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Molten Steel Level Detection by Temperature Gradients With a Neural Network

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ABSTRACT Molten steel level is difficult to measure as a result of the high-temperature melt and the covering flux. For the measurement, in our previous work, a novel principle by using the temperature gradient was proposed, and a refractory sensor was inserted into the metallurgical container to sense the temperature gradients of the flux and the molten steel. However, variations of temperature gradient distributions are large when the fluctuation speed of the molten steel level is fast, causing difficulties in the detection of the flux-steel interface. For this issue, a neural network is introduced to learn the features of the temperature gradients around the flux-steel interface, and the convolution of the neural network is developed to detect the flux-steel interface from the temperature gradient distribution. The numerical data obtained from the heat transfer model is used to train and test the detection method. The detection method gives a good performance with the numerical data. But for actual on-site applications, noise in the temperature gradient distributions affects the reliability and accuracy of the detection results. To improve the reliability of the detection method in practice, lifting of the sensor at the wave crest of the flux level is adopted to ensure the large temperature gradients around the flux-steel interface. The statistics show that the detection errors of the flux-steel interface are within ±5 mm with a confidence of 98.3%.

INDEX TERMS Molten steel level, fluctuation, temperature gradient, noise, neural network.

I. INTRODUCTION

Continuous casting of steel is a widely used process and is an important step in steel production. Tundish is the last metallurgical vessel through which molten steel flows before solidifying in the continuous casting mold. During the transfer of metal through the tundish, molten steel interacts with refractories, slag, and atmosphere [1]. However, as an important parameter, molten steel level is difficult to measure because of the following factors:

(1) The high-temperature melt and the harsh environment. Modern sensing technologies and sensors cannot work at temperatures up to 1500°C, i.e., pressure gauges [2], [3], thermistor [4], fiber laser sensors [5], [6] etc., disabling applications of contact measuring methods.
(2) The covering flux of varying thickness and physical forms floating on the molten steel. Noncontact measuring techniques have been adopted to measure the molten steel level by many researchers, such as ultrasonic waves [7], [8], optical measurement [9], [10] and microwaves [11], [12]. For these approaches, the signals are blocked by the covering flux and cannot reach the molten steel. Radioactive gamma rays [13], [14] have been employed for molten steel level measurement in the mold, but high energy radiation limits the applications in open places. Eddy current [15], [16] and electromagnetic induction [17], [18], due to severe attenuation of the signals, are effective only over a narrow range of measurement distance (50–200 mm). Nowadays, steel level in tundish is approximately measured via gravimetric gauges (load cells) placed underneath the tundish in practice, and the measuring uncertainty reaches 50 mm as a result of the wear and roughness of the refractory liner of the tundish.

A novel principle for molten steel level measurement in tundish by utilizing the strong stratification of the

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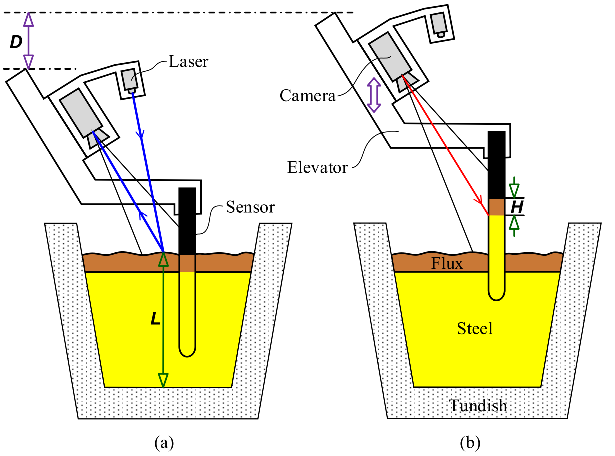

FIGURE 1. Measuring method based on machine vision [20]. (a) Flux level measurement. (b) Flux thickness measurement.

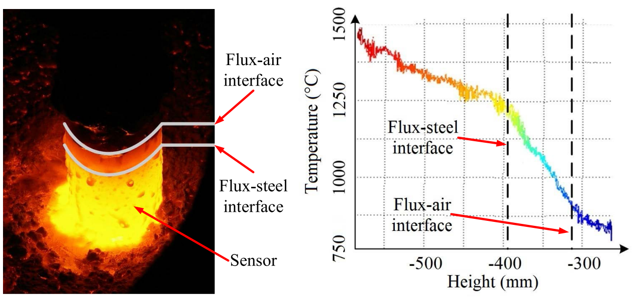

FIGURE 2. Thermal image and temperature distribution of the lifted sensor. (a) Thermal image. (b) Temperature distribution of the lifted sensor [20].

temperature gradients between the molten steel and the covering flux has been proposed in our previous work [19].

