QUALITY PREDICTION AND CONTROL IN ROLLING PROCESSES USING LOGISTIC REGRESSION

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ABSTRACT

With the advancement of distributed sensing technologies, abundant data are generated in rolling processes. While these data contain rich information about the process and product, it is a challenging task to develop a systematic method to model the relationship between process and product quality variables for quality improvements. This paper addresses this challenge by using logistic regression in which the quality measure is binary. Efforts are made to select minimum number of process variables in the model, based on which product qualities can be adequately predicted. If the predicted quality is worse than a target value, active control is initiated by adjusting key process variables. Considering the constraints of quality target, control costs and control feasibility, selecting appropriate control actions is formulated as mathematical optimization problems. Solutions and sensitivity studies are provided. Case studies using the data from real rolling lines are reported to demonstrate the effectiveness of this method.

1. INTRODUCTION

Rolling is a high-speed bulk deformation process that reduces the thickness or changes the cross-section of a long workpiece by compressive forces applied through a set of rolls. In steel industry, rolling is one of the key processes, usually the last one, to convert semi-finished steel into final products. Thus, a high scrap rate in rolling translates to a tremendous waste and also hinders the steel industry from timely delivering products to customers. Seam, one of the most common surface defects in rolling processes, is a critical quality concern impacting the scrap rate, as it results in stress concentration on the bulk material which may cause catastrophic failures when the rolled product is in use. Therefore, it is important to reduce the number of seams for quality assurance and scrap rate reduction in rolling.

The first step in seam reduction is to detect seams in real time during the production. To achieve this objective, a few attempts have been made to develop automatic sensing systems, which, however, are not very successful due to the harsh rolling environments (e.g., high temperature, high speed, and noisy surface conditions). For example, eddy-current sensors (Collins et al. 1996) must be placed extremely close to the inspected surface, which makes them vulnerable to the high heat generated in rolling processes. Sensing systems using the self-radiant light from the hot steel (Sugimoto and Kawaguchi 1998) can sense the temperature deviations caused by surface defects, but may hardly detect thin defects like seams. Due to the limitations of the sensing techniques in seam detection, little research has been found to study the relationship between seam generation and process variable settings for quality control and improvements.

In recent years, with the development of advanced imaging technologies, in-line vision sensors have been adopted in rolling process to measure product surface conditions. Based on image signals, efforts have been made to develop effective algorithms for seams detection (Li et al. 2006). With the success in seam detection, in conjunction with the wide adoption of distributed sensing networks (DSNs) to collect abundant information of the process, it now becomes possible for knowledge discovery and relationships modeling from the production data to facilitate quality improvements. Li and Shi (2006) proposed the use of a Bayesian network to learn and represent the causal relationships among process and quality variables. Jin et al. (2004) used a multi-level regression model to recognize the impacting factors of seams. These papers focus on identifying the relationship between *the number of seams per rolled product and the process variables on one sub-process* (called "casting"), but not covering the entire process of rolling, which in fact includes two sub-processes: casting and progressive rolling. In addition, existing research primarily focuses on using the identified relationships for process monitoring and quality prediction, few efforts have been found on developing effective active control strategies which aim to bring current product quality, if not satisfactory, to a target value.

This paper proposes a logistic regression based modeling and analysis method that takes a binary quality index (i.e., "good" and "bad" qualities) as the response variable, and builds a relationship between this binary response and process variables on progressive rolling processes. As a common practice in the rolling industry, binary quality measure has been widely adopted in quality control and assurance. For example, customers of rolling manufacturers usually require the products to contain no more than a certain number of seams (i.e., a threshold) and reject a product if the number of seams is larger than this threshold. This threshold will serve as a target that directs the manufacturers' efforts in quality control and improvements. In this scenario, to both the customers and manufacturers, it is not the exact number of seams that indeed matters but the binary information of whether the number of seams is below or above the threshold for a given sample, or lot.

This paper proposes to achieve the objective of quality improvements in a rolling process in two steps. The first step is quality prediction, which focuses on correctly predicting the product quality using the most parsimonious model. A parsimonious model is desirable in practice as it requires fewer process variables to be observed, which leads to lower costs in sensing, data acquisition and monitoring. If the current predicted quality is worse than a required quality target, control actions will be taken in the second step to alleviate or eliminate the quality problems. Because these actions involve actively manipulating (not passively observing, as in the first step) the process variables, this second step is called *active* quality control. In this research, active control is formulated as mathematical optimization problems considering the constraints of quality target, control costs and control feasibility. Solutions and sensitivity studies are provided.

