Molten Steel Level Control Based on an Adaptive Fuzzy Estimator in a Continuous Caster

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In this paper, we propose a molten steel level controller for a continuous caster that is based on an adaptive fuzzy estimator. The main objective of the proposed controller is to reject the bulging disturbance that occurs in the continuous casting process. If we know the bulging frequencies and phases, and the system time delay, then we can efficiently reject the bulging disturbance by using an adaptive fuzzy estimator. It generates the estimated bulging compensation signal taking the system nonlinearities and delay into account and this signal is added with the PID output to reject the real bulging disturbance efficiently. Computer simulations and experiments were executed with one-to-four-scale H/W simulator.

KEYWORDS: molten steel level; adaptive fuzzy estimator; bulging; disturbance; time delay.

1. Introduction

Recently, a number of steel companies are focusing on producing the high quality steel products fast. Controlling the molten steel level is very important in continuous casting because the stability of the molten steel level is highly correlated to the surface quality of the final products. So many researchers became interested in molten steel level control of the continuous caster that suffers from disturbances, time delays and nonlinearities. In a continuous caster, there exists disturbances such as surface waves in the mold, casting speed variations, tundish weight variations, clogging/unclogging in the nozzle and bulging disturbances. Among these disturbances, bulging would be the most severe disturbance that disturbs the level periodically. Normally, bulging is similar in shape to the combination of sinusoidal waves and causes a negative effect to the molten steel level control. This paper mainly focuses on rejecting the bulging disturbance.

Many researches have proposed various control strategies for molten steel level systems. Keyser (1997) used the master-slave PID controller where a slave PID control loop is used inside a master PID control loop to enhance the control robustness and performance. Barron (1998) estimated the unknown degree of clogging and nozzle discharge coefficients for stability and convergence in a continuous caster. Watanabe (1999) used the neural network model for stopper control to deal with the casting speed variations. Dussud (1998) had suggested using a fuzzy logic controller together with the PID in his control architecture. This controller focuses on eliminating the effect of nozzle clogging/unclogging. D. Lee (2003) proposed a notch filter technique in addition to the PID plus fuzzy logic controller to reject the periodic and non-periodic disturbances. But in these papers, there has been no control strategy that tries to estimate the existing bulging or to reject the bulging disturbance directly. Furtmüller (2006) has in fact modeled the bulging and applied it to his control strategy, but in order to use the proposed controller one has to measure the current signal of the roller motor under the mold, which is neither easy to measure in the field nor properly reflects the mold level disturbance due to bulging. So we propose an adaptive fuzzy estimator based controller that can be applied easily to the molten steel level system. The proposed estimator is responsible for rejecting the bulging disturbance while the PID controller mainly stabilizes the molten steel level.

This paper is organized as follows. Section 2 derives a mathematical model for the molten steel level system; Sec. 3 describes the proposed controller system configuration and introduces the bulging disturbance model; Sec. 4 explains the proposed adaptive fuzzy estimator; Sec. 5 describes the H/W simulator and experimental system configuration; Sec. 6 shows computer simulation results; Sec. 7 verifies the performance of the proposed controller by using the constructed H/W simulator. Finally, the conclusion is given in Sec. 8.

2. Overview and Mathematical Modeling of Molten Steel Level System

An overview of the continuous casting process is shown in Fig. 1. The molten steel in the ladle is poured into the tundish, which in turn is poured into the mold through the nozzle. The control process is activated to maintain the molten steel level at a preset value. The molten steel is cooled...
down first in the mold, and then further cooled down by the cooling units in the rolls under the mold. Finally the molten steel is shaped into slabs after passing through many rolls.

The detailed description of the tundish and mold is given in Fig. 2. The continuity equation of the molten steel in the mold is described as

$$\frac{dV}{dt} = Q_{\text{in}} - Q_{\text{out}} \quad \quad \quad (1)$$

where $Q_{\text{in}}$ (m³/s) is the incoming molten steel flow into the mold, $Q_{\text{out}}$ (m³/s) is the outgoing flow from the mold, and $V$ (m³) is the volume of the molten steel stored in the mold. $V$ is represented as $A \times Y$, where $A$ (m²) is the cross sectional area of the mold and $Y$ (m) is the molten steel level in the mold. $A$ is $W \times D$, where $W$ (m) is the width of the mold and $D$ (m) is the thickness of the mold. Then, Eq. (1) becomes

$$\frac{dY}{dt} = \frac{1}{A} (Q_{\text{in}} - Q_{\text{out}}) \quad \quad \quad (2)$$

where $Q_{\text{in}}$ and $Q_{\text{out}}$ are represented as follows:

$$Q_{\text{in}} = \sqrt{2gH} \cdot SG(u_s), \quad Q_{\text{out}} = A \cdot v_o \quad \quad \quad (3)$$

