

Improvement of Detection Performance of Pickling Scab Sensor

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Abstract:

At JFE Steel (Kurashiki District) Cold Rolling Mill, a surface inspection device (scab detection sensor) to detect defects (scab, cracked edge) on the surface of steel sheets that cause sheet breakage during rolling has been installed. When this device detects defects, the line is stopped and the operator takes corrective actions. However, unnecessary stops due to over-detection (judged to have defects even though there are no defects) occur in 35% of the total number of detections, and suppression of over-detection was required. This time, we have developed a defect judgment logic using machine learning and achieved a 50% reduction in over-detection. Here, we report the outline of this development.

1. Introduction

No. 1 Tandem Cold Mill (1TCM) at JFE Steel's West Japan Works (Kurashiki District) Cold Rolling Mill is a continuous line (2PL-1TCM coupled line) with No. 2 Pickling Line (2PL). A surface inspection device (scab detection sensor) is installed at the exit side of 2PL to detect defects (scab, cracked edge) of the steel sheet surface that cause sheet breakage during rolling by 1TCM. When the scab detection sensor detects a defect, the line is stopped and the operator performs treatment (visual inspection, removal of the defect, marking, reduced-speed or empty threading of the rolling mill). However, unnecessary stops due to over-detection by the scab detection sensor occurred in 35% of all detections, and had become a cause of reduced production capacity.

In order to reduce the number of unnecessary line stops, a decrease in over-detections by the scab detection sensor had been needed. Therefore, a new judgment logic applying machine learning was developed to increase production capacity by reducing over-detection by the scab detection sensor.

This paper presents an overview of the scab detection sensor and the developed defect judgment logic,

and reports the situation of its launch.

2. Cold Rolling Mill: Overview of 2PL-1TCM Coupled Line

At the 2PL-1TCM coupled line of JFE Steel's West Japan Works (Kurashiki District) Cold Rolling Mill, scale (iron oxide) on the surface of hot-rolled steel strips is removed in the pickling tanks, after which steel strips are finished to the target strip thickness by the rolling mill and then supplied to the subsequent process.

The scab detection sensor discussed in this paper is installed at the upper side of the bridge roll at the exit side of the pickling tank of No. 2 pickling line to prevent strip breakage during rolling, and is a JFE Steel "Only One" sensor for flaw detection of the strip surface. When a defect is detected, the line is stopped automatically, and the operator performs the necessary actions (visual inspection, removal of the flaw, marking, reduced-speed rolling or empty threading of the mill). An overview of the 2PL-1TCM coupled line is shown in Fig. 1.

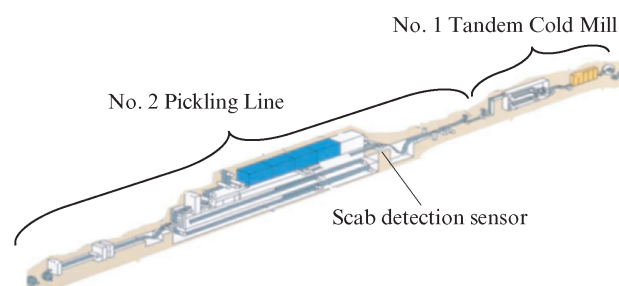


Fig. 1 Overview of 2PL-1TCM

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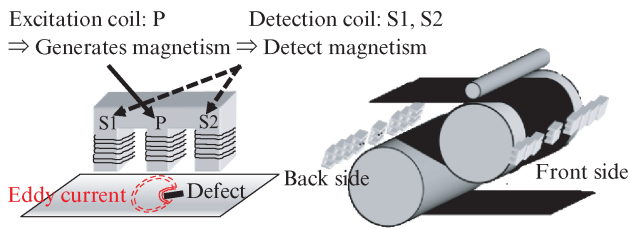


Fig. 2 Outline of scab detection sensor

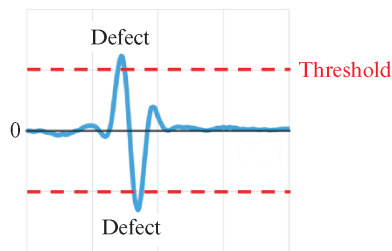


Fig. 3 Output signal and defects of scab detection sensor

3. Principle and Issues of Scab Detection Sensor

3.1 Principle of Scab Detection Sensor^{1,2)}

The scab detection sensor is an eddy-current type device that performs flaw detection by detecting changes in the eddy current generated when the surface of a steel strip is excited by an excitation coil. When a defect exists on the strip surface, the magnitude and distribution of the eddy current at the strip surface change, and the eddy-current type device detects the defect by capturing these changes.