And correspondingly, the measuring method is established as shown in Figs. 1, which consists of two parts as follows:

(1) Flux level measurement in real time [21]. Laser triangulation is adopted to measure the flux level in real time. A laser device projects a laser light section onto the flux surface. Only the laser light reflected by the flux surface is allowed to pass through the narrow band optical filter mounted in front of the CCD camera, ensuring reliable measurement of the flux level.

(2) Flux thickness measurement every few minutes [19], [20], [22]–[24]. A refractory bar/sensor is inserted into the tundish to sense the temperature distribution of the molten steel, the covering flux and the air. After adequate heat transfer, the refractory bar/sensor is lifted, and the temperature distribution of the bar/sensor is captured by an area CCD camera. Temperature gradients are extracted from the temperature distribution, and the significant differences in temperature gradients between the molten steel and the covering flux are utilized to detect the flux-steel interface as shown in Fig. 2.

However, there are still some problems for the flux thickness measurement. As known, thermal response has a long time lag. In practice, fluctuations of the molten steel level together with the flux level lead to relative motions between the sensor and the mediums in the tundish all the time. In general, the fluctuation period is about 12 min with an amplitude of 30–50 mm. With such slow fluctuations, the sensor has enough time to sense the temperature gradients of the mediums in the tundish [23]. But in some cases, the fluctuation period decreases to about 5 min, and the large differences in temperature gradients between the molten steel and the covering flux cannot be reflected on the sensor, causing difficulties in detection the flux-steel interface by the temperature gradients.

The objective of this article is to detect the flux-steel interface under rapid fluctuations of the molten steel level. Followed this brief introduction, variations of temperature gradients caused by fluctuations of the molten steel level are presented. Then, convolution of a neural network is introduced to detect the steel-flux interface and the detection method is detailed in Section III. Temperature gradient distributions obtained from numerical simulations under different casting conditions are used to train and test the detection method. In Section VI, data from actual on-site applications are used to verify the detection method. At last, conclusions are made at the end of this article.

II. PROBLEM DESCRIPTION

There are three layers in the tundish, molten steel as the bottom layer, covering flux as the middle layer, and air as the top layer. In general, the temperature variation of the molten steel in the whole tundish is less than 4°C while the temperature drop in the covering flux is larger than 500°C for temperature holding of the steel [19]. Therefore, strong stratification of the temperature gradients is formed between the different layers.

The reason for the stratification of the temperature gradients between different layers is the large differences in physical properties, especially the effective thermal conductivity, between the different layers. Molten steel is a good conductor, and thermal radiation can directly pass through the air, both yielding much better heat conductivity than the covering flux which is composed of metal oxides. In the tundish, heat flows from the molten steel up to the covering flux and then to the air. Heat flux can be expressed by the product of the thermal conductivity and the temperature gradient, and keeps the same value in the three different layers. Thus, temperature gradient is proportional to the inverse of the thermal conductivity. That is, with better thermal conductivity for a layer, the temperature gradients are smaller—like the molten steel and the air layers.

However, original temperature gradients of the three layers cannot be perceived by the sensor. The sensor can only be manufactured from one material, and cannot meet the requirements of the large differences in physical properties between the three different layers. Inevitably, the differences in temperature gradients between the three different layers perceived by the sensor are reduced. The only thing we can

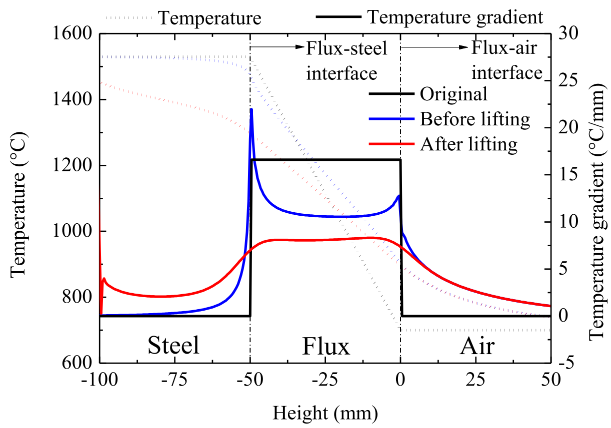

FIGURE 3. **Original and perceived temperature distribution and gradients for the three layers.**

