DIAGNOSIS SOLUTIONS FOR ROLLING CONDITION AND PRODUCT QUALITY AT METAL PLANTS*

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Abstract

The highly competitive business environment of the international metals industry is driving demand for more cost-effective operation of steel making facilities, rolling mills, and strip processing lines. Achieving stable operation is vital if the steel industry is to produce high-quality products constantly and productively. In recent years, advances in computer processing speeds, data acquisition rates, and data storage capacity have rapidly led to greater use of the new technologies of big data, analytics, the IoT, and AI by control system designers and process engineers, and the introduction of industrial applications. The “Smart Rolling Mill” solutions for hot strip mills have been developed by our group with the goal of achieving sophisticated, state of the art, and automated operation in steel rolling mills. The various solution engines improve process stability, increase the performance of mill equipment, and provide improved process control. These solution engines are based on extensive knowledge of the rolling process and the associated control systems. Two solution engines in particular are the diagnosis systems for rolling condition and for product quality that contribute to cost-effective operation and lower yield loss. This paper focuses on the diagnosis systems for rolling condition and for product quality in hot strip mills. Advanced information technologies using big data analytics and machine learning are applied to real-time data collected from the automation system that controls operation and the rolling process. We have developed diagnosis solutions for rolling condition and product quality utilizing predictive and clustering diagnosis. Predictive diagnosis prevents serious problems by detecting changes in the state of the plant or in the rolling condition. Clustering diagnosis classifies patterns of fluctuation in product quality trend charts, providing effective tuning guidance for improving product quality. This paper describes these applications with several examples.

Keywords: Diagnosis system; Product quality; Big data; Machine learning

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1 Introduction

To remain competitive, production lines in the manufacturing industry must maintain high product quality, high productivity and efficiency, and stable and precise operation. Operational practices and equipment configuration must provide the flexibility necessary to produce finished products in a manner that supports the 'just in time' procurement practices of downstream customers. Although, in theory, these capabilities can be realized using highly skilled human operators, this is not a cost-effective option as the highly skilled labor necessary becomes increasingly expensive or simply not available due to demographic, cultural, and economic changes world-wide. In addition, when a process requires frequent intervention for product changes or to maintain stable operation, dependence on human operators invariably results in adverse effects such as unwanted variations in product quality, productivity, output, and yield. To solve this problem, it becomes essential to mechanize and automate production lines to minimize the need for human intervention. This fundamental concept has been a major goal in the design of industrial equipment and the supporting control systems and the pace of change will only accelerate as advances in technology support the development of next-generation control and automation solutions [1][2][3][4][5].

To achieve the intended benefits, we are proposing the "Smart Rolling Mill" which is based on the concept of a cyber-physical system, as shown in Figure 1. This is well-known concept in the application of new IoT technologies but the method of collecting and accumulating data, and the optimum use of the data, is dependent on the operating characteristics, operating practices, manufacturing technology, and product mix of the production facility.
We supposed that the goal when designing a Smart Rolling Mill is to achieve a sophisticated, state of the art, and automated steel rolling mill that has the ability to:
(1) Predict and prevent abnormal operating conditions that can cause instability in mill operation or negatively impact product quality or process efficiency.
(2) Optimize control system performance by incorporating mathematical models that accurately define the electro-mechanical characteristics of the mill equipment and supporting motors, drives, and control systems.
(3) Provide an effective human-machine interface that allows human operators to quickly access mill operation and to take proper corrective actions when necessary.

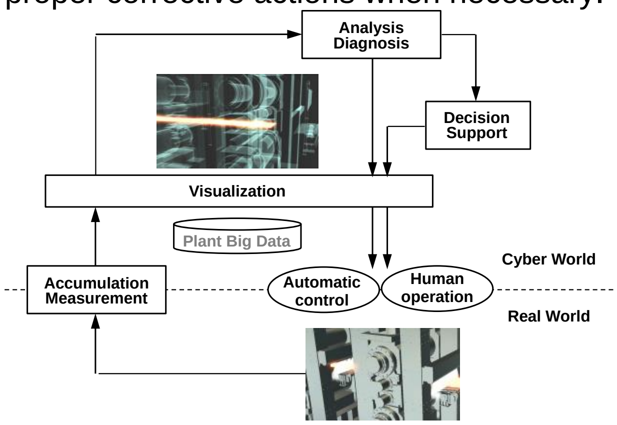


Figure 1. Concept of cyber-physical system

To achieve targeted improvements in plant performance through advanced automation, it is important to utilize big data collected from the rolling mill continuously and at high speed.
As the innovative technologies that make up the Smart Rolling Mill, we focused on these characteristics:
- Data acquisition and data management: High speed acquisition of big data
- Data analysis and diagnosis: Anomaly detection and prediction
- Examples of how to achieve more stable operation and better quality
- Support for human decision making
- Automation and control based on mathematical models and advanced data analytics
- Visualization: Advanced HMI technologies

Use of these technologies facilitates predictive and preventive maintenance, minimizes the need for human intervention, and optimizes mill operation and product quality.

