A Product-Oriented Synchronization and Effective Information Extraction of Continuous Streaming Data for Relationship Mining in a Hot Rolling Process

Massive continuous streaming data are generated over time during production in a multi-stage manufacturing process. This paper aims to develop a product-oriented synchronization and effective information extraction of continuous streaming data and further model the relationships among variables for knowledge discovery. Take the steel rolling process as an example; this paper proposes a three-step data analytics procedure for product-oriented synchronization of continuous streaming data, effective information extraction, and further conducting relationship mining between the roll gap adjustment operations and product shapes based on the product-oriented data. The developed procedure first converts the continuous streaming data generated over time in a production process to product-oriented data set, then extracts the information related to the causes and effects of roll gap adjustments, and finally fits the model describing the relationship among the roll gap adjustments, the change of rolling torques, and the change of product dimensions. This data analytics procedure facilitates the decision-making in the steel rolling process and illustrates an effective application of massive in-situ sensing data towards intelligent decision-making in data-rich manufacturing processes. [DOI: 10.1115/1.4053860]

Keywords: high-dimensional streaming data analysis, relationship mining, process data and product data synchronization, multistage manufacturing process, data-driven rolling process modeling, sensors

1 Introduction

The advancement of sensing technology enables manufacturing systems to equip with a large number of sensors. In a multistage manufacturing process (MMP), a plurality of in-situ sensors at each manufacturing stage continuously collect production data at a fixed sampling frequency over time. Because the collected massive data contain abundant process and production information, they have the potential to be used in diverse ways for numerous purposes. This calls for advanced techniques to extract useful or usable knowledge from the raw continuous production data. Enabling these raw data streams to act as primitives for solving the problems of interest remains to be a research topic [1].

The steel rolling process is a typical MMP with multiple sensors installed at each stage continuously recording the process variables during production. The collected rich data have enabled new methods and tools for the MMP modeling, monitoring, and root cause identification. Taking the hot rolling process as an example, Jia et al. [2] developed a defect detection approach based on machine vision and intelligent systems, and Li et al. [3] developed an online quality inspection algorithm for the surface defect of seam. Li and Shi [4] proposed a causal modeling approach and discovered the causal relationships between process variables and product quality in a hot rolling process. Jin et al. [5] applied logistic regression to model the relationship between process variables and a binary quality index in a rolling process for quality prediction and active control. Recently, Wang et al. [6] carried out a retrospective analysis to identify when and how multiple events occur in an MMP. Miao et al. [7] developed a structural tensor-on-tensor regression model with interaction effects considered in an MMP and applied it to a hot rolling process. Though the above research has demonstrated good performance in root cause identification and quality prediction, they are mainly focused on the analysis of a set of specific types of preprocessed data. However, there is typically a big gap between the raw data collected from the in-situ sensors and the decision that we aim to make on the process.

In a steel rolling process, the dimension quality and surface integrity are key quality characteristics of the rolled products. In literature, extensive research has been carried out to study the characteristics affecting the quality of the product during the rolling process based on physics-based mathematical models and finite element methods. To name a few, physics-based mathematical models have been developed to predict the strip thickness profile [8], to study the characteristics and mechanism of rolling instability and chatter [9], and to calibrate the position of work rolls for heavy plates [10]. Besides, an adaptive feedforward control strategy of the strip thickness has been developed using the physics-based mathematical model [11]. The finite element analysis has been conducted to study the rolling system configurations on leveling effectiveness [12,13], to study the metal strip texture transfer mechanisms in the lubricated skin pass rolling process [14], to simulate the chatter phenomenon in a cold rolling process [15], to study the roll-stack deflections and contact mechanics for strip rolling process [16], and to predict the strip profile shape [17]. However, the earlier research focuses mainly on the strips or plates rolling on one rolling stand rather than the relationship modeling across multiple consecutive rolling stands. In the bar rolling process, the...
cross-sectional shape of hot rolled bars is one of the key quality characteristics of the product. To ensure the final dimension accuracy of hot rolled bars, the roll gaps are occasionally adjusted during rolling to compensate for wears of roll grooves while maintaining the stability of the rolling process. It is critical to understand the relationship between roll gap adjustments and dimension changes of hot rolled bars to improve the roll gap adjustment performance. The large amount of rolling data containing rich information could enable a data-driven model to describe the relationship between roll gap adjustments and dimension changes of hot rolled bars. However, as we have discussed before and shall see in Sec. 2, significant efforts are required to synchronize multiple continuous streaming data, namely the original sensing signals sampled over time from in-situ sensors installed at each stage, into a process model based on the effect of roll gap adjustments.