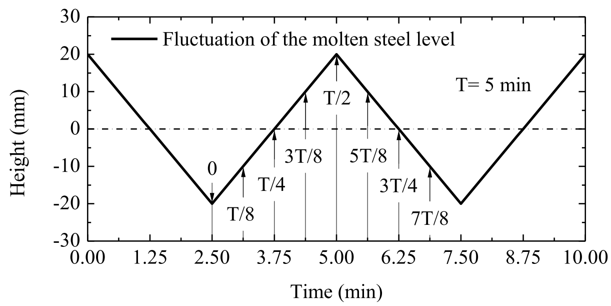

FIGURE 4. **Fluctuation of the molten steel level and the investigated wave phases of lifting of the sensor.**

do is material selection and structure design of the sensor, and the work has been done in our initial work [19].

Original temperature distribution and gradients of the three layers compared with those perceived by the sensor before and after lifting is shown in Fig. 3. In the tundish, original temperature gradients in the molten steel and the air layers are rather small and obvious temperature gradients only exist in the flux layer. But with the sensor inserted into the tundish, the original temperature distribution and gradients of the three layers near the sensor are corrupted as a result of another material—the sensor—involved. Even with a steady state and no fluctuations of the molten steel level, the temperature distribution and gradients perceived by the sensor, denoted as "Before lifting" (corresponding to the case of Fig. 1(a)) in Fig. 3, are obviously different from the original ones. And after the sensor is lifted (corresponding to the case of Fig. 1(b)), the temperature gradients for the molten steel and the air layers increase and the temperature gradients for the flux layer decrease (denoted as "After lifting" in Fig. 3), further reducing the differences in temperature gradients between the molten steel and the covering flux.

Fluctuations of the molten steel level are induced by the differences of the molten steel flowrate between the inlet and outlet of the tundish. Molten steel level is regulated by the slide gate nozzle at the inlet side. As a rule, fluctuations of the molten steel level have the form of triangular waves. If the fluctuation period decreases to 5 min with an amplitude

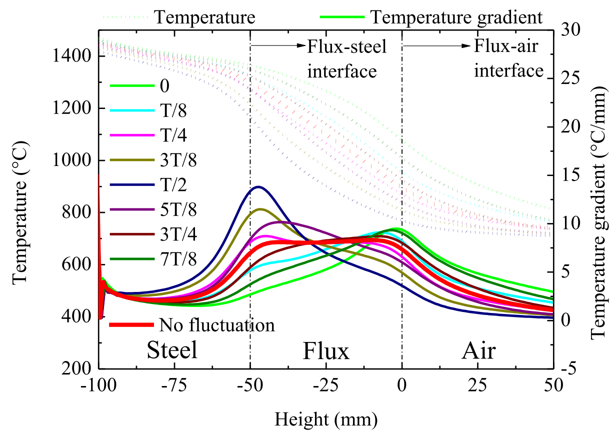

FIGURE 5. **Variations of temperature distribution and gradients with the fluctuation phase of lifting of the sensor.**

of 40 mm as shown in Fig. 4, temperature gradients for the three layers perceived by the sensor after lifting varies obviously with the wave phase when the sensor is lifted as shown in Fig. 5. For clarity, the labels for the curves in Fig. 5 are defined in Fig. 4.

According to Figs. 4–5, we can find that, at different wave phases, if temperature gradients increase at the flux-steel interface, they may decrease at the flux-air interface—and vice versa. The change extent of the temperature gradients at the flux-steel interface is always larger than that at the flux-air interface. Lifting of the sensor at the phase with a positive height value leads to larger temperature gradients at the flux-steel interface and smaller temperature gradients at the flux-air interface. And at the phases with the same height, lifting with the case of rising of the molten steel level results in larger temperature gradients at the flux-steel interface and smaller temperature gradients at the flux-air interface. Generally, temperature gradients around the flux-steel interface increase over the lasting time of rising of the molten steel level. It is found that temperature gradients around the flux-steel interface have the largest values when the sensor is lifted at the wave crest of the molten steel level.