The rest of the paper is organized as follows. Section 2 provides a description of the sensing system in typical rolling processes and the collected sensing data. Clustering the data to identify the binary quality index based on Principle Component Analysis (PCA) is also presented. Section 3 presents the logistic regression based method in quality prediction and control. This method is applied to the data collected from a rolling process and the results are reported. Finally, a summary and discussion is given in Section 4.

2. OVERVIEW OF ROLLING PROCESS, DISTRIBUTED SENSING AND DATA PRE-PROCESSING

2.1 Rolling Process and Distributed Sensing

A typical rolling process consists of two sequential sub-processes: casting and progressive rolling. An exemplary layout of the rolling process is given in Figure 1. In casting, ingots and scraps are heated and melted in a furnace. Then, liquid steel pours from a furnace into several stands of molds for continuous casting. The steel from each stand will be cut into 10~12 billets, which are then sent to progressive rolling containing 14~48 stands. The diameter of the billet is reduced every time it passes through a stand, and after the final stand, this billet, now becoming a rolled product called a "steel bar" here, is coiled for shipping.

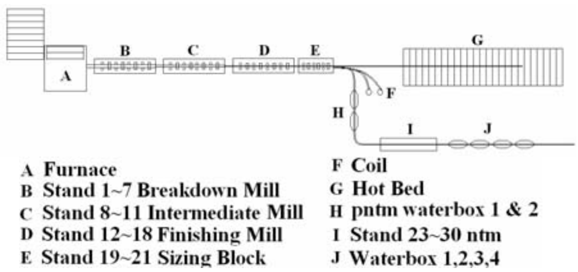

FIGURE 1. ROLLING LAYOUT.

Different types of sensors are installed along the rolling production line to collect both process and quality information. Typical sensors include those measuring temperature, speed, water flow, and surface defects (e.g. seams). Some information about the rolling product/process, such as material grade and length of steel bars, although not acquired through automatic sensing devices, is also available off-line. As this information may be related to the generation of seams, it is treated as sensing data in a general sense. Vision sensors are usually located at the last few stands of the progressive rolling to take images of the surface of steel bars. With the aid of the seam detection algorithms (Li et al. 2006), the images are processed and the number of seams per steel bar is recorded as the measurement of the product quality.

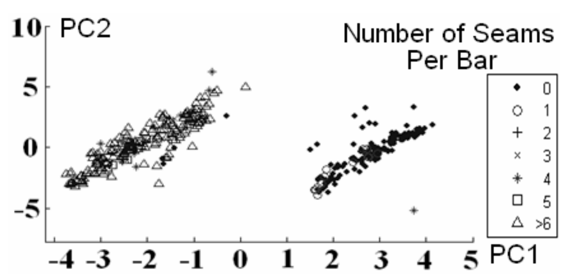

FIGURE 2. PINCIPLE COMPONENT ANALYSIS (PCA) PLOT.

The particular rolling process in this study has 26 stands. The sensing data contain measurements of 350 billets on 20 variables including the number of seams, material grade, bar length, temperature, water flows, and speed of the billet at several stands. Note that the original measure of product qualities is the number of seams, which can be transformed into a binary quality index, Y , based on a threshold T , i.e.,

$$Y = \begin{cases} 0 & \text{if the number of seams} \le T \\ 1 & \text{otherwise} \end{cases} \qquad (1)$$

T can be determined by identifying the inherent clusters in data, which will be discussed in the next section. The objective of this research is to develop an effective method to model the relationship between quality index Y and the process variables **X** for quality improvements through quality prediction and active control.

2.2 Data Clustering for Identification of Binary Quality Index Using PCA

In this study, data clusters are identified through PCA (Johnson and Wichern 1998), an effective tool to summarize the patterns of high-dimensional data in a lower dimension. PCA requires all variables to be numerical. Since material grade is categorical, it is replaced by three dummy variables as

$$[X_1, X_2, X_3] = \{[0,0,0],[1,0,0],[0,1,0],[0,0,1]\}$$

corresponding to material grade 2, 3, 5, and 6, respectively. Denote these dummy variables and the rest of the process variables as $[X_1, \ldots, X_s]$, where s is the total number of variables. PCA generates a set of new variables $[Q_1, \ldots, Q_s]$, called PCs, which are linear combinations of $[X_1, \ldots, X_s]$, i.e.,