2 Data analysis and diagnosis

It is important to predict when and where a problem is likely to occur and to determine if plant processes and equipment are operating normally. It is not possible for operators to constantly monitor and analyze all of the data collected from sensors and actuators. The automation system should alert operators when there is a problem and provide details on the nature of the problem and the physical location where the problem is occurring. The system should also provide information on possible corrective actions.
The process from data collection to diagnosis and response is shown in Table 1. The process is implemented using an equipment and quality diagnosis system (EQDS).

Table 1. Process of data analysis and diagnosis

Process flow	Input	Method
Preprocessing	Raw data of - equipment - absolute/dev	Filtering - High-pass filters - Low-pass filters
Analysis	Filtered signals	- Basic statistics - Probability density - Auto regressive modeling - FFT, etc.
Support for judgement	Indices derived by analysis	- Hotelling indices - Control charts - Thresholds - Machine learning etc.
Diagnosis Response	Aggregated information	Reasoning Likely causes Recommendations

An effective approach to narrowing down the root cause of an abnormal signal is to look at data acquired during rolling (under load) and data acquired when idling (under no-load conditions). For example, when data acquired during rolling and during idling both show a significant level of abnormal fluctuation, it is likely that the source of the fluctuation is in the electrical system, including the sensor and network. When the fluctuation is observed only in the data acquired during rolling, a mechanical abnormality is the likely cause due to the fact that higher mechanical loads will increase the magnitude of the fluctuations.

2.1 Diagnosis solutions for rolling condition

Plural analytic methods should be used to detect anomalies because this improves the probability of successfully identifying anomalies compared to using a single method. Useful analytic methods include the following:
Basic statistics can be used as numerical indices. Assume that a data set X is given as follows.

$$X = [x_1, x_2, \cdots, x_i, \cdots, x_n] \quad (1)$$

The average $\bar{x}$, average of absolute value $\bar{x}_{abs}$, standard deviation σ, root mean square x_{rms}, peak value x_p, and other such parameters can be calculated for the data set X. Skewness β_1 and kurtosis β_2 are defined as follows.

$$\beta_1 = \frac{1}{\sigma^3} \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{n-1} \quad (2)$$

$$\beta_2 = \frac{1}{\sigma^4} \frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{n-1} - 3 \quad (3)$$

For example, skewness and kurtosis can be used to detect abnormalities in bearings, gears, shafts, and other such equipment.

Probability density is also an effective tool for detecting abnormalities. Figure 2 shows an example of the probability density of a signal (red line) from a motor, with an abnormality being present in the upper graph (for stand F4) but not in the lower graph (for stand F5). The blue lines in the graphs represent the normal distribution. The probability density of the signal with the abnormality varies significantly from the normal distribution. The difference can be quantified using the Kullback-Leibler (KL) divergence or by other methods such as the sum-of-squared-errors. Kullback-Leibler divergence D_{KL} is defined as follows.

$$D_{KL} = \sum_x P_N(x) \log \frac{P_N(x)}{P_A(x)} \quad (4)$$

where $P_N(x)$ is the normal distribution and $P_A(x)$ is the probability density of x.

The KL plot for the same coil is shown in Figure 3. The KL value of the F4 red line in Figure 2 is more than five times that of F5.