Based on the measuring method shown in Fig. 1, the flux-air interface can be directly measured by the CCD camera, and only the flux-steel interface is needed to be identified by using the temperature gradients. For most of the time with a fluctuation period of 8–15 min, sequential clustering by using the temperature gradients and piecewise linear regression by using the temperature distribution are fused to identify the flux-steel interface in our previous work [23]. However, if the fluctuation period decreases to 5 min or even shorter, the previously proposed method fails to handle the data like in Fig. 5.

III. NEURAL NETWORK-BASED STEEL LEVEL DETECTION METHOD

Considering the fluctuations of the molten steel with a short period, difficulties in detection the flux-steel interface are induced by the varying characteristics of the temperature

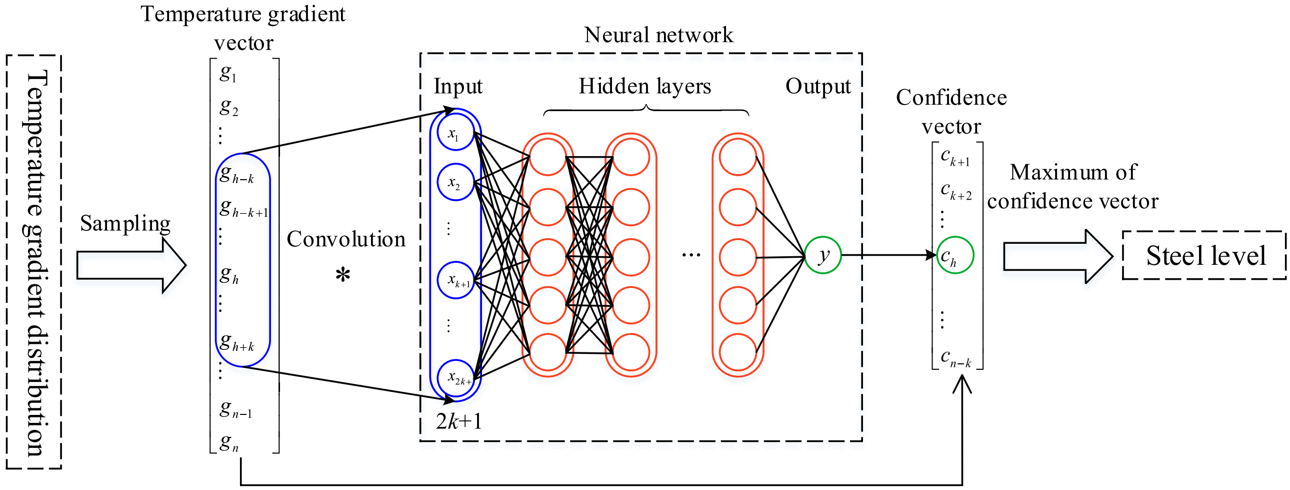

FIGURE 6. Architecture of the steel level detection method.

gradients at the flux-steel interface. The problem is how to extract the features of the temperature gradients at the flux- steel interface and how to locate the flux-steel interface according to the features.

Artificial neural network is effective in learning the features of data with multiple levels of abstraction [25]. There are many successful applications of neural network-based methods in steelmaking industry, such as crack detection for metallic surfaces [26], modeling and optimizing tensile strength and yield point for steel bars [27], control and optimization for blast furnace gas systems [28] and etc.

In this work, a neural network is introduced to learn the features of the temperature gradients around the flux-steel interface under various casting conditions, including different thicknesses of the covering flux, different thermal properties of the covering flux, especially different wave phases of lifting of the sensor. Then, convolution of the neural network is used to locate the flux-steel interface.

A. ARCHITECTURE OF THE DETECTION METHOD

Architecture of the steel level detection method is presented in Fig. 6. The key part is the neural network. To reduce the number of the network parameters and the size of the training sample set, there are no less than 3 hidden layers and each hidden layer has the same and small number of neurons. The input of the neural network is the vector of the local distribution of the temperature gradients $[x_1, x_2, \ldots, x_{2k+1}]^T$, and the output y represents the confidence on whether the local distribution of the temperature gradients is a flux-steel interface-centered vector. With a larger value of the output, the central element of the input vector, x_{k+1}, is more likely the steel-flux interface.