This paper aims to synchronize the continuous streaming data into product-oriented data and to conduct relationship mining in MMPs. Specifically, this paper exemplifies a data-driven analysis procedure for hot rolling processes to synchronize the continuous streaming data into a product-oriented data set, which includes all process signals from all manufacturing stages that fabricate a specific product and the corresponding quality measurement signals of the product. Furthermore, based on the obtained product-oriented data sets, we model the relationship between roll gap adjustments and final dimension changes of hot rolled bars. We start our procedure by converting continuous streaming data generated from the in-situ sensing system to product-oriented data sets, then effectively utilize process knowledge to extract useful information from the product-oriented data sets, and finally formulate an appropriate model.

To the best of our knowledge, this research is the first effort in mining the relationship between roll gap adjustments and rolled bars’ dimensions via data-driven analysis in a multistage rolling process. The limited existing literature on the relationship between roll gap adjustments and product shape changes usually focuses on physical models, either with models describing relationships between physical variables obtained from multiple stages [18] or with the detailed model of the deformation process through finite element analysis (FEA) [19,20]. However, these methods usually involve a large number of critical parameters, such as frictions, roll stiffness, and the inertia of rotational parts. These parameters are specific to a rolling process, and their values cannot be easily obtained. Additionally, it is generally infeasible to perform experimental studies for model calibration and validation as there is no perfect means to acquire these properties in a hot rolling process. Meanwhile, it is computationally intractable to build a complete FEA model for an entire rolling system. The physical model can typically represent the nominal operating conditions rather than the variations which can be quite significant for a hot rolling process, in which tight control is impossible. There is the real-time closed-loop control [21] based on the measuring data of the profile measurement system for quality assurance; however, it is limited to the finished block of a rolling process rather than being applied to the entire rolling process.

This paper makes the following two contributions:

- The paper develops an automatic procedure of product-oriented synchronization for continuous streaming data in an MMP. Specifically, massive sensor-based continuous streaming data are collected over time in all stages of a manufacturing process. A generic strategy of data-driven decision-making is proposed according to the configuration of the manufacturing systems, which convert the continuous streaming data into product-oriented data sets. This data synchronization procedure is generic and implementable to numerous MMPs.
- The paper develops models and strategies for automatic roll gap adjustments in bar rolling processes. In steel bar rolling applications, adjusting the roll gaps is a key decision-making task. While there is current literature on the physical modeling of a rolling process or feedback control system, they do not develop roll gap adjustment schemes for multiple rolling stations simultaneously. To address this challenge, we directly use the raw data generated from the continuous rolling process to derive a model that associates the roll gap adjustments with the final shapes of the hot rolled bars. It is promising for generic automatic in-process roll gap adjustments.

In the remaining part of the paper, Sec. 2 introduces the layout of a bar rolling process, the challenges in data analytics, and the proposed solution. Section 3 details the procedures of the proposed information extraction and modeling approach. Section 4 demonstrates the application of the proposed solution to a real hot rolling process. Section 5 concludes the paper.

2 The Rolling Process and the Challenges of Data Analytics

This section presents a steel bar rolling process that motivates our research. Figure 1 presents the layout of a bar rolling system consisting of K alternating horizontal-vertical milling stages. As shown in Fig. 1, sensors are applied to the system to measure equipment parameters, such as the torque and the roll gap of each stage, continuously during production. Following the final stage of the
rolling line, a laser diameter gauge equipped with multiple laser sensors measures the diameters of the passing steel bars’ cross-sectional areas along $Q$ orientations. Each sensor records its readings with a prescribed sampling frequency and generates a stream of data over time during the production. Each data stream can be represented by a long vector, which contains the information of all hot rolled bars manufactured in a time frame. Specifically, the data streams of torque at the stage $k$, the roll gap at the stage $k$, and the axis $q$ diameter are respectively represented as $\tau_k$, $g_k$, and $d_k$, $k = 1, \ldots, K$ and $q = 1, \ldots, Q$. Figure 1 shows one interval, marked by the red boxes, of these data streams, from which we can see that each data stream consists of multiple segments. Each segment corresponds to the readings along the length of one bar, obtained when the bar passes through the sensors at each stage. There would be a time delay from one stage to the immediate next stage. Also, as the bar is being rolled to a smaller diameter, the bar will elongate and the segment would be longer at a later stage.

From these raw streaming data, we aim at (1) converting the multiple continuous streaming data into data segments corresponding to each rolled bar, e.g., product-oriented data set; and (2) answering how the roll gap adjustments affect the dimensions of the final product, as discussed in the Introduction.

3 Proposed Three-Step Data Analytics Procedure

From the rolling process introduced in Sec. 2, we can see that there is a significant gap between the massive continuous streaming data and our inference goal. This section proposes a three-step systematic solution that utilizes the production data to understand the relationship between the roll gap adjustments and dimension changes of hot rolled bars. The schematic diagram of the developed framework is presented in Fig. 2. These three steps and corresponding challenges are summarized as follows.

