Evaluation of deoxidation state in molten steel using image recognition technique of reduction slag by machine learning

T. Sowa, Y. Seki, T. Suzuki, S. Tanaka

Recently, Digital Transformation (DX), promoted by machine learning, Artificial Intelligence (AI), and the Internet of Things (IoT), has been disseminated in various industrial fields. Steelmaking in Japan Steel Works M&E, Inc., however, still depends on man-powered work and adept persons. One of the processes that require high proficiency is the projection of progress in deoxidation during secondary refining from the appearance of the reduction slag (hereinafter, referred to as slag) in a ladle furnace. Although up to now, the work has been done visually by operators, the image recognition technology with machine learning was employed to remove the variability attributed to differences in the operators' ability. The technology enabled us to evaluate the state of deoxidation in molten steel during ladle-refining with a consistent accuracy,

-implying that some parts of the steelmaking process can possibly be automated, as well as reducing refining time.

KEYWORDS: SECONDARY REFINING, REDUCTION SLAG, MACHINE LEARNING, COLOR, IMAGE RECOGNITION

INTRODUCTION

Our company manufactures forged steel products of various steel grades in small lots by ingot casting (IC). In our steel making shop, steel ingots required for these products are manufactured in a process that consists of an electric furnace, secondary refining (LF: Ladle Furnace), vacuum casting for steel ingots over 75 tons, and bottom casting for steel ingots of 60 tons or less. In our LF process, reduction refining (hereinafter referred to as "refining"), vacuum degassing (VD), and composition adjustment are performed using a ladle-refining method. Slag containing CaO, CaF_2 , and SiO_2 is used for refining, and slag deoxidation and desulfurization are carried out by the redox reaction between the slag and molten steel. The slag is a mixture of colors of low-grade oxides such as CaO, CaF_2 , and SiO_2 , and the operator can visually and empirically judge the deoxidation state from aspects of its appearance such as color, gloss, and surface roughness. However, using visual judgment, problems such as poor deoxidation and component defects have occurred due to variations in skill among operators and errors in judgment. Therefore, we attempted to improve DX in the steelmaking process by using image recognition technology, which is used in various fields, to mechanically judge the deoxidation status of slag through machine learning of its image.

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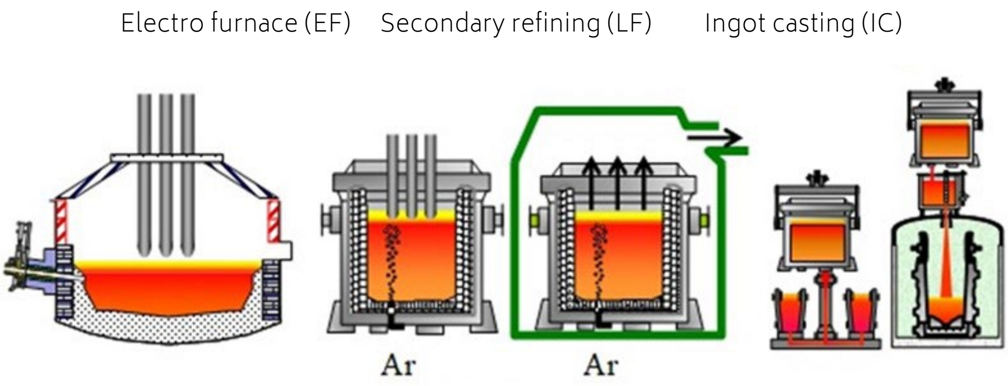

Fig.1 - Summary of our steel making shop.