According to Fig. 6, the steel level detection procedure is detailed as follows: (1) The temperature gradient distribution is obtained from the temperatures on the sensor surface by the CCD camera via radiation thermometry; (2) The temperature gradient distribution are sampled into a vector with a desired spatial size $[g_1, g_2, \ldots, g_n]^T$; (3) $2k + 1$ adjacent elements of the temperature gradient vector, $[g_{h-k}, g_{h-k+1}, \ldots, g_{h+k}]^T$, are selected as the input of the neural network, and after calculation, the output of the neural network is denoted as c_h; (4) Convolution of the neural network is conducted with the temperature gradient vector $[g_1, g_2, \ldots, g_n]^T$ from $h = k + 1$ to $h = n - k$, and the outputs form a confidence vector $[c_{k+1}, c_{k+2}, \ldots, c_{n-k}]^T$; (5) Maximal element of the confidence vector $[c_{k+1}, c_{k+2}, \ldots, c_{n-k}]^T$ is denoted as c_i, and i is the detected flux-steel interface.

Training the neural network is needed before applications of the detection method. Temperature gradient distributions and corresponding flux-steel interfaces obtained from numerical simulations with the validated heat transfer model [19] under different casting conditions are divided into the training and the testing sample sets. The training sample set with known flux-steel interfaces are used to train the neural network. For a certain temperature gradient vector $[g_1, g_2, \ldots, g_n]^T$ with the flux-steel interface at g_t, the labels of the output confidence vector $[c_{k+1}, c_{k+2}, \ldots, c_{n-k}]^T$ should satisfy:

$$c_i = \begin{cases} 1, & i = t; \\ 0, & i \neq t. \end{cases} \tag{1}$$

A temperature gradient vector $[g_1, g_2, \ldots, g_n]^T$ can provide $n-2k$ samples of local temperature gradient distribution to train the neural network. But among these samples, there is only one sample with its central element locating at the flux-steel interface while the rest $n - 2k - 1$ samples are not. Training of the neural network is terminated when the product of the total errors of the training sample set and the testing sample set could not further decrease.

B. TESTING OF THE DETECTION METHOD

Several different structures of the neural network are investigated to optimize the detection method between the generalization capability and the simplicity of the method. Finally, the parameters for the detection method are selected as follows:

(1) Spatial size for sampling of the temperature gradient distribution is 1.0 mm.

(2) 3 hidden layers are adopted in the neural network and each hidden layers have 5 neurons.

(3) The input dimension of the neural network is 21 ($k = 10$), that is, the space length of the input dimension is 20.0 mm.

(4) The activation function of the neural network is ReLU (Rectified Linear Unit) [25], and NAG (Nesterov's Accelerated Gradient) [29] is selected as the optimization algorithm for training the neural network.

Training sample set of the detection method is composed of 80 temperature gradient distributions. After sampling, there are about 100 elements in the temperature gradient vector for each temperature gradient distribution. So, the number of the training samples for the neural network is about 6400. Another 100 temperature distributions are used to test the detection method.

A testing example of the trained detection method is presented as shown in Fig. 7. In the figure, responses of the neurons in different layers are given to understand the mechanism of the detection method. In the first hidden layer, two of the five neurons are activated around the flux-steel interface for the input temperature gradient distribution. It means that, for this case, neurons 2 and 5 are suitable to extract the features around the flux-steel interface. Later in the second and the third hidden layers, the responses of the activated neurons are kept while the responses of the other 3 neurons in the first hidden layer are filtered. Finally, the output of the detection method takes a maximum confidence value at the flux-steel interface (as shown in Fig. 7(d)), which is in consistence with our original thought. Therefore, the position where the confidence vector responding to the input temperature gradient distribution takes the maximum value is the detected flux-steel interface.

Detection error of the detection method is defined as the difference between the true and the detected flux-steel interface. Testing results with the testing sample set show that the detection error is 0.0 mm with 87 temperature gradient distributions while the detection error is ±1.0 mm with the rest 13 temperature gradient distributions including the case shown in Fig. 7.

IV. ACTUAL ON-SITE APPLICATIONS OF THE DETECTION METHOD

The proposed measuring principle and method shown in Fig. 1 have been put into use in the steel plants for more than five years. The measuring system installed in the steel plants and the manual measuring method of the flux-steel interface to validate the detection method is detailed in [19].