1. We first convert the raw continuous streaming data over time to product-oriented data set corresponding to each rolled bar, i.e., conducting segmentation for the data streams corresponding to all sensors to the data sets of each product. The main challenge of this step lies in different rolling times for the rolling bars across all stages due to process variations. Additionally, errors such as missing values sometimes appear in the raw data. Thus, a well-designed algorithm is needed to integrate data characteristics and manufacturing process knowledge to achieve high precision and robustness in data segmentation.

2. The product-oriented data sets then need to be analyzed to identify the process change information related to each roll gap adjustment. The main challenge is to preserve the dimensional variability of the rolled bars’ measurements that are associated with the roll gap adjustments while reducing other sources of uncertainties and noises in the process.

3. Once the information of each roll gap adjustment is extracted, a predictive model is built to associate any changes in the bar dimensions with the roll gap adjustments and other related process variables such as torque. The challenge of this step is to incorporate the characteristics of the rolling process so that the model has both good interpretability and good predictive performance.

The specific steps in the proposed procedure are detailed in Secs. 3.1–3.3.

3.1 Convert Continuous Streaming Data Over Time to Product-Oriented Data Set. In our study, there are $2K + Q$ data streams over time obtained from the data acquisition systems in a multistage hot rolling process, where $2K$ data streams represent the continuous readings of torque and roll gap from $K$ stages, and $Q$ is the number of axes for dimension measurements of a rolled bar. Here denote the measurements of the roll gap as $g_k$, the torque as $\tau_k$ at stage $k$, $k = 1, \ldots, K$, and $d_q$ as the diameters of the rolled bar at axes $q = 1, \ldots, Q$. Vectors $g_k$, $\tau_k$, and $d_q$ represent the entire continuous data streams of measurements obtained from respective sensors. The goal of the first step of data analysis is to synchronize these raw data streams into product-oriented data set including the processing data and dimensional measurements associated with each hot rolled bar. To achieve this, we need to identify the time points when each rolling bar enters and exits a sensor in a rolling station. Then, we can carve out the corresponding segments of all data streams for every bar according to these critical time points and put them together as the product-oriented data set of this bar.

Fig. 2   Schematic diagram of the developed framework

In a rolling system, sensors are installed at each stage to measure the roll gap and torque. The data streams generated from these two sensors at each stage share the same starting time and ending time for each bar being rolled. Similarly, all $Q$ data streams of diameter measurements are generated from the laser gauge and thus share the same starting and ending time. Therefore, we will only use $\tilde{t}_i$, and $d_i$ to find the time points when bar $n$ enters and exits stage $k$ and the laser gauge.

One challenge of this task is how to ensure data fidelity and maximize the number of rolling bars whose complete data are preserved by improving the robustness against possible missing values in the data. To address this challenge, we use two algorithms sequentially, by improving the robustness against possible missing values in the stages and the laser gauge are $(\tilde{t}_i, d_i)$ from each list of segmental intervals, and we obtain $L_k = \{s_{k1}, t_{k1}\}, \ldots, \{s_{kN_k}, t_{kN_k}\}$, $k = 1, \ldots, K$, where $L_1, \ldots, L_K$ are the sets of intervals disassembled from $\tilde{t}_1, \ldots, \tilde{t}_K$, and $L_{K+1}$ is the set of intervals disassembled from $d_1$. Then, Algorithm 2 matches the intervals in $L_1, \ldots, L_{K+1}$ corresponding to the same bar, and derives the output list $L$, which contains data sets of individual bars $n = 1, \ldots, N$. The times that bar $n$ enters and exits all stages and the laser gauge are $(\tilde{t}_n, d_n)$, $k = 1, \ldots, K+1$.

Algorithm 1: Disassemble a single data stream $\xi$

Algorithm 1 gives the procedure to disassemble every data stream $\xi$ of length $T$. It relies on two functions: up ($\xi, t$) and down ($\xi, t$). Each function returns a Boolean value, denoting whether there is a bar starting or ending at time $t$. Note that their forms are subjective, depending on the characteristics of the data stream $\xi$. For example, if the data stream $\xi$ represents torque, we may define up ($\xi, t$) as an indicator that $\xi(t−1) < H_2$ and $\xi(t) ≥ H_1$ where $H_1$ is a prescribed threshold. The algorithm scans the entire signal sequence, and the Boolean variable status indicates whether the current time $t$ is in the middle of a bar. Line 6 in Algorithm 1 detects if a new bar starts when the previous time $t−1$ is not in a bar. While the current time is in the middle of a bar, line 8 abandons the current item if isan ($\xi, t$) is true, meaning that the value at time $t$ is missing in the signal $\xi$. Line 9 updates the latest appearance of a bar to avoid incomplete bar measurements, and line 10 outputs a complete bar by finding its ends.