The detector has an E type shape consisting of an excitation coil P, which generates a magnetic flux, and two detection coils, S1 and S2, which detect changes in the magnetic flux. In the eddy-current type device, the influence of fluctuations in the distance between the strip and the sensor is reduced by outputting the difference between the two detection coils S1 and S2. Flaw detection of the entire width and length of the front and back sides of the steel strip is performed by arranging this detector in transverse direction.

In surface flaw detection by the scab detection sensor, the output of the detection coil when there is no defects on steel strip is substantially 0 [V], but when a defect passes directly under the detector, the detection coil generates an output of approximately several [V]. Defects are judged by setting a threshold value for this output.

An outline of the scab detection sensor is shown in Fig. 2, and a schematic diagram of the output signal and defects judgement is shown in Fig. 3.



(a) Visual inspection



(b) Removal of defects

Photo 1 Visual inspection and removal of defects by operator

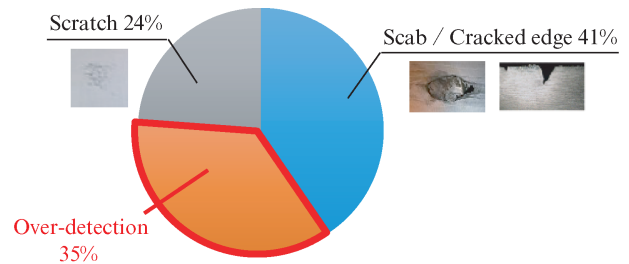


Fig. 4 Ratio of detection by scab detection sensor

3.2 Operation and Issues of Scab Detection Sensor

When a defect is detected by the scab detection sensor, the line is stopped automatically to prevent strip breakage at No. 1 Cold Tandem Mill, and the operator performs a visual inspection of the strip surface at the inspection area. When the results of this inspection indicate that the defect (scab, cracked edge) may cause strip breakage in the rolling mill, the operator performs the necessary actions (visual inspection, removal of the defect, marking, reduced-speed rolling or empty threading of the mill). However, over-detection by the scab detection sensor leads to unnecessary line stops and visual inspections, and thus becomes a cause of reduced production.


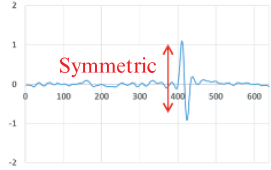
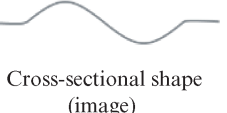
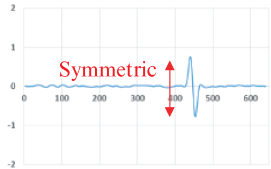
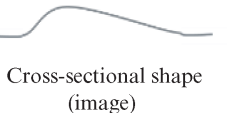
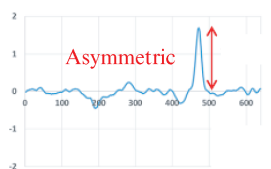
Photo 1 shows scenes of visual inspection and removal of defects by the operator, and Fig. 4 shows the ratio of defects detected by the scab detection sensor.

4. Development of Over-Detection Countermeasure Logic

4.1 Factors and Countermeasures in Over-Detection

The factors responsible for over-detection are mainly related to fluctuations in the distance between the steel strip and the sensor (i.e., ① poor shape of the steel strip, ② swelling of the running strip). Other companies apply methods of reducing over-detection by

Table 1 Characteristics of defects and output waveform of scab detection sensor

Type	Figure / image	Sensor output	Countermeasure
Scab / Cracked edge	 Scab Cracked edge		
Over-detection	Out of shape (70%)  Cross-sectional shape (image)		<u>Hardware improvements (sensor development)</u> ·Cost : Large ·Target: Out of shape Swelling ·Production period: Long
	Swelling (30%)  Cross-sectional shape (image)		<u>Software improvements (logic development)</u> ·Cost : Small ·Target: Swelling ·Production period: Short

sensors that combine cameras and multiple eddy-current type devices.

Over-detection countermeasures include hardware-based measures (detection of poor strip shape and swelling by sensors) and software-based approaches (differentiation between actual defects and over-detection from the sensor output). Although hardware measures have the potential to reduce over-detection to zero, the cost is high and cost-effectiveness is slight. In contrast, although software approaches cannot completely eliminate over-detection, cost-effectiveness is large because development costs can be held down. For this reason, we implemented software measures, which have large cost-effectiveness.