$$Q_j = e_{j1} X_1 + \cdots + e_{js} X_s ,\ j = 1, \ldots, s , \qquad (2)$$

where $[e_{j1}, \ldots, e_{js}]$ is the eigenvector of the j^{th} largest eigenvalue λ_j for the covariance (or correlation) matrix of $[X_1, \ldots, X_s]$. Figure 2 provides the plot of the first two PCs for the 350 data points, which clearly shows two clusters. The shape of a point indicates the number of seams that the corresponding steel bar contains. Obviously, the threshold in Eq.(1) should be set as $T = 1$. Using $T = 1$ to binarize the number of seams for logistic regression confidently ensures the model-based quality improvement actions to satisfy the engineering specification, which defines good products as those containing less than 5 seams.

3. LOGISTIC REGRESSION BASED QUALITY PREDICTION AND ACTIVE CONTROL

Logistic regression (McCullagh and Nelder 1998) models the relationship between a binary response variable Y and the predictors $\mathbf{X}=[X_1,\ldots,X_s]$. It takes the form

$$\mathrm{logit}(p)=\ln\left(p/(1-p)\right)=\boldsymbol{\beta}\mathbf{X}^T=\beta_0+\beta_1 X_1+\cdots+\beta_s X_s, \quad (3)$$

where $p=\Pr(Y=1)$ is the probability of bad products. β_j ($j=1,\ldots,s$) is interpreted as: a unit increase in X_j with other predictors held fixed will increase $\ln(p/(1-p))$ by β_j , where $\ln(p/(1-p))$ is called the log-odds of $Y=1$.

Estimates of the regression coefficients, $[\hat\beta_0,\ldots,\hat\beta_s]$, are obtained by Maximum Likelihood Estimation (MLE) based on a dataset $\mathbf{D}=[\mathbf{x}_1^T,\ldots,\mathbf{x}_N^T]^T$, where $\mathbf{x}_i=[x_{i1},\ldots,x_{is}]$ is a vector of measurements on the predictors. For a given observation $\mathbf{x}_0=[x_{01},\ldots,x_{0s}]$, $\hat{\mathrm{logit}}(\hat p_0)=\hat\beta_0+\hat\beta_1 x_{01}+\cdots+\hat\beta_s x_{0s}$. Thus, the predicted probability $\hat p_0$ is

$$\hat p_0=e^{\hat\beta_0+\hat\beta_1 x_{01}+\cdots+\hat\beta_s x_{0s}}\Big/\left(1+e^{\hat\beta_0+\hat\beta_1 x_{01}+\cdots+\hat\beta_s x_{0s}}\right). \quad (4)$$

Based on the $\hat p_0$,the Y_0 can be predicted, i.e., $\hat Y_0=1 \;\; \mathit{if} \;\; \hat p_0>0.5$; and $\hat Y_0=0$ otherwise. Using a normal approximation, the confidence interval of $\mathrm{logit}(\hat p_0)$ is

$$\mathrm{CI}_{\mathrm{L\backslash U}}^{\mathrm{logit}(\hat p_0)}=\hat{\mathrm{logit}}(\hat p_0)\pm z_{\alpha/2}\sqrt{\mathbf{x}_0\left(\mathbf{D}^T\mathbf{W}\mathbf{D}\right)^{-1}\mathbf{x}_0^T}, \quad (5)$$

where $\mathbf{W}$ is a weight matrix generated by MLE. Thus, the confidence interval of p_0 is

$$\mathrm{CI}_{\mathrm{L\backslash U}}(p_0)=e^{\mathrm{CI}_{\mathrm{L\backslash U}}^{\mathrm{logit}(\hat p_0)}}\Big/\left(1+e^{\mathrm{CI}_{\mathrm{L\backslash U}}^{\mathrm{logit}(\hat p_0)}}\right). \quad (6)$$

3.1 Quality Prediction

The objective of the research in quality prediction is to find the most parsimonious model that can adequately predict the qualities of steel bars. To achieve this objective, backward stepwise regression (McCullagh and Nelder 1998) is adopted, which begins with a full model and eliminates the predictors in an iterative manner. This procedure is applied to the sensing data, and the final model for quality prediction is:

$$\mathrm{logit}(p)=\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\beta_4 X_4+\beta_5 X_5 \quad (7)$$

where $X_j\,(j=1,2,3,4,5)$ are three dummy variables for material grade, average water flow (Gallon/Min) over two PNTM water boxes, and average water flow (Gallon/Min) over four water boxes after the last stand (see Figure 1 for locations of water boxes); and $\{\hat\beta_0,\hat\beta_1,\hat\beta_2,\hat\beta_3,\hat\beta_4,\hat\beta_5\}$ ={30.00,3.40,-0.76, 8.99, -0.09, -0.11}.

