_{ij} + U_{ij} \qquad (2)$$

where we assume: $E(r_{0j})=0$, $E(r_{1j})=0$, $Cov(r_{0j},U_{ij})=0$, $Cov(r_{1j},U_{ij})=0$, and denote $Var(r_{0j})=\tau$.

Equation 2 is called the full model of two-level regression analysis. However, in many cases random slope effects are not very significant and thus only random intercept effects are considered in the model, i.e. assuming $\alpha_{1j} \equiv \alpha_1$ is a constant. The new simpler model is called random intercept model (3).

$$Y_{ij} = \alpha_{0j} + \alpha_1 X_{ij} + U_{ij}, \; U_{ij} \sim N(0, \sigma^2) \qquad (3)$$

where $\alpha_{0j} = \beta_{00} + r_{0j}$. Also, we can substitute the expression of α_{1j} into (3) to get a combined random intercept only model,

$$Y_{ij} = \beta_{00} + \alpha_1 X_{ij} + r_{0j} + U_{ij} \qquad (4)$$

Intraclass Correlation Coefficient $\rho = \frac{Var(r_{0j})}{Var(r_{0j} + U_{ij})} = \frac{\tau}{\tau + \sigma^2}$ measures the proportion of variance that is between different schools to the fitted variance of the model. Value σ^2 represents the within-group variation and τ captures the between-group variation.

Variance estimation theory in multilevel analysis is based on maximum likelihood method. The basic idea of maximum likelihood is to choose estimates of α, τ and σ^2 for which the likelihood of observing the actual data Y is at its maximum. A complete result of two-level multilevel analysis can be found in (Raudenbush and Bryk, 1992). Here we will only present the maximum likelihood function along with the estimated parameters that maximize the likelihood function:

$$\log[f(Y,r|\sigma^2,\tau)] \propto -N\log(\sigma^2) - J\log|\tau| - \sum U_j^{'}U_j/\sigma^2 - \sum r_j^{'}\tau^{-1}r_j,$$

maximized at $\hat{\sigma}^2 = \sum U_j^{'}U_j/N$ and $\hat{\tau} = J^{-1}\sum r_j r_j^{'}$ where N is the total number of level-1 observations and J is the effective number of level-2 observations for estimation. U_j (j=1,2,…,N) represents random effects at level-1 and r_j (j=1,2,…,J) represents random effects at level-2.

The extension of the two-level regression model to higher levels is straightforward. However, higher-level models become much more complicated. Multilevel regression analysis can be done using software such as SAS, SPSS, and HLM, etc. In this paper, we choose "GLIMMIX" macro in SAS to implement all the data analysis and illustrate the procedure on how to compare and identify the most important variation source in the hot rolling processes.

Random Intercept *Regression Model*

Our goal is to find out the possible relationship between one response variable "defects per billet" and three predictors—Heat number, Strand number, and Billet-location. Our response variable is "defects per billet". It is a typical count data and well known to conform to Poisson distribution [Snijders 1999]. Our distribution test of the HotEye data also verifies this result. To obtain a linear model, we apply a natural logarithm to the Poisson model. Now we start our model with the simplest random intercept model.

Historical studies have shown that billet speed is a significant factor to the number of defects. Hence, we will always include billet speed as an independent variable in all the models presented in this paper. According to the physical structure of HotEye data, billet speed is taken as the level-1 variable, Strand number and Billet-Location are taken as level-2 variables, and Heat number is taken as level-3 variable. The three-level model is presented as follows,

$$Ln(Y_{ijk}) = \alpha_{ijk} + \alpha_1 \times SPEED + U_{ijk} \quad (5)$$

where $\alpha_{ijk} = \beta_{00k} + \beta_{i00} + \beta_{0j0}$, $\beta_{00k} = \gamma_{000} + \gamma_{00k}$,

Y_{ijk} is number of defects detected on the i-th strand, the j-th billet-location in the k-th heat. U_{ijk} is the level-1 model error. α_{ijk} is level-1 random intercept. α_1 is constant coefficient of billet SPEED variable. β_{00k} is level-2 random intercept. β_{i00} is level-2 error associated with average number of defects for strand i. β_{0j0} is level-2 error associated with average number of defects for billet-location j. γ_{000} is the grand mean of number of defects. γ_{00k} is level-3 error associated with average number of defects for heat k. Maximum likelihood method is chosen to estimate the parameters and variances. The results of the fitted multilevel regression analysis are presented in Table 2.