Algorithm 1: Disassembling signal $\xi$

1 Input: data stream $\xi$ of length $T$
2 Output: A list of intervals $L$
3 set status = False; $L$ = empty list;
4 for $t = 1, 2, \ldots, T$:
5 $\text{if }$ status and up ($\xi, t$):
6 $\text{if }$ begin = $t$, status = True;
7 $\text{else:}$
8 $\text{if }$ isan ($\xi, t$), status = False; continue;
9 $\text{if }$ up ($\xi, t$), begin = $t$;
10 $\text{if }$ down ($\xi, t$), append (begin, $t$) to the list $L$;

Algorithm 2: Match intervals according to the same bars

In the second algorithm, we match the time intervals in which a bar passes stage 1, ..., $K$ and the laser gauge by picking up its corresponding interval ($s_{k}^i$, $t_{k}^i$) from each list $L_k$, $k = 1, \ldots, K+1$. To achieve this, we cannot simply sort the intervals in each list $L_k$ and take it for granted that the intervals with the same index correspond to the same product. In Algorithm 1, the intervals of some bars may be ignored due to the missing values in the data stream, and some bars may even be cobbled or removed from the rolling line in the middle of the $K$ stages without arriving at the laser gauge. To limit the chance of errors and maximize the number of bars whose data are preserved, we propose to trace back the time intervals of each product from the laser gauge to stages $K, K−1, \ldots$ and finally to stage 1 individually. The detailed procedure is given in Algorithm 2.

Algorithm 2: Matching intervals according to the same rolling bars

1 Input: lists of disassembled intervals $L_k = \{(s_{k1}^i, t_{k1}^i)\}, \ldots, \{(s_{kN_k}^i, t_{kN_k}^i)\}$
2 Output: list $L$
3 set array $i_k = N_k$, $k = 1, \ldots, K+1$;
4 for $n = N_{K+1}, N_{K+1}−1, \ldots$:
5 $\text{set } (s_{k1}^*, t_{k1}^*) = (s_{k1}^{i_k}, t_{k1}^{i_k})$;
6 $\text{set skip = False}$
7 $\text{for }$ $k = K, \ldots, 1$:
8 $\text{for } i = i_k, i_k−1, \ldots$:
9 $\text{if } s_{k1}^i < s_{k1}^*; \text{ set } s_{k1}^i = s_{k1}^*; \text{ and } t_{k1}^i = t_{k1}^*; \text{ break; }$
10 $\text{if } i ≤ 0; \text{ stop; }$
11 $\text{if } s_{k1}^i − s_{k1}^* ≥ \Delta_s, \text{ set skip = True and break; }$
12 $\text{set } i_k = i$;
13 $\text{if skip, continue; }$
14 $\text{append } (s_{k1}^i, t_{k1}^i), \ldots, (s_{kN_k}^i, t_{kN_k}^i) \text{ to } L$.

In Algorithm 2, the list $L$ stores the data corresponding to each individual bar. The loop from line 4 to line 13 traces $N_{K+1}$ intervals of those bars that pass the laser gauge reversely. To promote computational efficiency, we store $i_k$, the index of the last possible interval for stage $k$ of the current bar being rolled. The pair ($s_{k1}^*, t_{k1}^*$) denotes the starting and ending time of the current bar being rolled on stage $k$. The Boolean variable skip denotes whether the data from the current bar are complete and will be saved into $L$ (lines 11 and 13): if the difference between the time that a bar arrives at stage $k$ and stage $k+1$ is greater than a prescribed limit $\Delta_s$, the algorithm decides that the intervals from lists $L_k$ and $L_{k+1}$ cannot be matched and thus skip this bar. The physical meaning of $\Delta_s$ is the time interval between two consecutive rolling bars in the rolling production line.

The $K+1$ intervals in the $nth$ component of the list $L$ are $(s_{n1}, \Delta_{n_1}), \ldots, (s_{nK+1}, \Delta_{n(K+1)})$ where $n = 1, \ldots, N$ and $N$ is the number of items in the output list $L$. Typically, $N$ is slightly smaller than $N_{K+1}$ due to the missing data of certain bars. With these intervals, we can cut off a segment of each data stream corresponding to product $n$, and obtain $2K+Q$ segments $g_{nk} = \overline{g}_{(s_{nk}, t_{nk})}$, $\overline{t}_{nk} = \overline{t}(s_{nk}, t_{nk})$, and $\overline{d}_{nk} = \overline{d}_{(s_{nk}, t_{nk})}$, $k = 1, \ldots, K$, $q = 1, \ldots, Q$. Here, vector $g_{nk}$ and $t_{nk}$ denote the signals of roll gap and torque at stage $k$ corresponding to the $nth$ bar, respectively, and vector $d_{nk}$ denotes the diameter measurements of the $nth$ bar along axis $q$. As we are more concerned with between-bar variation instead of within-bar variation, we finally calculate the average roll gap of stage $k$, the average torque of stage $k$, and the average diameter along axis $q$, denoted respectively as $\overline{g}_{nk}$, $\overline{t}_{nk}$, and $\overline{d}_{nk}$, by averaging the values of all elements in $g_{nk}$, $\overline{t}_{nk}$ and $\overline{d}_{nk}$ for bar $n$.