When most predictors in a logistic regression model are continuous variables, goodness-of-fit test is not appropriate for checking the model adequacy (McCullagh and Nelder 1998). Rather, residual analysis is commonly adopted by examining a set of residual plots. Figure 3 shows these plots and Table 1 summarizes the purpose and interpretation of each plot. It can be seen that the data can be adequately fit by the model in Eq.(7) except that data point 32 may be an outlier.

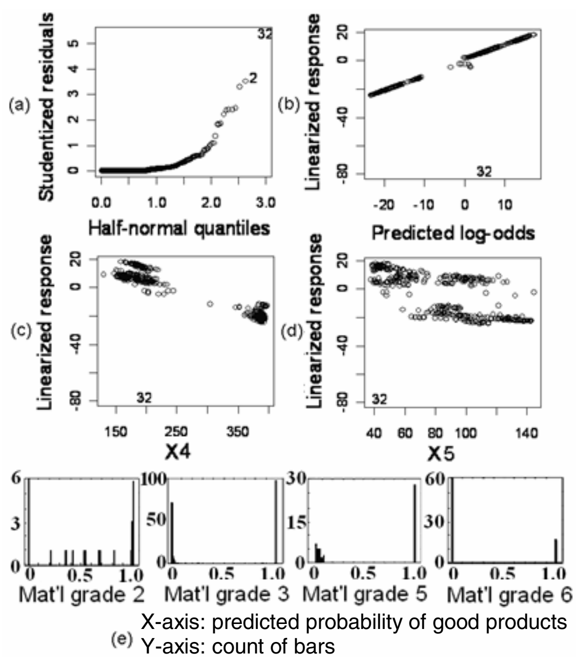

FIGURE 3. RESIDUAL PLOT.

Prediction errors of the model are estimated using cross-validation (Stone 1978). Specifically, 95% of the data are randomly selected to fit the model in Eq.(7); this model is then used to predict the rest 5% of the data and the prediction error is computed. This procedure is repeated for 1000 times, and the mean and standard deviation of the prediction errors are calculated. Following this procedure, three types of prediction errors are obtained, i.e., overall misclassification rate 2.67% $\pm$ 3.57%; false alarm rate 3.38% $\pm$ 6.81%; and miss-detection rate 1.85% $\pm$ 3.74%. Feedbacks from our industrial partners confirmed that these error rates are acceptable according to engineering specifications, indicating that the model in Eq.(7) can be implemented in real rolling environments for quality prediction.

TABLE 1. INTERPRETATION OF RESIDUAL PLOT.

Plot	Purpose	Interpretation
(a) Residual half-normal plot	Detect outliers: points extremely far from the majority considered as outliers	Point 32 outlier
(b) Linearized response vs. predicted log-odds	Adequacy check the of logit function: straight line implies adequacy.	Logit function adequate
(c,d) Linearized response vs. numerical predictors	Adequacy check of linear relationship: straight line implies adequacy.	No higher-order terms needed
(e) Histogram of $1-\hat{p}$ for each material grade	Check how well predictions are differentiated: U-shape desirable; Check how well model predicts bad/good qualities: symmetric U-shape desirable	Predications for material grade 2 not well different--iated. For 3 and 5 better prediction in good quality than in bad quality.

3.2 Active Quality Control

3.2.1 Formulation and Solution. In active control, the goal is to achieve the target quality with an acceptable control cost through adjusting some of key process variables. In the context of binary quality index and logistic regression, active control requires the identification of $\mathbf{x}_T = [x_{T1}, \ldots, x_{Ts}]$, i.e., certain values of the process variables $\mathbf{X} = [X_1, \ldots, X_s]$, that satisfy three inequalities representing the constraints on quality, control cost and control feasibility, respectively, i.e.

$$\begin{cases} \hat{\boldsymbol{\beta}}(\mathbf{x}_T)^T \leq \text{logit}(p_0) \\ (\mathbf{x}_T - \mathbf{x}_C)\mathbf{C}(\mathbf{x}_T - \mathbf{x}_C)^T \leq f_0 \\ x_j^L \leq x_{Tj} \leq x_j^U,\ j = 1, \ldots, s \end{cases} . \tag{8}$$