SLAG AND REFINING:

Deoxidation in our refining is classified into two types, Al deoxidation using Al as the deoxidant and Si deoxidation using Si, and the slag composition differs for each deoxidation method (Table. 1-1, Table. 1-2). Slag is mainly composed of CaO and CaF_2 derived from tailings materials, SiO_2 derived from deoxidizers, Al2O_3, FeO, MnO, Cr_2O_3 derived from molten steel elements and MgO derived from refractory materials. The addition of deoxidizers during refining causes equilibrium reactions at the slag-metal interface, reduc-ing the oxygen concentration in the molten steel and reducing lower oxides such as FeO, MnO, and Cr_2O_3. The color of the slag is a mixture of the colors of the lower oxides, and the approximate composition of the slag can be estimated from the color (Table. 2). When the oxygen concentration at the end of primary melt-ing in an electric arc furnace is approximately 800-1000 ppm, the slag is black in color, mainly FeO, but as deoxidation progresses and reduction of FeO, MnO, and Cr_2O_3 proceeds, it becomes green to white in color (Fig. 2). Therefore, it is possible to visually determine the deoxidation status of molten steel to some ex-tent.

Table 1-1 - Composition of slag (Si killed steel).

Si killed steel	composition,mass%								
	CaO	SiO_2	CaF_2	MgO	MnO	Cr_2O_3	FeO	Al_2O_3	S
before VD	49～55	17～21	15～20	3～7	0.2～0.7	0.5～1.7	1.5～2.5	2.2～3.2	0.06～0.11
After VD	48～53	18～22	12～16	7～12	0.03～0.1	0.02～0.1	0.1～1.2	3.5～7.0	0.09～0.15

Table 1-2 -Composition of slag (Al killed steel)

Al killed steel	composition,mass%								
	CaO	SiO_2	CaF_2	MgO	MnO	Cr_2O_3	FeO	Al_2O_3	S
before VD	45～51	8～12	2.2～3.4	4.2～7.0	0.3～0.5	0.1～0.2	0.5～0.9	25～30	0.06～0.11
After VD	38～46	9～13	3.1～3.8	8.7～11.1	0.1～0.3	0.03～0.04	0.09～0.16	31～35	0.12～0.26

Table 2 - Color of slag

CaO	SiO_2	CaF_2	MgO	MnO	Cr_2O_3	FeO	Al_2O_3
White	White	Light Green	Yellow-green	Light Green	Green	Black	Light Orange

Fig.2 - Condition of slag and oxygen concentration.

One of the roles of the refining process is to deoxidize molten steel. The purpose of deoxidation is to prevent the formation of oxidized inclusions such as Al_2O_3, SiO_2, and MnO, which are types of sand defects in steel ingots. For this reason, deoxidation is essential for highly cleanliness steel ingots. Therefore, a cer-tain amount of slag deoxidation is necessary before VD to prevent deoxidation failure in the VD conducted in the refining process. For general forgings such as reinforcing rolls, the deoxidation status is determined visually by the refiner. On the other hand, in the case of rotor shafts made of NiCrMoV steel, which are used for power generation, our main product, control values are set for the oxygen concentration before and after VD because poor deoxidation and desulfurization after VD can cause the formation of inclusions such as deoxidation products and MnS. The oxygen concentration in molten steel is measured by a 3 mm x 60 mm dia. quartz tube and measuring it with a gas analysis instrument (Fig. 3). It takes 15 minutes to ana-lyze the collected sample, during which time the refiner stands by and compensates for the temperature drop by energized heating. Sample defects, such as minute cracks or pinholes in the sample, occur with some frequency, causing errors in the gas analysis equipment.

As described above, immediate analysis of the deoxidation state of slag during refining by its color is im-portant, but since judgment based on slag color depends on the skills of experienced workers, it is neces-sary to develop a method that does not do so. Therefore, we attempted to use machine learning by image recognition as an alternative method to visual judgment.

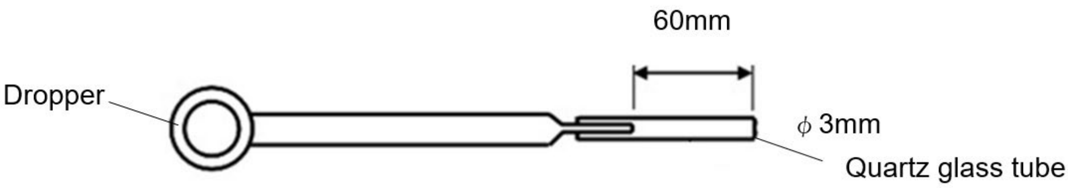

Fig.3 - Sampling instrument of oxygen analysis sample.