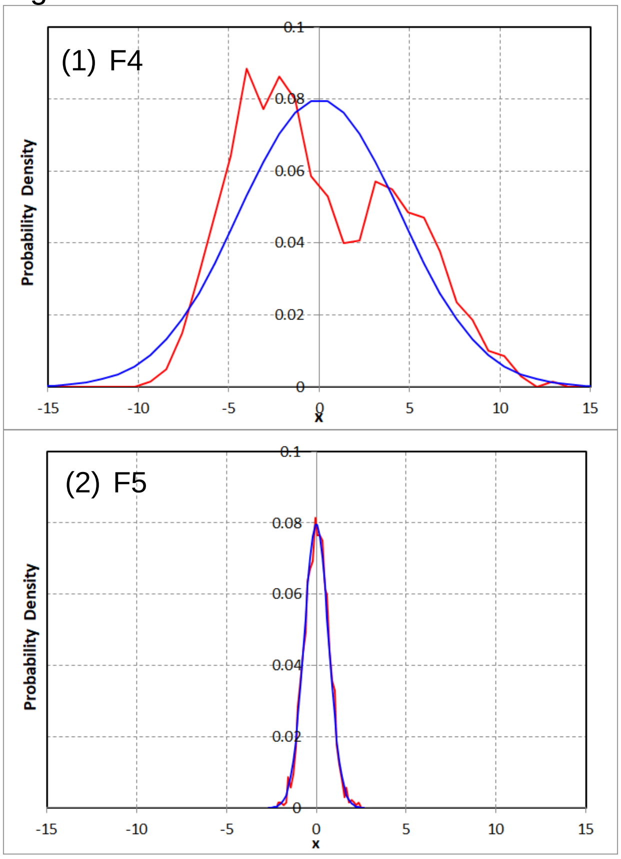


Figure 2. Probability density

The reason for the large difference in probability density between an abnormal signal and a normal distribution is as follows. A deviation signal (signal after passing through a high-pass filter) shows a near normal (Gaussian) distribution because the signal is largely white noise. An abnormal signal on the other hand will likely contain distorted components that cause a deviation from the normal distribution.

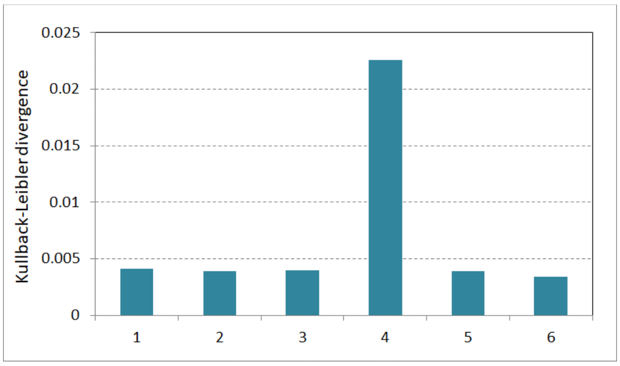


Figure 3. Kullback-Leibler divergence

Autoregressive (AR) modeling can also be used to detect abnormalities. The AR model is expressed as follows.

$$x(m) = a_0 + a_1 x(1) + \cdots + a_{m-1} x(m-1) + \varepsilon \quad (5)$$

where ε is white noise and a_0, a_1, …, a_{m-1} are coefficients determined by regression analysis.

Figure 4 shows an example of coefficients calculated by AR modeling for the same signal acquired for several rolled coils [1]. The value of 'm' in equation (5) is 13. The two bold red and blue lines are very different from the other lines. Abnormalities were present for the coils represented by these two lines. A comparison of the coefficients identified by AR modeling can be used to identify abnormalities.

Figure 4. Coefficients identified by AR mode

2.2 Diagnosis solutions for product quality

In the rolling process, signals obtained from process and equipment sensors, or from control system signals, have elements that can be correlated to specific mechanical, operational, or control system problems. Operators and engineers can potentially detect these unique signal patterns and investigate the causes. However, the success of the detection and investigation process is limited when it is dependent on human beings. It is difficult for a human to observe all the signals from an operating plant. It generally takes a long time for human analysts to uncover causal relationships and find the root cause of a problem, even if a unique rolling signal pattern is detected.

Figure 5 shows an example of anomaly detection employing automatic clustering techniques.