As a result of an investigation of the output signals of the scab detection sensor, a pattern in which the waveform, which should normally be output in both the positive and negative directions, was output to only one side due to strip swelling was observed in 30% of cases of over-detection. In the following, this pattern is termed “over-detection (unilateral).” Focusing on this difference in the waveform pattern, we developed a new logic that can identify over-detection (unilateral) by using machine learning. **Table 1** shows the characteristics of defects and the corresponding outputs of the scab detection sensor.


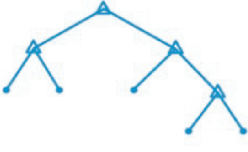

4.2 Selection of Machine Learning Method

Machine learning can be classified as “Classification (differentiation of data)” or “Regression (prediction of numerical values).” However, a technique suitable for

“Classification” was used in this development in order to differentiate over-detection. The general approaches used in “Classification” include techniques such as “Deep learning,” “Decision tree” and “Regression analysis,” and the model equations become increasingly complex as accuracy improves. Here, we selected a technique from the viewpoints of ① the model equation is easy to understand, and evaluation is possible by comparing the model equation and physical quantities, and ② tuning can be performed easily.

Deep learning is applied in various fields since selection of features is not necessary and prediction accuracy is high, but because the model is a black box, it is difficult to identify the cause when a malfunction such as misidentification occurred. In the “Decision tree” technique, the model output value is “Class,” and when tuning is performed, it is necessary to review the threshold values for each branch condition. Since the requirements of this development were ① model equation is easy to understand, and evaluation is possible by comparing the model equation and physical quantities and ② tuning can be performed easily, “Logistic regression analysis” was selected because tuning is possible using only the threshold value for the output and ③ accuracy is on a level suitable for practical use. **Table 2** shows a comparison of these machine learning methods.

Table 2 Comparison of machine learning methods

Methods		Deep learning		Decision tree		Logistic regression analysis	
Figure							
Property	Model equation	Black box		Understandable		Understandable	
	Number of threshold	Black box		Multiple thresholds (Number of branches)		1 Threshold	
	Output format	Class		Class		Numerical value	
Evaluation	Clarity of model equation	Black box	1	Understandable relationship with property	5	Understandable relationship with property	5
	Ease of adjustment	Number of layers, weight adjustment	1	Threshold for each branch condition	3	Threshold for output	5
	Accuracy	High	5	Medium	5	Low (Level of usability)	5
Total				7		13	
						15	

4.3 Selection of Features and Evaluation of Learning Model

4.3.1 Evaluation Function (Eq. (1))

Since logistic regression analysis cannot differentiate the shapes of waveform data, it is necessary to express the difference between the waveforms of defects and over-detection (unilateral) as features (numerical values). In defects and over-detection (unilateral), ① defects have an output waveform that displays line symmetry with respect to the x-axis, whereas over-detection (unilateral) has an output waveform on only one side of the x-axis, and ② the signal level of defects is higher than that of over-detection (unilateral). Therefore, we devised the evaluation function $E(x)$, which quantifies the difference between these output waveforms, and attempted to differentiate over-detection by using this a feature together with the signal level.

The evaluation function $E(x)$ was designed to increase in case of defects (positive-negative symmetrical waveform) and be 0 in case of over-detection (unilateral). This evaluation function makes it possible to evaluate the difference between the waveform shapes of defects and over-detection (unilateral) as a numerical value by multiplying the peak-peak value ($E_{pp}(x)$) of the output value $E(x)$ of the scab detection sensor by $\exp \{-f(x) + f(x+k)\}$, a term for evaluating symmetry

which is large when the output has positive-negative symmetry and is close to 0 in case of a unilateral waveform.

4.3.2 Logistic Regression Model (Eq. (2))

Based on the results described above, a logistic regression model was created by using the evaluation function and the output level as a feature. This model is considered to correspond to a physical quantity, as the output approaches 1 (defect) when the evaluation function and output level increase, and approaches 0 (over-detection) when their values decrease.

$$E(x) = |f(x) - f(x+k)| \times \exp\{-|f(x) + f(x+k)|\} \dots (1)$$

$$q(x) = \frac{1}{1 + e^{-y}} \dots (2)$$

$$y = -4.179 + 3.746x_1 + 0.247x_2$$

x_1 : Output value of evaluation function

x_2 : Detection level

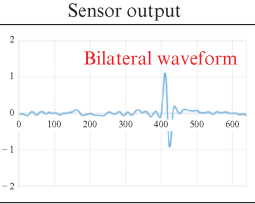
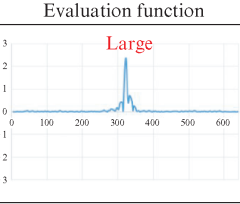
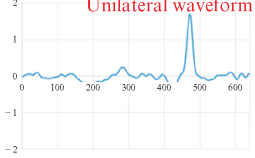
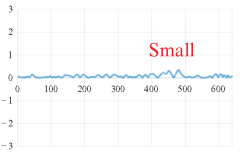
Number of learning data Defect: 60,