IMAGE RECOGNITION AND MACHINE LEARNING:

Image recognition is a technique that allows a computer to recognize objects in an image. [1] However, a computer reads an image as a collection of pixel data, and to recognize "objects" in an image, it needs to learn the characteristics of the surrounding pixel data. Image data is stored per pixel in the three primary colors (Red, Green, and Blue) or the HSV (Hue, Saturation, and Value) color space as numerical values. Machine learning is an iterative learning using large amounts of data to find patterns hidden in them. Machine learning can be used for images by converting data into numeric values, and methods such as convolutional neural networks have been proposed to better capture features. The Python language was used for training, image processing with OpenCV, and machine learning with Keras. The slag for the machine learning was collected by immersing a steel plate welded to the end of a round bar into molten steel which then adhered to it (Fig. 4). The slag was collected immediately before and after VD of NiCrMoV steel refining and again at the end of refining.

Images were cropped to 256 pixels x 256 pixels to remove the background. The color of the slag varies from black to green to white depending on the oxygen concentration, but the RGB system may be strongly affected by the green color, so the color was preprocessed to be converted to the HSV system. The number of samples used as input for machine learning and the distribution of oxygen concentration are shown below (Table.3, Fig.5).

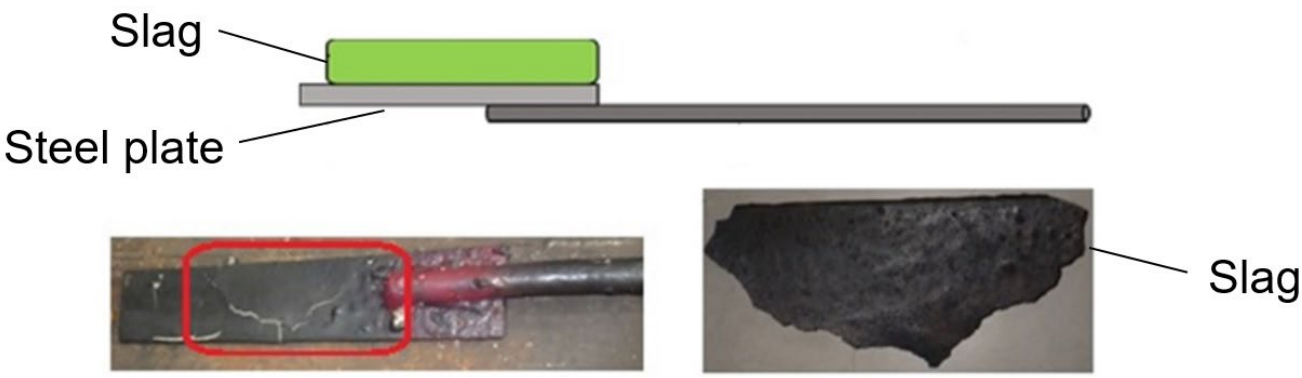

Fig.4 - Sampling instrument of slag.

Tab.3 - Number of samples.

	before VD	After VD	Finish LF	Total
Number of sample	300	156	192	648

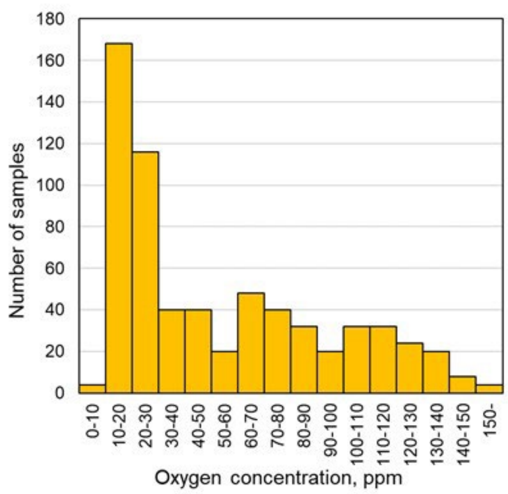

Fig.5 - Oxygen concentration of samples.