3.2 Extract the Process Information on Each Time of Adjustment

After we convert the data streams to the product-oriented data sets, it is desirable to extract the information related to each roll gap adjustment. In reality, the frequency of the adjustment is relatively low to ensure production stability and to maximize the throughput of the process. If we use all the production data to model the relationship between the bar dimensions and the corresponding roll gaps, the changes of the bar dimensions caused by roll gap adjustments will be submerged by the variations from other sources, and thus, the effect of roll gap adjustments on the final dimensions may not be revealed. After the information related to each roll gap adjustment is extracted, the data-driven model we developed can be more accurate.

Our strategy for this step is to first locate the bars fabricated right after a roll gap adjustment and then extract the process information related to this roll gap adjustment. To identify the time of roll gap adjustment, we find the indices of all bars
following an adjustment

\[ A = \left\{ n: \max_{1 \leq k \leq K} |\bar{\delta}_{n,k} - \bar{\delta}_{n-1,k}| > \varepsilon \right\} \quad - A_0 := \{ n_1, n_2, ..., n_I \} \quad (1) \]

where \( \left\{ n: \max_{1 \leq k \leq K} |\bar{\delta}_{n,k} - \bar{\delta}_{n-1,k}| > \varepsilon \right\} \) denotes the set of rolling bars with a changed roll gap value at one or more stages and \( I \) denotes the identified total times of roll gap adjustments. A prescribed limit \( \varepsilon \) distinguishes active roll gap change from random roll gap disturbances. Any roll gap change may be caused by either roll gap adjustment or the replacement of a roll in which a new roll gap level is set. From the management log file, the initial products following replacements of a roll can be identified, whose indices are in the set \( A_0 \). Note that changes of rolls occur much rarer than the roll gap adjustments in a rolling production process.

Now, we extract the changes of roll gaps, the torque, and the diameter of rolling bars for each time of roll gap adjustment. To reduce the effects of random measurement disturbance during the manufacturing process, we adopt a technique motivated by the kernel smoothing method (Chapter 6 in Ref. [22]). Specifically, for the \( i \)th roll gap adjustment on bar \( n_i \in A \), we calculate

\[ \bar{\delta}_{n_i,k} = (\bar{\delta}_{n_i-1,k} + \cdots + \bar{\delta}_{n_i-m,k})/m \]
\[ \bar{\delta}_{n_i,k} = (\bar{\delta}_{n_i,k} + \cdots + \bar{\delta}_{n_i+m,k})/m \]

denoting the average value of \( m^- \) bars before the adjustment and \( m^+ \) bars after the adjustment. The \( i \)th roll gap adjustment on stage \( 1, \ldots, K \) can thus be represented as \( K \)-dimensional vector

\[ \delta_i^g = (\bar{\delta}_{n_i-1,k} - \bar{\delta}_{n_i-1,k}, \ldots, \bar{\delta}_{n_i,k} - \bar{\delta}_{n_i,k}) \in \mathbb{R}^K \]

Similarly, we calculate \( \bar{\tau}_{n_i,k} \) as the average stage-\( k \) torque for multiple bars before and after the \( i \)th roll gap adjustment and obtain

\[ \delta_i^r = (\bar{\tau}_{n_i-1,k} - \bar{\tau}_{n_i-1,k}, \ldots, \bar{\tau}_{n_i,k} - \bar{\tau}_{n_i,k}) \in \mathbb{R}^K \]

Similarly, we calculate \( \bar{d}_{n_i,q,k} \) as the average axis-\( q \) diameter for multiple bars before and after the \( i \)th roll gap adjustment, and obtain

\[ \delta_i^d = (\bar{d}_{n_i-1,q,k} - \bar{d}_{n_i-1,q,k}, \ldots, \bar{d}_{n_i,q,k} - \bar{d}_{n_i,q,k}) \in \mathbb{R}^Q \]

Here vectors \( \delta_i^g \), \( \delta_i^r \), and \( \delta_i^d \) contain the extracted information from the \( i \)th roll gap adjustment. The process information of all the \( I \) times of roll gap adjustments can be summarized as data matrices \( \Delta^g \), \( \Delta^r \), and \( \Delta^d \), which completes the data preprocessing procedure. In the next subsection, these data will be used for developing process models.