TABLE 2. FITTED RESULT OF THREE-LEVEL MODEL (5).

Effect	Intercept	SPEED	Heat	Strand
Estimate	-1.0511	0.01767	1.7845	0.3596
Effect	Location	Residual	Extra-Dispersion	
Estimate	0.5861	1.0192	1.0192	

The estimated regression equation and related parameters:

$$Ln(DefectsPerBillet) = -1.0511 + 0.01767 * SPEED \quad (6)$$

Residual=Level-1 variance =Var(U_{ijk})= 1.0192. Strand Effect (Estimated Variance) =Var(β_{i00})= 0.3596. Billet-location Effect (Estimated Variance) = Var(β_{0j0})=0.5861. Both Strand Effect and Billet-location Effect are considered as Level-2 Variance. Heat Effect (Estimated Variance) = Var(γ_{00k})=1.7845. Heat Effect is considered as a Level-3 Variance. Intraclass correlation $\rho = \frac{0.3596+0.5861+1.7845}{0.3596+0.5861+1.7845+1.0192} = 72.8\%$.

Intraclass correlation ρ=72.8% means that 72.8% of the variance is at the group level (include strand group effect, billet-location group effect, and heat group effect), which is very high. It is compelling evidence that we should include the "group effect" into our model to do multilevel analysis.

Extra-Dispersion is 1.0192. In the Poisson distribution, the mean and variance are equal, but empirical count data normally have a variance greater than the mean. This phenomenon is called Extra-Dispersion. In our case, it is very close to one, which shows the Poisson assumption in our model is still valid.

From our regression model, Heat group has the most significant variance in the causes of number of defects per billet. Billet-location group has slightly stronger effects than the strand group. The relative weight of the three group effects within the explained variance is equal to:

heat variance: strand variance: billet-location variance= 1.7845 : 0.3596 : 0.5861 = 5 : 1 : 1.6.

Sufficiency of Random Intercept Model

The full model with both random intercept and random slope effect is also fitted to check if the existing random intercept model is sufficient to explain the variation of HotEye data. Due to the complexities of the three-level full model equations, we will only show the estimated variances of the random slope coefficients in Table 3. From Table 3, we can see that all the slope variances caused by the three groups are very close to zero. Hence, it would be sufficient to fit the HotEye data with only the simplest random intercept regression model.

TABLE 3. ESTIMATED VARIANCES FOR SLOPE COEFFICIENTS IN FULL MODEL.

Effect	Heat	Strand	Billet-Location
Estimate	0.002969	0.000527	0.000358

Verify the Significance of Heat Effect

Since heat number is highly correlated with material grade, it is possible that the large variation of number of defects is caused by material grade instead of the heat effect. To verify the significance of the heat effect, we choose a frequently used material grade 4037 to eliminate the variation caused by material grade and thus verify that the large variation is caused by the heat effect indeed. Twenty-four heats in total are included in our sub-dataset sorted by the same material grade 4037.

We will still use three-level regression model (5) as the regression model. The fitted regression result is shown in table 4.

TABLE 4. FITTED RESULTS OF (5) FOR SUB-DATASET SORTED BY MATERIAL GRADE 4037.

Effect	Intercept	SPEED	Heat	Strand
Estimate	-2.3215	0.03767	2.3459	0.0000
Effect	Billet-location	Residual	Extra-Dispersion	
Estimate	0.3814	1	1	

The regression results can be interpreted as follows. The estimated regression equation and related parameters:

$$Ln(DefectsPerBillet)=-2.3215+0.03767 * SPEED \quad (7)$$

Heat Effect (Estimated Variance) = 2.3459. Billet-location Effect (Estimated Variance) = 0.3814. Strand Effect (Estimated Variance) = 0.0000.