RESULT OF MACHINE LEARNING FOR OXYGEN CONCENTRATION PREDICTION:

The oxygen concentration in molten steel was predicted from slag images converted to HSV system using two types of models: regression and binary classification (hereinafter referred to as classification). Of the teaching data, 5% was used as test data and the remainder as training data. In the regression, the oxygen concentration in the test data was predicted quantitatively, and in the classification, two threshold values were set: 85 ppm, which is the control value for whether VD can proceed, and 30 ppm, which is the control value for judging whether the deoxidation status in VD is good or bad.

Comparing the predicted and measured oxygen concentrations during refining by regression, the difference between the predicted and measured values was less than 10 ppm, which is lower than the analysis error of the gas analysis equipment, and there were also data exceeding 80 ppm. The standard deviation of the difference between the predicted and measured values was 40.13 (Fig.6-1,6-2).

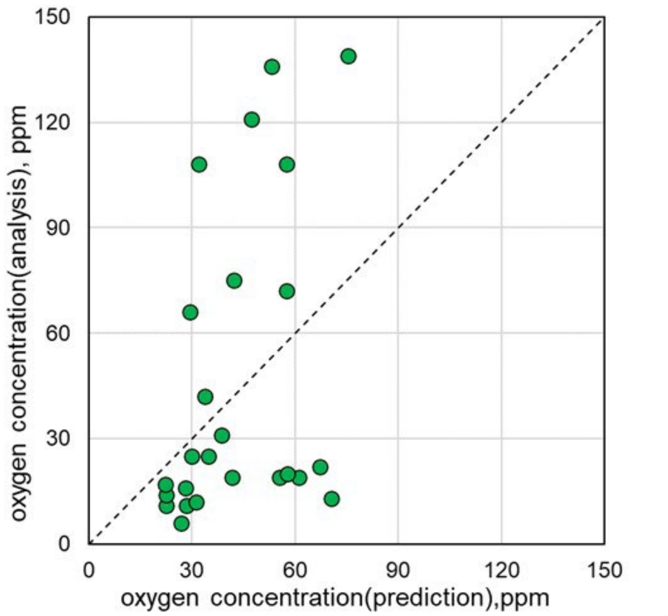

Fig.6-1 - Relationship between analysis and prediction.

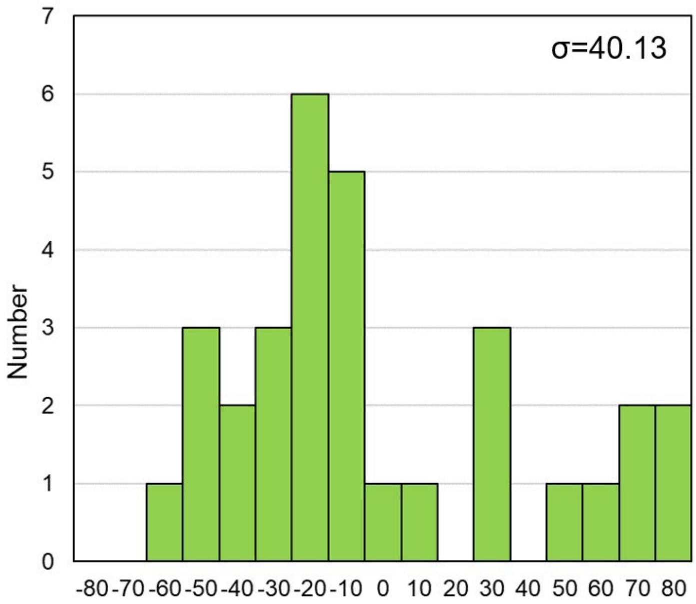

Fig.6-2 - Error between analysis and prediction.