The key problem for actual on-site applications of the detection method is that obvious noise exists in the temperature distributions as show in Fig. 2. In section III, the detection method is trained and tested with the temperature gradient distributions obtained from the numerical simulations based

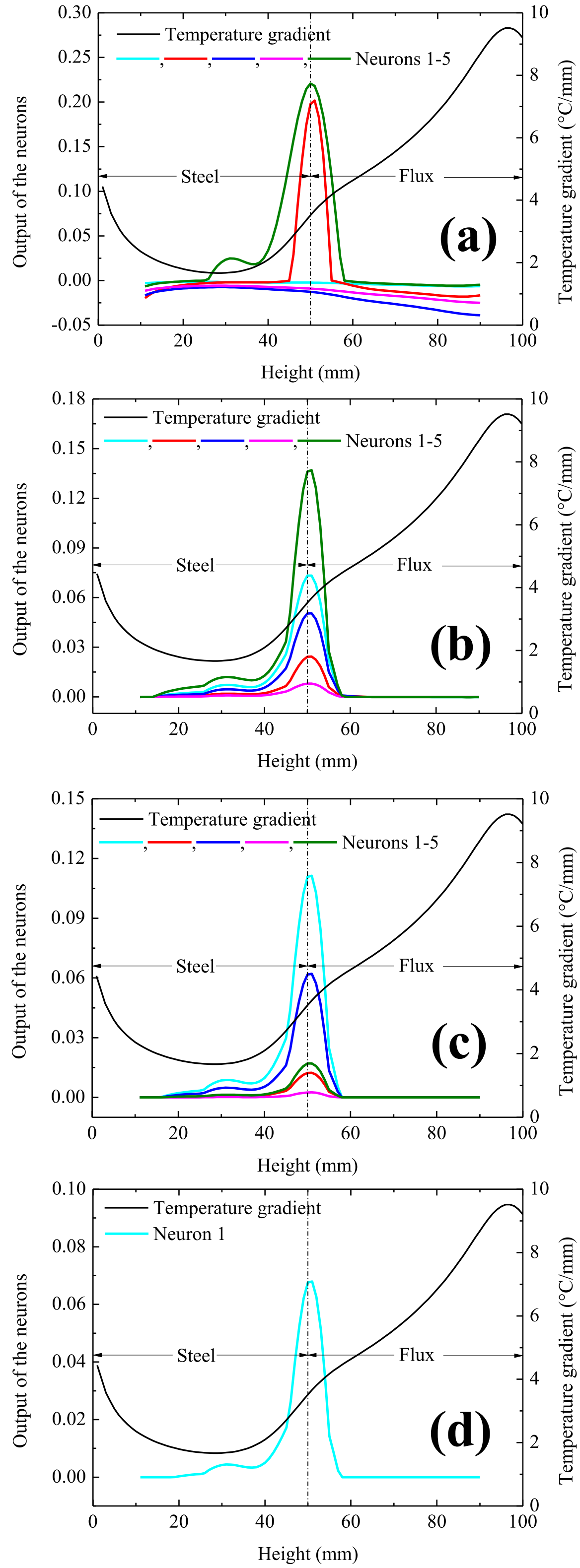

FIGURE 7. Responses of the neurons in different layers of the detection method. (a) The first hidden layer, (b) the second hidden layer, (c) the third hidden layer, and (d) the output layer.