Here, $g$(m/s²) is the acceleration of gravity; $\sqrt{2gH}$ is the outgoing velocity of molten steel from the tundish; $H$(m) is the height of molten steel in the tundish; $SG(u_s)$ (m³) is the area through which the molten steel is flowed into the mold; $u_s$(m) is the input reference of the slide gate; $v_o$(m/s) is the casting speed.

$SG(u_s)$ as shown in Fig. 3 is determined by the overlapped area between the circular shape slide gate with the nozzle hole. The sliding gate position is in turn determined by the slide gate input reference. If the sliding gate begins to overlap with the nozzle hole, then the opening begins and the molten steel starts to flow from the tundish into the mold. Molten steel level control is to stabilize the molten steel level $Y$ in the mold by controlling the slide gate input reference $u_s$. $SG(u_s)$ can then be calculated as follows:

$$SG(u_s) = \begin{cases} 0, & u_s \leq z \\ \frac{\pi r^2 - 2r^2 \sin^{-1} \left( \frac{b - u_s}{2r} \right)}{2r}, & u_s > z \end{cases} \quad \quad \quad (4)$$

where $z$(m) is the dead zone as specified by Fig. 3, $r$(m) is the radius of the slide gate, and $b$(m) is the maximum moving distance of the slide gate.

3. System Configuration and Bulging Disturbance Modeling

Figure 4 explains the block diagram of the overall molten steel level control system with the proposed adaptive fuzzy estimator. The PID controller is responsible for the overall control stability. The saturation function block is introduced to describe the limitation on the slide gate. $SG(\cdot)$ is the linearized overlapped area. Multiplying $SG(\cdot)$ by the outgoing velocity of molten steel from the tundish we can determine the incoming flow $Q_{\text{in}}$ to the mold. Adding the outgoing flow $Q_{\text{out}}$ from the mold to $Q_{\text{in}}$, we can then determine the amount of the molten steel poured into the mold. This is the input to the mold transfer function. Then the bulging disturbance is added to the output of the mold transfer function, which results in the molten steel.
level \( Y \). More specifically, \( Y \) is computed as

\[
Y = \frac{1}{A_s} (V_1 \cdot SG(SG_d \cdot u) - Q_{out}) + d \quad \text{............(5)}
\]

where \( V_1 = \sqrt{2gH} \) is the outgoing velocity from the tundish, \( SG \) is the linearized overlapped area, and \( SG_d \) is the slide gate dynamics. \( u = r_{\text{PID}} - d \) is the slide gate input, where \( r_{\text{PID}} \) is the PID output and \( d \) is the estimated disturbance compensation signal which is employed at the slide gate input to cancel a real disturbance at the molten steel level in the mold. Substituting \( u = r_{\text{PID}} - d \) into Eq. (5), results in

\[
Y = \frac{1}{A_s} (V_1 \cdot SG(SG_d \cdot r_{\text{PID}}) - Q_{out}) - \frac{1}{A_s} (V_1 \cdot SG(SG_d \cdot d)) + d \quad \text{............(6)}
\]

If \( \dot{d} \) becomes

\[
d^* = SG_d^{-1} \cdot SG^{-1} \left( s \frac{AV}{V_1} \right) \quad \text{............(7)}
\]

then \( Y \) becomes

\[
Y = \frac{1}{A_s} (V_1 \cdot SG(SG_d \cdot r_{\text{PID}}) - Q_{out}) = \frac{1}{A_s} (Q_{in} - Q_{out}) \quad \text{............(8)}
\]

Therefore, if \( \dot{d} \) is the same as \( d^* \), then we can completely reject the existing bulging disturbance in the molten steel level system. However, since all the parameters are not fully known in reality and there are unmodeled dynamics and nonlinearities, we cannot determine \( d^* \) accurately. Also, linearizing the overlapped area can cause additional error. Therefore \( \dot{d} \) that is reasonably close to \( d^* \) are to be estimated from the adaptive fuzzy estimator.