The predicted results of the classification are generally evaluated in a confusion matrix [2] (Table.4-1,4-2). For oxygen concentrations during refining, each region has the following meaning.

TP (True Positive): Oxygen concentration prediction result is below the threshold value and the actual measured value is also below the threshold value.
FP (False Positive): Oxygen concentration prediction result is below the threshold value, but the measured value is higher than the threshold value.
FN (False Negative): Oxygen concentration prediction result is higher than the threshold value, but the actual measured value is below the threshold value.
TN (True Negative): Oxygen concentration prediction result is higher than the threshold value, but the actual measured value is also higher than the threshold value.

The oxygen concentration prediction results of machine learning by classification are shown (Table. 4-1,4-2). In machine learning by classification, it is common to express the results in terms of correctness rate, fit rate, reproducibility rate, and F value as evaluation indices. The values calculated from the oxygen concentration prediction results of this machine learning were more accurate with the threshold value of 85 ppm than with 30 ppm (Table.5). This suggests that black to green before VD is easier to discriminate by machine learning than light green to white after VD. White tends to reflect light, so variations in the image are thought to be responsible for the lower accuracy.

Tab. 4-1 - Confusion matrix (85 ppm).

Oxygen concentraiton		Analysis	
		≦85ppm	>85ppm
Prediction	≦85ppm	24 (TP)	2 (FP)
	>85ppm	6 (FN)	0 (TN)

Tab. 4-2 - Confusion matrix (30 ppm).

Oxygen concentraiton		Analysis	
		≦30ppm	>30ppm
Prediction	≦30ppm	15 (TP)	4 (FP)
	>30ppm	7 (FN)	6 (TN)

Tab. 5 - Result of prediction.

threshold value of oxygen concentration	Accuracy =(TP+TN)/(TP+FP+FN+TN)	Presision =TP/(TP+FP)	Recall =TP/(TP+FN)	F value (Harmonic average between recall and presision) = {2×(Presision)×(Recall)} / {(Presision)+(Recall)}
30ppm	0.66	0.79	0.68	0.73
85ppm	0.75	0.92	0.80	0.86

USING IN ACTUAL OPERATION:

The following is a discussion of the Process in actual operation. The results of oxygen concentration prediction by regression have a standard deviation of σ = 40.13, which is a 47% variation from the control value of 85ppm for VD progression, and thus have low reliability.

For FN and TN, deoxidation is continued in refining and the possibility of VD progress is checked again by oxygen concentration analysis, thus avoiding deoxidation failure. Deoxidation failure can be avoided. Therefore, FN is acceptable from the viewpoint of preventing quality defects in terms of oxygen concentration prediction classification, and evaluation by the compliance rate is suitable for predicting oxygen concentration during refining. The accuracy of the prediction of oxygen concentration in the classification is 0.79 at the oxygen concentration threshold of 30ppm and 0.92 at the oxygen concentration threshold of 85ppm, the latter of which can be said to be accurate enough to be utilized in actual operations. In addition, by utilizing machine learning in actual operations, data will be accumulated as actual results, which will lead to improved accuracy in the future.

COST REDUCTION EFFECT:

Using this machine learning model is expected to result in an 8.3% reduction in electricity consumption rate and an improvement in ladle refractory material consumption rate by omitting the waiting time for oxygen concentration analysis before VD, resulting in a 10% improvement in productivity.

CONCLUSION:

We created a model to determine the deoxidation state by machine learning the color information using data from images of slag in the refining process. We obtained the following findings.

1) By machine learning the slag image and outputting it as oxygen concentration, it is now possible to mechanize the determination of the deoxidation state of molten steel, which until now has depended on human skills.

2) The model for predicting oxygen concentrations from slag images was more accurate in predicting oxygen concentrations by binary classification than by regression, which outputs quantitative prediction results.

REFERENCES

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