### 3.3 Model the Relationship Between Process Variables and Quality Responses

In this subsection, we aim at modeling how the roll gap adjustments and the changes of torque measurements influence the changes of final rolled bar dimensions. For the development of a data-driven model, we standardize the columns of \( \Delta^g \), \( \Delta^r \), and \( \Delta^d \), and obtain the data matrices

\[ X_1 := \begin{bmatrix} x_{1,1} \end{bmatrix}, \quad X_2 := \begin{bmatrix} x_{1,2} \end{bmatrix}, \quad \text{and} \quad Y := \begin{bmatrix} y_1 \end{bmatrix} \]

where \( x_{1,j} \) the change of \( a_j \) and \( y_1 \) the change of \( y_1 \)

\[ \text{roll gaps is the main reason for the change of the bar dimensions. Besides, the variations of the rolling force lead to the variations of the roll gap [23] due to the elastic behavior of all parts in the rolling mills. Thus, the torque measured at each stage should also be included as covariates in the model. Therefore, we aim to develop a data-driven model in the form of Eq. (2)}

\[ y_i = f(x_{1,i}, x_{2,i}) \]

\[ (2) \]
In general, any method of predictive analysis can be used to obtain the estimation of $f$, as long as it is interpretable and gives an accurate prediction. In literature, state-space models describe the relationship between process and quality variables of consecutive stages in an MMP [24]. Although it accurately expresses the engineering knowledge of a rolling process, it is less effective for predicting the final shape of the products, because we do not have the measurements of the diameters after each stage. In this paper, we provide an alternative approach for process modeling.

Based on the previous research findings by Byon et al. [19], the variation of the exit cross-sectional area is linearly dependent on the variation of the exit cross-sectional area is linearly dependent on the variation of the diameter. Zero coefficient $w_{ij}$ denotes the $j$th coefficient at the $i$th input variable, and $s$ is the tuning parameter.

As the dimension of the model input $P$ is large and the output is a multivariate variable, it is important to incorporate appropriate regularizations on the coefficient matrix $W$ to increase the model interpretability and the predictive accuracy. We propose to use the multitask-lasso penalty [25] on the regression coefficient matrix $W$

$$p(W) = s \sum_{i=1}^{P} \| W_{i} \|_{2,1}$$

where $\| W \|_{2,1} = \sqrt{ \sum_{j=1}^{Q} \| W_{ij} \|_{2}^{2} }$ is a $L_{2,1}$-norm regularizer with $w_{ij}$

denoting the $j$th coefficient at the $i$th input variable, and $s$ is the tuning parameter.

Let $w_{ij} \in \mathbb{R}^{Q}$, $i = \ldots, P$, denote the model coefficient vector for the $i$th input variable, and the coefficients in $w_{i}$ are selected or eliminated simultaneously: if an input variable affects the product dimension, it affects the diameter of the rolled bar on all axes. Otherwise, it does not affect the diameter on any axis. In this way, the $L_{2,1}$ regularizer helps predict multivariate output variables with variable selection. Consequently, the model structure is interpretable.

**Incorporating Eqs. (4) and (5) together, we give the objective function of the problem in Eq. (6), which estimates the regression coefficient matrix $W$**

$$\arg \min_{W} \frac{1}{2F} \| Y - XW \|^{2}_{F} + s \sum_{i=1}^{P} \| W_{i} \|_{2,1}$$

Considering the stability and scalability, the block-wise coordinate descent (BCD) algorithm has been proposed to estimate the model coefficient matrix [25,26]. The basic idea of the BCD algorithm is to iteratively update one component of the model coefficients at a time to minimize the objective while fixing all other coordinates. To be specific, each $w_{ij} \in \mathbb{R}^{Q}$, $i = \ldots, P$, is regarded as a block in Eq. (6). The coefficients within each $w_{i}$ are simultaneously updated. More details of the algorithm can be found in Refs. [25,26].

In practice, the roll gap adjustment will affect all six-dimensional measurements in a rolled bar. To consider this fact, the estimation process in Eq. (3) can be modified based on additional considerations of data characteristics. If we observe a high correlation among elements of $y$, or if it has a limited number of variation patterns, for example, we can further incorporate the low-rank structure of $W$ in Eq. (3) through nuclear-norm penalization or other methods like Partial Least Square Regression and Reduced Rank Regression. In general, the predictive model should be a model with good predictive performance and corresponding to the data and systems characteristics.

![Histogram of $R^2$ score](image)

**Case Study for Relationship Exploration and Explanation**

In this section, we demonstrate how the framework developed in Sec. 3 is applied to a hot bar rolling process. We download the data from the process data management system in the form of $2K + Q$ long data streams for a period of 12 months. In the rolling process that we investigate, there are $10$ rolling stages, and the dimensional measurements are the diameters on $Q = 6$ axes.