In Eq.(8), p_0 is a pre-defined target quality (i.e., target probability of bad products). $\mathbf{x}_C$ is a vector of the current observed values for $\mathbf{X}$. $\mathbf{C} = \text{diag}([c_1, \ldots, c_s])$. $c_j(x_{Tj} - x_{Cj})^2$ is the cost of bringing x_{Cj} to x_{Tj}. Here, the cost is assumed to be a quadratic function of the amount of adjustment $|x_{Tj} - x_{Cj}|$, while other forms of functions such as linear functions can be adopted if they are more appropriate. f_0 is a pre-defined acceptable cost for the control; $[x_j^L, x_j^U]$ is the feasible range for adjusting X_j.

In general, it is a challenging task to solve the $\mathbf{x}_T$ in a s- dimensional space if s is large. In this study, a special case of $s = 2$ based on the model in Eq.(7) is investigated. In Eq.(7), $[X_1, X_2, X_3]$ are associated with material grade, so they are not controllable. Process variables X_4 and X_5 are controllable but their feasible range for control may vary across different material grades, which may result in a different $\mathbf{x}_T$ for each material grade. This phenomenon also exists in some other process variables and is fairly common in manufacturing due to safety or feasibility considerations. Thus, the model in Eq.(7) is split into four models, each corresponding to a specific material grade. For example, letting $[X_1, X_2, X_3] = [0,1,0]$, Eq.(7) is converted to a model for material grade 5:

$$\text{logit}(p) = 29.24 - 0.09X_4 - 0.11X_5 . \tag{9}$$

In what follows, the procedure of solving for the $\mathbf{x}_T = [x_{T4}, x_{T5}]$ is discussed based on Eq.(9), while similar procedures can be developed for other material grades.

Geometrically, the possible values of $\mathbf{x}_T = [x_{T4}, x_{T5}]$ form an area on a 2-D plane, which is the intersection of a half-plane, an ellipse, and a rectangle, defined by those three inequalities in Eq.(8). This intersection is shown as the shaded area in Figure 4. Specifically, the 1st inequality (i.e., the quality constraint) represents the half-plane above line A_1A_2, where A_1A_2 is $29.24 - 0.09X_4 - 0.11X_5 = \text{logit}(p_0)$. Because the intercept of A_1A_2 is $(29.24 - \text{logit}(p_0))/0.11$, the smaller p_0 is, the higher line A_1A_2 is. The 2nd inequality (i.e., the cost constraint), equivalently expressed as $(x_{T4} - x_{C4})^2/(f_0/c_4) + (x_{T5} - x_{C5})^2/(f_0/c_5) \leq 1$, represents an ellipse, with semi-major and semi-minor axes being $\sqrt{f_0/c_4}$ and $\sqrt{f_0/c_5}$. Thus, the larger f_0 is, the larger the ellipse is. Finally, the 3rd inequality (i.e., the feasibility constraint) defines the rectangle by specifying the feasible range for adjusting each variable.

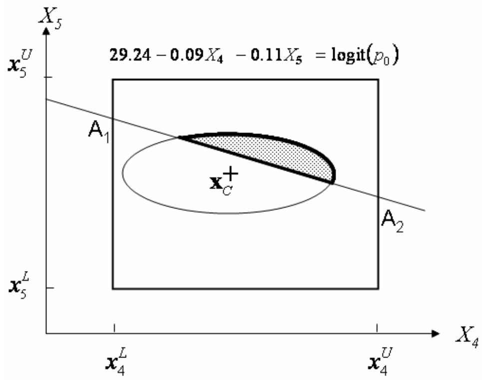

FIGURE 4. GEOMETRIC MEANING OF EQ.(8).