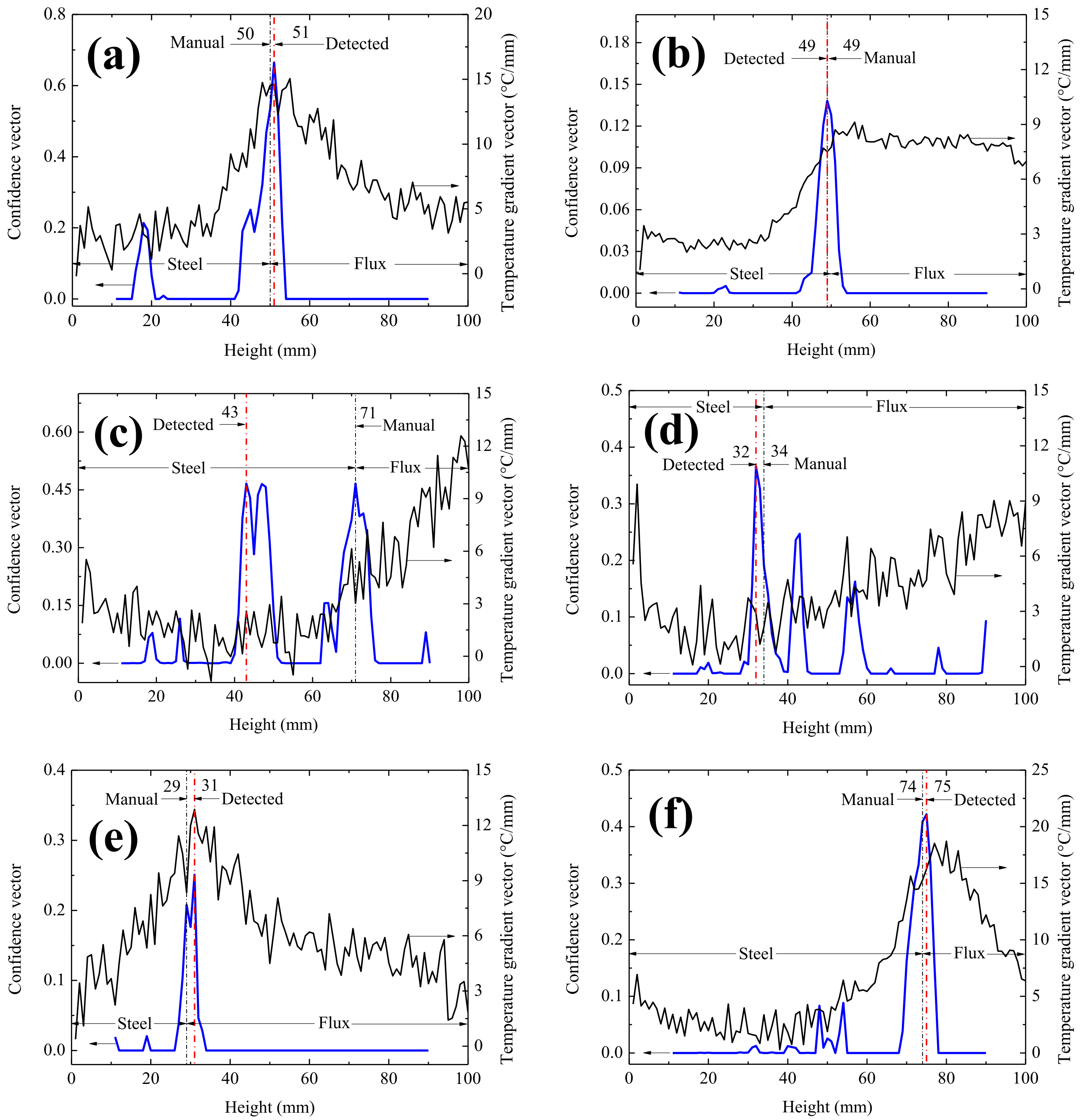

FIGURE 8. **Applications of the detection method. (a) Flux thickness = 50 mm, (b) flux thickness = 51 mm, (c) flux thickness = 29 mm, (d) flux thickness = 66 mm, (e) flux thickness = 71 mm, and (f) flux thickness = 26 mm.**

on the validated heat transfer model [19], and no noise is considered in the temperature gradient distributions. The reason for doing so is that, noise in the actual on-site temperature gradient distributions causes deviations, and errors exist in the manually measured flux-steel interfaces, being unfavorable to training the detection method. To achieve a better performance of the detection method, the temperature distributions and the manually measured flux-steel interfaces obtained from the actual on-site applications are used to improve the heat transfer model. Then, numerical data obtained from the improved model is used to train the detection method as in section III.

According to our previous work [23], median filter for the actual on-site temperature distributions is adopted to reduce the noise level in temperature gradient distribution. Even so, standard deviation of noise in the temperature gradient distributions still can reach 1.0°C/mm. Some examples of applications of the detection method in the steel plants are presented in Fig. 8. In Fig. 8, the blue and bold curves are the output of the detection method, namely the confidence vector,

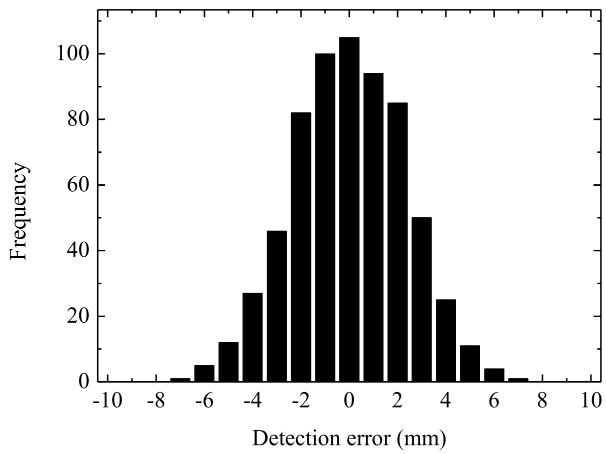

FIGURE 9. Errors of the detection method at the steel plants.

while the black and bold curves are the input of the detection method, namely the temperature gradient vector. It is noted that the flux-air interface keeps the same at the height with 100 mm in Fig. 8.