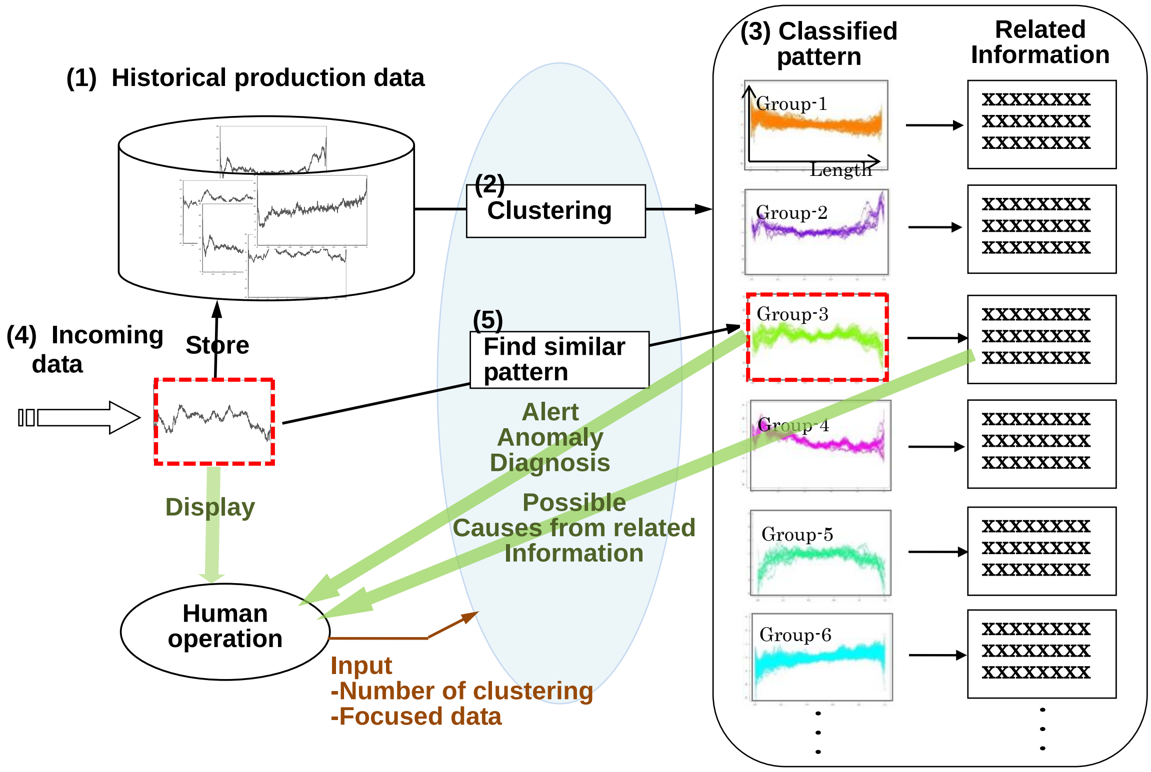


Figure 5. Anomaly detection employing automatic clustering techniques

This system can easily find and distinguish “something different” and “unique patterns” in data associated with specific equipment or specific areas of production. The rolling signal data includes data on product characteristics such as thickness, width, and temperature along with control and equipment data such as looper angle, motor current, and the vibration of mill stands. This system automatically classifies historical production data and newly acquired production data into categories by clustering the rolling signal features. In Figure 5, (1) shows historical production data and (3) shows the classified pattern by clustering function (2). (4) and (5) show the function to find similar pattern for new production. In Figure 5, when rolling signals from new production are gathered, this system classifies it into group-3. In this system, each classified pattern has related information such as production quality accuracy, production steel grade, production targets, and rolling conditions. Therefore, operators and engineers can determine which patterns indicate a problem and the causal relationship between a problem pattern and particular rolling conditions. This can greatly reduce the effort it takes to determine effective countermeasures to correct the problem.

In this system, production quality diagnostics is implemented as follows. At first the operator indicates which signals to

focus on for clustering and anomaly diagnosis and how many clusters to use. Next, operators respond to system alerts from the on-line diagnosis system. When an alert occurs, operators investigate the possible causes of production quality problems using guidance provided by the system.
An example of clustering for product width is shown in Figure 6.

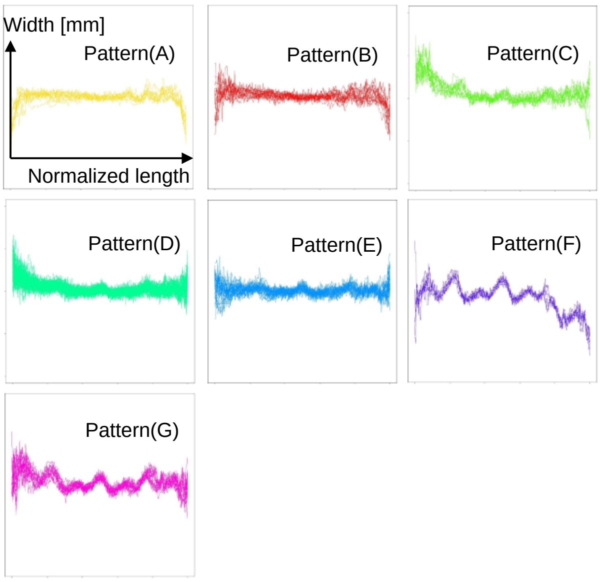


Figure 6. Strip width pattern classification

There are many possible disturbances in a hot strip mill that can lead to lower product width performance. The in-bar width change can be classified into several patterns, as shown in Figure 6. This example uses seven clusters to achieve a good representation of the different width patterns. The relationships between these patterns and the disturbances that give rise to them make it easy to detect the causes of poor width performance. To achieve this, however, the width patterns must be classified correctly and the relationships between patterns and causes must be identified.