Based on the data processing procedures presented in Sec. 3.1, we obtained the data set for all rolled bar manufactured during this 12-month period. According to the procedure in Sec. 3.2, we identified $I = 871$ times of roll gap adjustments, extracted the information from each time of adjustment, and formed data matrices $X \in \mathbb{R}^{871 \times 10}$, $X_{i} \in \mathbb{R}^{871 \times 10}$ and $Y \in \mathbb{R}^{871 \times 6}$. Then, we form data matrices $X \in \mathbb{R}^{120 \times 120}$ as described in Sec. 3.3 and use $X$ and $Y$ to fit the regression model to understand how roll gap adjustments and the changes of torque relate to the dimension changes.
We randomly divide the collected data samples into a training set (80%) and a testing set (20%), which contain \( I_{\text{train}} = 696 \) samples and \( I_{\text{test}} = 175 \) samples, respectively. We estimate the model parameters based on the training data set, predict the output dimension changes for the testing data set, and evaluate the prediction accuracy. The performance measure of the prediction accuracy is \( R^2 \) score, calculated by \( R^2 \) score = 1 - MSE/VAR, where MSE = \( 1/I_{\text{test}} \sum_{i=1}^{I_{\text{test}}} \| y_i - \hat{y}_i \|^2 \) is the mean squared prediction error on the test data set, and \( \text{VAR} = 1/I_{\text{test}} \sum_{i=1}^{I_{\text{test}}} \| y_i - \bar{y} \|^2 \) calculates the total variance of the response on the test set. Intuitively, \( R^2 \) score \( \leq 1 \), a large value of \( R^2 \) score indicates that the prediction error is small relative to the variation of the diameter measurements. That is, if the value of \( R^2 \) score is closer to 1, it indicates that the prediction is closer to the samples’ truth value; if \( R^2 \) score = 0, it indicates that the variance of the prediction residual is the same as the variance of the ground truth, and if \( R^2 \) score \( < 0 \), it indicates that the variance of the prediction residual is even larger than that of the ground truth. The parameter \( \alpha \) is selected by a fivefold cross-validation on the training set.

We repeat the estimation procedure 50 times to identify the mean and the standard deviation of the \( R^2 \) score, which are 68.91% and 3.80%, respectively. The histogram in Fig. 4 shows the distribution of the obtained \( R^2 \) score. As it is illustrated in Fig. 4, the \( R^2 \) score is larger than 60%, which means that the majority of the variability can be explained by the model. This result indicates that the proposed method can effectively mine the relationship between process variables and dimensional quality and interpret causes of the majority of the variability of dimensional quality. Moreover, we presented the histogram of the mean-squared error (MSE) calculated by 50 times of repetition in Fig. 5 whose mean value and standard deviation are 1.595e-5 and 2.596e-6, respectively. As the standard deviation of MSE is only one-sixth of the mean value, it reflects the stability of the estimated results.

The estimation of the corresponding regression coefficient matrix \( W = [W_1, W_2, W_{1:2}] \in \mathbb{R}^{120x128} \) presented in Figs. 6(a)–6(c), where \( W_1, W_2 \), and \( W_{1:2} \) represent the regression coefficients of the standardized roll gap adjustments \( X_1 \), the standardized torque changes \( X_2 \), and the first-order interaction between the roll gap adjustments and the corresponding changes of the torque \( X_{1:2} \), respectively.

We have the following observations from the estimation results on how roll gaps affect the final dimensions:

1. Figure 6(a) shows that the roll gap adjustments of stages 9 and 10 have the most significant effects on the changes of the final dimensions.
2. It is also observed that the roll gap adjustments of stage 9 and 10 have the most significant positive effects on \( y_1 \), while those of stage 10 have the most significant positive effects on \( y_3 \). The scatter plots between the roll gap adjustments of stages 9–10 and the changes of the final dimensions presented in Figs. 7(a1) and 7(b4) further illustrate this finding.
3. The roll gap adjustments of stage 9 also strongly affect \( y_2 \) and \( y_5 \) as seen in Figs. 7(a2) and 7(b6), and the roll gap adjustments of stage 10 also positively strongly affect \( y_3 \) and \( y_5 \) as shown in Figs. 7(b3) and 7(b5).
4. The roll gap adjustments of stage 10 negatively affect \( y_1 \).