Figure 8 shows that noise in the temperature gradient distributions affects reliable detection of the flux-steel interface. The detection method even fails to predict the flux-steel interface within an acceptable error range (error $\leq \pm 10$ mm) with the case as Fig. 8(c). Compared with Fig. 8(a), it is found that, with the decrease of the noise level, reliability of the detection method is improved as shown in Fig. 8(b). Meanwhile, with about the same noise level, reliability of the detection method is much higher with larger temperature gradients around the flux-steel interface compared between Figs. 8(a), (e) and Figs. 8(c), (d).

As larger temperature gradients around the flux-steel interface will improve the reliability of the detection method, the time when the sensor is lifted is specially chosen to ensure large temperature gradients around the flux-steel interface. Figure 5 shows that, temperature gradients around the flux-steel interface have the largest values when the sensor is lifted at the wave crest of the molten steel level. Therefore, we can lift the sensor at the wave crest of the molten steel level to improve the reliability of the detection method. According to the measuring method, fluctuations of the molten steel level can be reflected by the flux level. Thus, lifting of the sensor is done when the flux level reaches the wave crest for actual on-site applications.

The algorithms for the detection method have been implemented into the software of the measuring system at the steel plants for about one year. The detection errors with 648 temperature gradient distributions are presented in Fig. 9. The standard deviation of the detection error is 2.3 mm, and the measurement accuracy reaches ± 5.0 mm with a confidence of 98.3%, which meets the accuracy requirement for molten steel level measurement in the tundish. By utilizing the detection method, the proposed measuring principle and method are effective in predicting the flux-steel interface under different casting conditions, including different fluctuation periods of the molten steel level, different flux thicknesses, different thermal properties of the flux and etc.

V. CONCLUSIONS

Since we proposed the new principle and method for molten steel level measurement, the subject on their actual on-site applications have been studied by us for more than 8 years. During this period, we have encountered many problems. Development of the measuring device working in the harsh environment was the first one. We spent 3 years and a lot of money to develop the device. After that, we thought that there would be no big problems in the measuring principle and method because they had been validated via the preliminary study in the laboratory. However, when we put the method into use at the steel plants through the developed measuring device, we found that the real problems just begun.

The first problem in the measuring method was continuous measurement of the flux level. At the beginning, we wanted to detect the flux-sensor interface to obtain the flux level. Disappointed, due to irregular radiations from the high-temperature flux, the original idea failed and finally laser triangulation was introduced to continuously measure the flux level [21].

The biggest problem in the measuring method was flux thickness measurement based on the proposed principle. There are two main challenges: (1) Flux adhesion on the sensor surface. Sometimes, liquid flux adheres to the senor surface. In these cases, true temperature distribution and gradients on the sensor surface cannot be obtained. To fix this problem, characteristics of the adhesive flux is developed to identify the flux-steel interface [20], [22]. (2) Variations of temperature gradient distributions under different casting conditions. For most of the cases, true temperature gradients can be obtained from the lifted sensor surface. Piecewise linear regression and sequential clustering are combined to identify the flux-steel interface [23]. But for some rare cases, the fluctuation speed of the molten steel level is fast, and the features of the temperature gradients at the flux-steel interface vary all the time. To detect the flux-steel interface under rapid fluctuations of the molten steel level, the work in this article is carried out.

So far, most of the problems in applications of the proposed principle and method for molten steel level measurement have been addressed. The technique has been out into use at six steel plants in China, providing improvements in billet quality, yield rate of the steel, and production efficiency for steelmaking industry.

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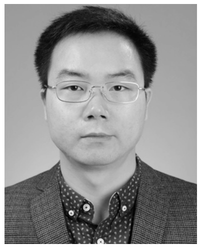

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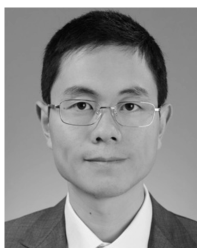

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