3 Support for human decision making

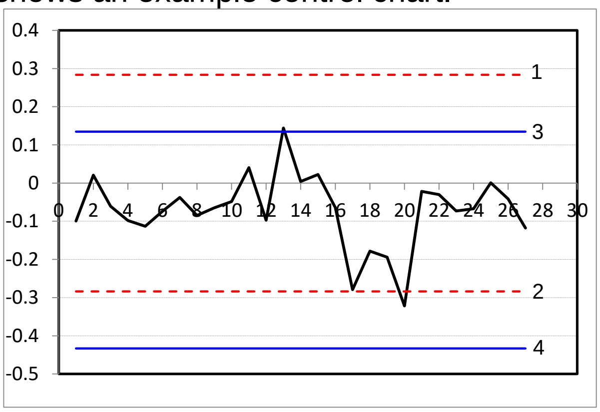
There are several indices useful for determining abnormal conditions as shown above. If threshold values are appropriately set for these indices, it is possible to determine if equipment is operating normally or abnormally. There are several methods for calculating the probability of abnormal operation. One of these is Hotelling's theory and the χ^2 distribution.

The data set X in equation (1) is assumed to have normality when the quantity of data is large. When X has a small number of abnormal data points with most of the data being normal, the index of abnormality calculated using Hotelling's theory is:

$$H(x) = \frac{(x-\overline{x})^2}{\sigma^2} \tag{6}$$

Here, $H(x)$ has a χ^2 distribution with a degree of freedom = 1. For example, in the case when $H(x)$ = 5.7, the probability that x is abnormal is more than 1-0.0097=99.03%. That is, x can be said to be abnormal with a probability of 99.03%.
If we have many Kullback-Leibler divergences D_{KL} of probability densities for a signal data set accumulated for many coils, and the data set satisfies the above assumption, then Hotelling's theory can be applied to the D_{KL} for a new coil. $H(x)$ substituted by the new D_{KL} into x in equation (6) will have a χ^2 distribution with a degree of freedom = 1.

Another method for calculating the probability of abnormality is to use the upper control limit (UCL) and lower control limit (LCL) in a control chart, as is commonly used for quality control. Figure 7 shows an example control chart.



1:UCL, 2:LCL, 3 and 4: Compensated UCL/LCL at 3σ

Figure 7. Example of control chart

The black line in the figure represents actual time-series data and shows a shift in the negative direction (a negative skew). A method is available for compensating for this skew [6]. The UCL and LCL values after compensating for skew are shown as lines 3 and 4 in Figure 7.

As a summary of analytical methods and diagnostics, examples of index usage are listed in Table 2.
These indices are used to identify abnormalities in product quality. Usually product performance is expressed as the percentage of measured values that lie within the target range. The product performance can be used as the 1st index in Table 2.

Table 2. Examples of index usage

Case	Index			Criterion
	1st	2nd	3rd	
1	Statistics		Hotelling	χ^2 distribution
2	Statistics			Control chart
3	Probability density	KL	Hotelling	χ^2 distribution
4	Probability density	KL		Control chart
5	AR model		Hotelling	χ^2 distribution
6	AR model			Control chart

There are multiple indices that can be useful for determining the probability that data is normal or abnormal. However, this can cause confusion and make judgment more difficult, because the indices will not always indicate the same condition for a given data set. Because of this, it is useful to use machine learning methods such as neural networks (NN) to make a final judgment. Figure 8 shows an example in which machine learning generates outputs from an input dataset.

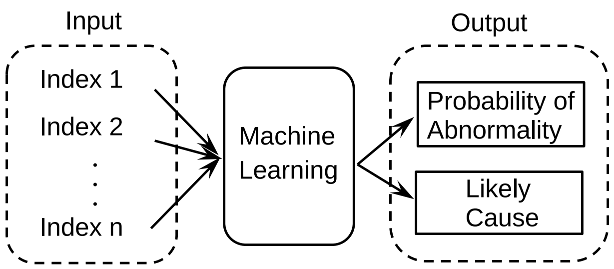


Figure 8. Machine learning for judgment

4 Conclusions

This paper has described the proposed Smart Rolling Mill solution. It also discussed the analysis methods for rolling condition and product quality that are used for diagnosis. The diagnosis solutions for rolling condition and for product quality contribute to cost-effective operation and lower yield loss.
We intend to continue improving the effectiveness of the diagnosis solutions by incorporating additional technologies.

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