In a molten steel level system, periodic bulging is usually generated due to periodic shrinkage and expansion of the molten steel when it passes through the casting rollers underneath the mold. The molten steel that comes out from the mold is solidified on the outside but the inside of the molten steel is not. When the molten steel passes through the rolls, the unsolidified part expands between the rolls and shrinks if the same part meets the next roll. Figure 5 shows this phenomenon. This bulging disturbance is directly reflected on the molten steel level of the mold and it is hard to regulate by the conventional control methods.

In the field, the tight and nonperiodic roll placement may be able to reduce the effect of the bulging but it never disappears. So one needs to reject the remaining bulging using either a control or an estimation technique. As given in Fig. 6, the periodic bulging is in general of the form of two sine waves and their amplitudes are almost same in the field. So we can assume that they are the same and derive the bulging model as follows:
time delay into account in the estimated disturbance case of our one-to-four-scale H/W simulator. Taking this actually measure this time delay, which is about 2 s in the way can reject the real bulging disturbance. We can shows that the estimated disturbance compensation signal output. So we have to take this time delay into account in some period of time.

In this molten steel level system, the time delay is the most important part to consider to achieve good performance. The slide gate has its own dynamics and the molten steel takes time to pass through the nozzle. So there is non-trivial time delay from the slide gate input to the mold level output. So we have to take this time delay into account in order to reject the bulging disturbance effectively. Figure 7 shows that the estimated disturbance compensation signal in this way can reject the real bulging disturbance. We can actually measure this time delay, which is about 2 s in the case of our one-to-four-scale H/W simulator. Taking this time delay into account in the estimated disturbance compensation signal \( \hat{d} \), we have

\[
\hat{d}(\hat{x}) = \hat{A} \sin(w_1 t + \phi_1) + \sin(w_2 t + \phi_2) ...
\]

where

\[
w_1 = \frac{2 \pi}{T_1}, \quad w_2 = \frac{2 \pi}{T_2}, \quad \text{and}
\]

\[
T_i [s] = \frac{\text{Roll pitch [mm]}}{\text{Casting speed [m/min] \times 1000}} \cdot i = 1, 2
\]

Here \( \hat{A} \) is the amplitude of the two sine waves, \( w_1, w_2 \) are their two frequencies, \( T_1, T_2 \) are their two periods, and \( \phi_1, \phi_2 \) are their two phases. In the experimental simulator, we create the bulging by using the sine wave generators and these phases are predetermined. Even in reality, they can be estimated by observing the shape of the molten steel level for some period of time.

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\[
\hat{d}(\hat{x}) = \hat{A} \sin(w_1 t + \phi_1 + w_1 T_{dp}) + \sin(w_2 t + \phi_2 + w_2 T_{dp}) ...
\]

where input \( x \) consists of the mold level error and PID output, \( \hat{A} \) is an estimated amplitude, \( T_{dp}(s) \) is the system delay, and \( w_1 T_{dp}, w_2 T_{dp} \) are the additional time delay compensation terms. Figure 7 shows that the estimated disturbance compensation signal in this way can reject the real bulging disturbance. We can actually measure this time delay, which is about 2 s in the case of our one-to-four-scale H/W simulator. \( \hat{d} \) is created from the adaptive fuzzy estimator where \( \hat{A} \) is updated to compensate for \( SG, SG_2 \) and \( V_1 \) in Eq. (8). \( \hat{d}(\hat{x}) \) is then added to the PID output and the added signal serve as the input to the real plant. The output of the real plant due to input component \( \hat{d}(\hat{x}) \) is expected to cancel the real bulging disturbance \( \hat{d} \).

Frequencies of the bulging disturbances can be calculated or determined. They can be calculated from roll pitch and casting speed information as in Eq. (9) or can be determined from Fast Fourier Transform (FFT) result. As for the system time delay, we measured it directly as in Fig. 8 in the case of our one-to-four-scale H/W simulator. We applied the input sinusoidal signal off-line to the slide gate with the same frequency as the bulging frequency. Then if we measure the time difference between the input slide gate signal and output mold level signal, the system time delay can be measured as shown in Fig. 8. We can estimate the system time delay, but the wrong value can give a bad effect on the mold level, and even cause mold level divergence. Therefore the off-line measurement is safe and easy.