While all points in the intersection area of Figure 4 are solutions to the joint inequalities in Eq.(8), some of them are of particular interests in practice, including:

(i) The $\mathbf{x}_T$ (denoted by ${}^B\mathbf{x}_T$) that leads to *the possible best quality* ${}^B p$ for a given acceptable cost f_0 . This ${}^B\mathbf{x}_T$ is the solution to an optimization problem converted from Eq.(8), i.e.,

$$\begin{aligned}&\text{Objective funtion: } \min \text{logit}(p) = \hat{\boldsymbol{\beta}}(\mathbf{x}_T)^T\\&\text{Constraints: } (\mathbf{x}_T - \mathbf{x}_C)\mathbf{C}(\mathbf{x}_T - \mathbf{x}_C)^T \le f_0,\\&\qquad x_j^L \le x_{Tj} \le x_j^U,\ j = 1,\ldots,s.\end{aligned} \quad (10)$$

To minimize $\text{logit}(p)$ is equivalent to maximizing $I(p) = (29.24 - \text{logit}(p))/0.11$ (the intercept of a line parallel to A_1A_2 in Figure 4). Considering the geometric interpretations of the constraints in Eq.(10), the maximum $I(p)$ is achieved when the line is a tangent to the ellipse; and the tangent point is the optimal solution ${}^B\mathbf{x}_T$. Based on ellipse's properties, it can be derived that

$${}^B x_{T5} = \sqrt{(f_0/c_5)/(1+81/(121r_C))} + x_{C5}, \quad (11)$$

$${}^B x_{T4} = (9/(11r_C))\sqrt{(f_0/c_4)/(1+81/(121r_C))} + x_{C4}, \quad (12)$$

$$\text{logit}({}^B p) = 0.11D - 0.11\sqrt{f_0/c_5}\sqrt{1+81/(121r_C)}, \quad (13)$$

where $r_C = c_4/c_5$, $D = (29.24 - 0.11x_{C5} - 0.09x_{C4})/0.11$.

(ii) The $\mathbf{x}_T$ (denoted by ${}^M\mathbf{x}_T$) that leads to *the minimum control cost* ${}^M f$ for a given target quality p_0 . This ${}^M\mathbf{x}_T$ is the solution to an optimization problem converted from Eq.(8), i.e.,

$$\begin{aligned}&\text{Objective funtion: } \min f = (\mathbf{x}_T - \mathbf{x}_C)\mathbf{C}(\mathbf{x}_T - \mathbf{x}_C)^T\\&\text{Constraints: } \hat{\boldsymbol{\beta}}(\mathbf{x}_T)^T \le \text{logit}(p_0),\\&\qquad x_j^L \le x_{Tj} \le x_j^U,\ j = 1,\ldots,s.\end{aligned} \quad (14)$$

Based on geometric interpretations, ${}^M f$ corresponds to the ellipse with A_1A_2 as its tangent and ${}^M\mathbf{x}_T$ is the tangent point. Thus,

$${}^M x_{T5} = (D - \text{logit}(p_0)/0.11)/(1+81/(121r_C)) + x_{C5}. \quad (15)$$

$${}^M x_{T4} = (9/(11r_C))(D - \text{logit}(p_0)/0.11)/(1+81/(121r_C)) + x_{C4}. \quad (16)$$

$${}^M f = (D - \text{logit}(p_0)/0.11)^2 c_5/(1+81/(121r_C)). \quad (17)$$

3.2.2 Sensitivity Study. In a manufacturing system, it is of interest to study how much the control objective function will deviate from the optimum with a small perturbation in the optimal solution of the controlled variable. This knowledge is important in control variable selection, control actuator specification, and cost-effectiveness analysis. Thus, sensitivity study is conducted to investigate the control performance under the two objective functions.

(i) Sensitivity of the possible best quality ${}^B p$ with respect to ${}^B\mathbf{x}_T$. Consider a small perturbation $\Delta{}^B\mathbf{x}_T = [\Delta{}^B x_{T4}, \Delta{}^B x_{T5}]$ in ${}^B\mathbf{x}_T$ and denote the point after the perturbation as ${}^B\mathbf{x}_T - \Delta{}^B\mathbf{x}_T$. Note that $\Delta{}^B x_{T4} \ge 0, \Delta{}^B x_{T5} \ge 0$ in order for ${}^B\mathbf{x}_T - \Delta{}^B\mathbf{x}_T$ to satisfy the cost constraint in Eq.(10). Inserting ${}^B\mathbf{x}_T$ and ${}^B\mathbf{x}_T - \Delta{}^B\mathbf{x}_T$ into the objective function of Eq.(10) and taking the difference,

$$\Delta\text{logit}({}^B p) = 0.09\Delta{}^B x_{T4} + 0.11\Delta{}^B x_{T5}. \quad (18)$$

Here, $\text{logit}(p)$ is adopted as the measure of quality to facilitate the computation and interpretation. It can be seen that the possible best quality, measured by $\text{logit}({}^B p)$, is slightly more sensitive to ${}^B x_{T5}$ than ${}^B x_{T4}$.