All observations above are consistent with our understanding of the rolling process. As the bars’ dimensions are measured right after stage 10, the roll gap adjustments of later stages have more significant effects on the final dimensions of a rolled bar. As shown in Fig. 8, axis 1 and axis 4 are aligned with the vertical and horizontal directions, and stages 9 and 10 squeeze the bars along these directions, respectively. The diameters measured on axis 2 and axis 6 are two adjacent directions of axis 1; axis 3 and axis 5 are adjacent to axis 4, so they are also respectively affected by the roll gap adjustment operations along axis 1 and axis 4. Finally, the vertical diameter of the cross-sectional area of the bar becomes larger as stage 10 squeezes the horizontal direction.

\[
\begin{align*}
(1) \quad & \text{Figure 6(a) shows that the roll gap adjustments of stages 9} \\
& \text{and 10 have the most significant effects on the changes of the final dimensions.} \\
(2) \quad & \text{It is also observed that the roll gap adjustments of stage 9} \\
& \text{and 10 have the most significant positive effects on } y_1, \text{while those of stage} \\
& \text{10 have the most significant positive effects on } y_3. \text{The scatter plots} \\
& \text{between the roll gap adjustments of stages 9–10 and the changes of the final dimensions presented} \\
& \text{in Figs. 7(a1) and 7(b4) further illustrate this finding.} \\
(3) \quad & \text{The roll gap adjustments of stage 9 also strongly affect } y_2 \text{ and } y_5 \text{ as seen in Figs.} \\
& \text{7(a2) and 7(b6), and the roll gap adjustments of stage 10 also positively strongly affect } y_3 \text{ and } y_5 \text{ as} \\
& \text{shown in Figs. 7(b3) and 7(b5).} \\
(4) \quad & \text{The roll gap adjustments of stage 10 negatively affect } y_1.
\end{align*}
\]
As for the changes of torque, we observe from Fig. 6(b) that stages 4, 6, 8, 9, and 10 have important effects on the changes of the final dimension. This can be explained by the fact that stages 8, 9, and 10 are the last three stages and thus have direct effects on the dimensional changes. Meanwhile, stages 4 and 6 are two stages situated in a second place of a horizontal-vertical rolling mill combination, and thus, they are more important in dimension correction for the hot rolled bars.

From Fig. 6(c), we observe that there are interaction effects between the roll gap adjustments \( X_i \) and the changes of torque \( y_2 \), though they are weaker than the main effects. The interaction effects between the roll gap adjustments on stages 9 and 10 and the changes of torque are relatively more significant than other interaction regression coefficients in Fig. 6(c).

In summary, the results above not only explain and quantify the relationship between the roll gap adjustments and the dimension changes but also provide good predictive performance. The obtained results thus provide a better understanding of the bar rolling process for further effective dimensional control.

## 5 Conclusion

This paper demonstrates an integrated and automatic system that uses massive raw production data to understand the effect of roll gap adjustments in a rolling process. The system first converts the original sensor-based continuous streaming data over time to product-oriented data sets of individual bars and then extracts the features essential to the roll gap adjustments while minimizing the influence of other disturbances. Finally, it models the relationship between the roll gap adjustment operations, the changes of torque, and the changes of dimension on the rolled bars with good interpretability and predictivity. The proposed three-step data analytics procedure is demonstrated through a case study with real production data to validate its effectiveness.

The final predictive model obtained from the process data has the potential to be used to derive a data-driven approach to adjust the roll gaps so as to achieve optimal shapes of the final product. To achieve this, we need to determine the roll gap adjustment vector \( x_{i,1} \) so that the expectation of \( y_i \) is the desired diameter. However, there are two challenges involved: First, the torque after the adjustment is unknown, and therefore, we will need another predictive model to predict the torque after roll gap adjustment. Second, an adjustment cost should be considered as we cannot adjust the roll gaps after the production of every billet to compromise the system throughput. Therefore, we leave this topic for future study.

It is worthy to notice that similar data scenarios appear in many multistage manufacturing systems. These manufacturing systems involve multiple stages, where typically, multiple in-situ sensors are installed in each stage to measure process variables over time along the production line. At the same time, in-situ sensors are used to measure the intermediate product quality between two stages of operations. Each in-situ sensor repetitively measures the process variable or the product quality with fixed sampling frequency, generating continuous streaming data over time. All data streams are recorded by data acquisition and management software and stored in a database. Currently, those types of data acquisition processes and storage are common in many manufacturing systems. Though those data streams contain much invaluable information about the production conditions and their relationship with product quality, there are few efforts in synchronizing those data streams into product-oriented data sets for specific or individual products and further using the data sets for data-driven process modeling. The method presented in this article aims to exemplify an approach of using the data appropriately and effectively, to preprocess the data so as to match the process sensing data with product quality data, to develop an effective model so as to link the process variable with product quality, and to assist smart decision-making processes so as to improve quality. It is promising to expand the proposed method to other manufacturing systems and consider other types of models once a product-oriented data set is ready for modeling and analysis.

References