Over-detection (unilateral): 20

4.3.3 Simulation Results

When the model created as described above was applied to samples, the output value of the regression model was 0.4 or more for defects and less than 0.2 for over-detection, confirming that over-detection can be

Table 3 Scab detection sensor output and evaluation function

	Sensor output	Evaluation function
Scab / Cracked edge		
Over-detection		

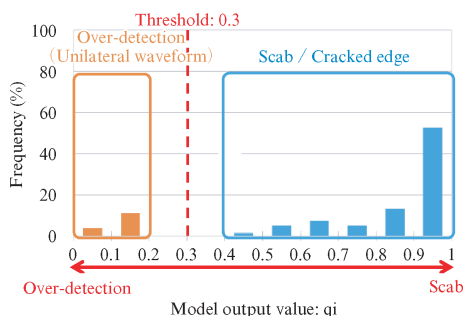


Fig. 5 Model output value distribution (Simulation results)

differentiated by setting a threshold value of 0.3. The scab detection sensor output and evaluation function are shown in Table 3, and the results of an offline simulation are shown in Fig. 5.

5. Situation of Startup

Since the effectiveness of the new logic was confirmed by an offline verification, operation began from October 2018. In the operational results for the first month after startup, over-detection decreased by 50% (24% → 12%), and strip breakage at the rolling mill did not occur when over-detection (unilateral) was judged, confirming the effectiveness of the new logic and achieving an increase in production capacity.

Figure 6 shows the model output value distribution after startup of the new logic, and Fig. 7 shows the results of detection after startup of the new logic.

6. Conclusion

A new defect judgment logic was proposed with the aim of reducing lost production capacity due to over-detection by the surface inspection device (scab detection sensor) at No. 2 Pickling Line of the Cold Rolling Mill at JFE Steel’s West Japan Works (Kurashiki District), and the following results were

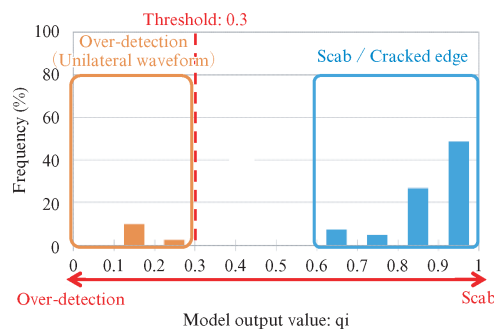


Fig. 6 Model output value distribution after launching new logic

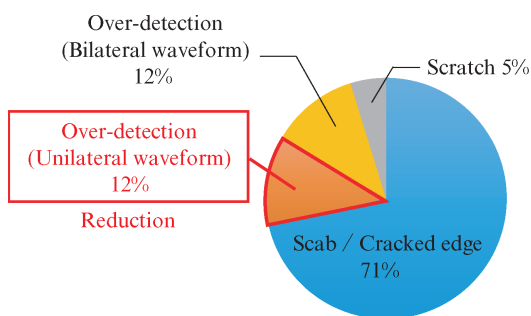


Fig. 7 Result of new model

obtained.

- ① Logistic regression analysis was selected as the machine learning method.
- ② An evaluation function which quantifies the characteristics of signal output in over-detection was proposed.
- ③ Over-detection was reduced 50% by the proposed judgment logic, achieving an increase in production capacity.

The new logic was put into operation in October 2018 and is contributing to an increase in production capacity. In the future, we will study a new sensor system combining the scab detection sensor and sensors using other methods (distance meter (laser distance sensor), cameras, etc.) with the aim of further reducing over-detection.

References

- 1) The Japanese Society for Non-Destructive Inspection. Non-Destructive Testing Series: Eddy Current Testing II. 1995, 156 p.
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- 3) Berry, M, J. A.; Linoff, G. Data Mining Techniques. Kaibundo Publishing, 1999, 329 p.
- 4) Shigefuji, Y.; Iwata, T. Development of Technology to Improve Detection Performance of Pickling Scab Sensor. IEEJ Technical Meeting. 2022, MZK22009, p. 13-17.

This paper reproduces the paper listed as reference 4), which was written by the same lead author, with revisions of some expressions.