(ii) Sensitivity of the minimum control cost ${}^M f$ with respect to ${}^M\mathbf{x}_T$. Consider a small perturbation $\Delta{}^M\mathbf{x}_T = [\Delta{}^M x_{T4}, \Delta{}^M x_{T5}]$ in ${}^M\mathbf{x}_T$ and denote the point after the perturbation as

${}^{M}\mathbf{x}_T + \Delta^{M}\mathbf{x}_T$. Note that $\Delta^{M} x_{T4} \ge 0, \Delta^{M} x_{T5} \ge 0$ in order for ${}^{M}\mathbf{x}_T + \Delta^{M}\mathbf{x}_T$ to satisfy the quality constraint in Eq.(14). Inserting ${}^{M}\mathbf{x}_T$ and ${}^{M}\mathbf{x}_T + \Delta^{M}\mathbf{x}_T$ into the objective function of Eq.(14), taking the difference, and neglecting the 2nd-order terms of $\Delta^{M} x_{T4}$ and $\Delta^{M} x_{T5}$,

$$\Delta f_M = 2c_4\left({}^{M}x_{T4} - x_{C4}\right)\Delta^{M} x_{T4} + 2c_5\left({}^{M}x_{T5} - x_{C5}\right)\Delta^{M} x_{T5} \qquad (19)$$

It can be seen from Eq.(19) that f_M is more sensitive to the variable with a higher cost of adjustment and a longer adjustment interval.

3.3 Procedure of Quality Prediction and Active Control in Rolling Process

A flow chart of the proposed methods in quality prediction and active control is given in Figure 5. Based on the current observed values for the process variables, i.e., $\mathbf{x}_C = [x_{C1}, x_{C2}, x_{C3}, x_{C4}, x_{C5}]$, and the prediction model in Eq.(7), the current product quality p_C can be predicted and its confidence interval $[\mathrm{CI_L}(p_C), \mathrm{CI_U}(p_C)]$ can be estimated using Eq.(4) and Eq.(6), respectively. If the target quality p_0 is less than the lower bound of the confidence interval $\mathrm{CI_L}(p_C)$, i.e., the current quality p_C is significantly worse than the target quality p_0 , then an active control action is needed. Given p_0 and an acceptable control cost f_0 , an area can be identified which contains all the $\mathbf{x}_T$'s satisfying the quality, cost and feasibility constraints in Eq.(8). In particular, ${}^{B}\mathbf{x}_T$ and ${}^{M}\mathbf{x}_T$ are computed, corresponding to the $\mathbf{x}_T$'s that lead to the possible best quality ${}^{B}p$ for the given f_0 and the minimum control cost ${}^{M}f$ for the given p_0 , respectively. The sensitivities of ${}^{B}p$ and ${}^{M}f$ with respect to small perturbations in ${}^{B}\mathbf{x}_T$ and ${}^{M}\mathbf{x}_T$ can be assessed. Finally, decision makers will evaluate all the information, including ${}^{B}p$, f_0 , p_0 , ${}^{M}f$ and their sensitivities, to determine a most appropriate control action, and complete the active control by shifting $\mathbf{x}_C$ to $\mathbf{x}_T$ (e.g., ${}^{B}\mathbf{x}_T$ or ${}^{M}\mathbf{x}_T$).

3.4 Case Study

An example is provided in this section to demonstrate the procedure in Figure 5. Given $\mathbf{x}_C = [0,1,0,59.16,198.75]$, $\hat{p}_C = 0.9$ and $[\mathrm{CI_L}(p_C), \mathrm{CI_U}(p_C)] = [0.67, 0.98]$ using Eq.(4) and Eq.(6). If $p_0 = 0.2$, an active control action is needed because $p_0 < \mathrm{CI_L}(p_C)$. Other fixed parameters are given as follows: $[x_4^L, x_4^U] = [37.76, 144.73]$, $[x_5^L, x_5^U] = [130.19, 397.89]$, $r_C = 4$, and $f_0/c_5 = 1500$.