The fitted regression results show that heat effect still plays the most important roll even after the material grade change is eliminated. It is still much more significant than strand effect and billet-location effect.

Comparison *of Strand Effect and Billet-location Effect*

Under the dominant effect of heat group, both strand effect and billet-location appear to be very small and similar to each other. To compare the strand effect and billet-location effect, we further eliminate the heat effect by choosing a specific heat group 858600 to fit a two-level Poisson regression. The Two-level regression model is presented as (8),

$$Ln(Y_{ij}) = \alpha_{ij} + \alpha_1 \times SPEED + U_{ij} \quad (8)$$

where $\alpha_{ij} = \beta_{00} + \beta_{i0} + \beta_{0j}$. Y_{ij} is number of defects detected on *i*-th strand, *j*-th billet-location in heat group 858600. U_{ij} is the level-1 model error; α_{ij} is level-1 random intercept; α_1 is constant coefficient of billet SPEED; β_{00} is grand mean of number of defects in heat 858600; β_{i0} is the level-2 error associated with average number of defects for strand *i* in heat 858600; β_{0j} is the level-2 error associated with average number of defects for billet-location *j* in heat 858600. The fitted regression result is shown in Table 5.

TABLE 5. FITTED RESULTS OF (8).

Effect	Intercept	SPEED	Strand
Estimate	-3108.8	68.6088	0.0000
Effect	Billet-location	Residual	Extra-Dispersion
Estimate	0.4251	1	1

The estimated regression equation and related parameters:

$$Ln(DefectsPerBillet)=-3108.79+68.6088* SPEED \quad (9)$$

Billet-location Effect (Estimated Variance) = 0.4251. Strand Effect (Estimated Variance) = 0.0000. From the fitted regression result, we can see that the strand effect is almost ignorable within this given heat, while billet-location group still has some effects, though it is not very large compared with the level-1 residual error. Hence, it is safe to conclude that billet-location effect is slightly stronger than strand effect in this particular heat.

Some Issues on the Multilevel Regression Model

Due to the complexity of the model, normally we do not seek for higher-order interactions unless large residual errors are detected and cannot be explained by the existing simple model.

In our example, only random intercept is assumed in our model since no slope effects for the process variables are known to relate with any of the group effects. If new process variable is found or suspected to be involved, we should also include the new process variable into our model and assume the random slope effect of the process variable to check if there is group effect on it.

Multilevel analysis has the ability to handle unbalanced data since it does not require the numbers of available measurements for all individuals are the same. This is very important in our case because not all the billets from the same heat are rolled at the same time and thus measured data for a full heat usually are not available. Sometimes the available data can be extremely unbalanced because some billets from the same heat are rolled half a year later than the others are.

Hypothesis tests are also available to test if a specific strand or billet-location or heat number caused more variation than the others did. Due to the privacy reasons, we did not list the results in this paper.

CONCLUDING REMARKS

This paper presented multilevel Poisson regression analysis technique to identify the important variation sources that have main contributions to the large variation of the number of the defects per billet. The response variable is the number of defects on any given billet, which is measured by advanced HotEye sensing system. This is a significant improvement on the hot rolling quality control procedure. Analysis based on number of surface defects of hot rolling steel becomes possible since the detailed surface information is now available.

Though it has important applications in social science research, multilevel regression is still a new technique to many engineering researchers. The application of this new technique to the hot-rolling process is significant since most of the variation of the number of defects can be explained by the new multilevel model, which confirmed the long-term industrial belief that casting process, instead of rolling process itself, are critical to the surface quality of the hot rolling process.

Based on our analysis, heat group effect is the most important variation source to steel surface quality. Industrial experience can also explain its significance. Heats with the same material grade can be melted at very different date, which definitely have certain impacts on relevant process parameters, thus affecting the steel surface quality. We would suggest some process variables could be identified to relate with the heat group variation. Hence, we could identify the root cause of large variation in heat group eventually. This is the future research.

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