The $\mathbf{x}_T$'s that satisfy the constraints in Eq.(8) are $\left\{ \begin{array}{l} \mathbf{x}_T \mid 52.73 \le x_{T4} \le 76.55,\ 278.42 - 0.82x_{T4} \le x_{T5} \\ \le 198.75 + \sqrt{1500 - 4\left(x_{T4} - 56.16\right)^2} \end{array} \right\}$, which form the shaded area in Figure 4. ${}^{B}\mathbf{x}_T = [66.49, 234.60]$ yields the possible best quality ${}^{B}p = 0.072$ for the given control cost $f_0/c_5 = 1500$. ${}^{M}\mathbf{x}_T = [64.64, 225.53]$ yields the minimum control cost ${}^{M}f/c_5 = 837.48$ for the given target quality $p_0 = 0.2$.

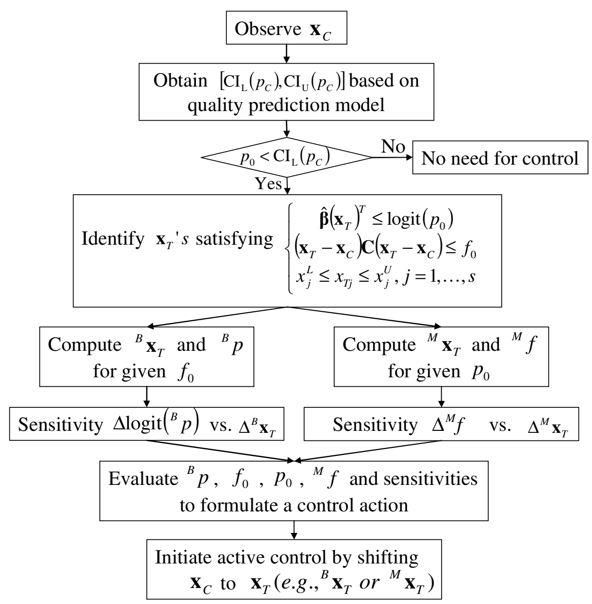

FIGURE 5. ACTIVE CONTROL PROCEDURE.

If there is a small change in ${}^{B}\mathbf{x}_T$, the sensitivity of $\Delta\mathrm{logit}({}^{B}p)$ can be assessed using Eq.(18), that is, a unit decrease in ${}^{B}x_{T4}$ (or ${}^{B}x_{T5}$) will degrade the possible best quality (i.e., increase the possible lowest log-odds of bad quality) by $0.09/\mathrm{logit}(0.072) = 3.5\%$ (or $0.11/\mathrm{logit}(0.072) = 4.3\%$).

So, $\mathrm{logit}({}^{B}p)$ is slightly more sensitive to ${}^{B}x_{T5}$ than ${}^{B}x_{T4}$. Similarly, if there is a small change in ${}^{M}\mathbf{x}_{T}$, the sensitivity of Δf_{M} can be assessed using Eq.(19), i.e., $\Delta f_{M}/c_{5} = 43.84\Delta^{M}x_{T4} + 53.56\Delta^{M}x_{T5}$, that is, a unit increase in ${}^{M}x_{T4}$ (or ${}^{M}x_{T5}$) will increase the minimum control cost f_{M}/c_{5} by $43.84/837.48 = 5.2\%$ (or $53.56/837.48 = 6.4\%$). So, f_{M}/c_{5} is slightly more sensitive to ${}^{M}x_{T5}$ than ${}^{M}x_{T4}$.

4. CONCLUSION

Quality improvement for rolling processes under distributed sensing environments is a challenging issue. Effective modeling and inference methods need to be investigated to realize data fusion, quality prediction, and active quality control. This paper proposed to use logistic regression models to build the relationship between process variables and a binary quality index in a rolling process for quality prediction and active control. Backward stepwise logistic regression was adopted to search for the most parsimonious model that can adequately fit to the data. This model was used for quality prediction purposes. The overall predictor error, estimated by cross validation, was around 2.67% (3.38% and 1.85% as false positive and miss-detection rates, respectively), which satisfied engineering requirements. Active quality control strategies were developed based on this model, which aimed to bring the current quality level, if not satisfactory, to a target level. Mathematical formulation and solution procedures were given to identify alternative active control actions that satisfied the constraints on quality, control cost and control feasibility. Two control actions were of particular interest in practice, i.e., the control that leads to the possible best quality for a given control cost constraint, and the control that leads to the minimum control cost for a given quality target. Thus, solutions with geometric interpretations and sensitivity studies regarding these two controls were provided. A case study based on production data was preformed to illustrate the procedure of the quality prediction and active control in rolling processes.

Future work will focus on implementing the active control strategies in the rolling mill. Several practical issues are to be addressed, including feasibility studies, cost and risk analysis, etc.

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