4. Adaptive Fuzzy Estimator

Using \( r_{PID} \) and \( y \), the proposed adaptive fuzzy system updates \( \hat{A} \) and then generate \( \hat{d} \) so as to improve the output regulation performance in the next sample time. Using the singleton fuzzifier, the product inference rule, and the center average defuzzifier, and the triangular membership functions, the output of the conventional fuzzy system becomes

\[
A = \frac{\sum_{i=1}^{M} y_i \left[ \prod_{j=1}^{a} \exp \left( - \frac{x_i - \tilde{x}_j^i}{\sigma_j^i} \right)^2 \right]}{\sum_{i=1}^{M} \prod_{j=1}^{a} \exp \left( - \frac{x_i - \tilde{x}_j^i}{\sigma_j^i} \right)^2} \] ..........................(11)

where \( M \) is the number of the linguistic rules, \( x_i \) is the \( i \)th input, \( \tilde{x}_j^i, \sigma_j^i \) are respectively the average value and the standard deviation of the membership function for the \( j \)th rule and the \( i \)th input, and \( y_i \) is the consequence part value of the \( i \)th rule. By defining \( z_l^i, l = 1, \ldots, M, a, b \) as follows,

\[
z_l^i = \prod_{j=1}^{a} \exp \left( - \frac{x_i - \tilde{x}_j^i}{\sigma_j^i} \right)^2, \] ..........................(12)

we have \( f(x) = b/a \). The proposed adaptive fuzzy system updates \( \hat{y}^j_l \) by minimizing the cost function
\[ e = \frac{1}{2} \left[ f(x_0) - y_0 \right]^2 \]  
where \( x_0, y_0 \) are respectively the real input and the real output values. Then \( y' \) is updated as:

\[ y'(q + 1) = y'(q) - \alpha \frac{\partial c}{\partial y'}(q) = y'(q) - \alpha \frac{f - y_0}{b} z' \]

where \( l = 1, 2, \ldots, M, q = 0, 1, 2, \ldots \), and \( \alpha \) is the constant step size.

The membership functions for the level error and the PID output value are shown in Fig. 9 and the 49 linguistic initial rules are shown in Table 1. The first row represents the level error and the first column represents the PID output. Each input consists of 7 membership functions. Its output \( \hat{d} \) in Eq. (10) becomes the estimated bulging compensation signal consisting of two sine waves. The adaptive fuzzy estimator determines the amplitude \( \hat{A} \) of the estimated bulging compensation signal by using adaptive fuzzy algorithm (11) and (14).

The membership functions for the level error and the PID output value are shown in Fig. 9 and the 49 linguistic initial rules are shown in Table 1. The first row represents the level error and the first column represents those of the PID output. NB represents negative big; NM represents negative medium; NS represents negative small; ZO is zero; PS represents positive small; PM represents positive medium; PB represents positive big; VS represents very small; S represents small; MED represents medium; B represents big; VB represents very big. Each input consists of 7 membership functions. Its output \( \hat{d} \) in Eq. (10) becomes the estimated bulging compensation signal consisting of two sine waves. The adaptive fuzzy estimator determines the amplitude \( \hat{A} \) of the estimated bulging compensation signal by using adaptive fuzzy algorithm (11) and (14).

### Table 1. Initial fuzzy rule table. The first row represents the fuzzy set of the level error and the first column represents those of the PID output.

|       | ZO | VS | S | MED | B | VB |
|-------|----|----|---|-----|---|----|
| NB    | b  | b  | b | b   | b | b  |
| NM    | b-n| b  | b | b   | b | b  |
| NS    | b  | b-n| b-n| b-am| b | b  |
| ZO    | b  | b-n| b-n| b-am| b | b  |
| PS    | b  | b  | b  | b   | b | b  |
| PM    | b  | b  | b  | b   | b | b  |
| PB    | b  | b  | b  | b   | b | b  |

5. Experimental Setup of the Overall System

We built a one-to-four-scale H/W simulator to test the molten steel level system experimentally and executed the control program in a VME system with the vxWorks O/S. The control software is programmed with a PLC (Programmable Logic Controller) tool where ladder, FBD (Function Block Diagram) and C programming are possible. In addition, we developed the user monitoring program MoldView for real time monitoring of the data. Figure 10 shows the total system configuration. The H/W simulator is a hardware model system that uses water instead of molten steel and there is a bulging generator to produce the bulging disturbance artificially.

Tundish, mold, bulging generator and water tank are the main parts of the H/W simulator. In order to produce the bulging disturbance, the two servo motors were used. When these motors move up and down, water comes in and goes out of the mold repeatedly through the pipe connected with the mold. If we regulate the motor movement properly, we can obtain the bulging that has the shape of a composition of two sine waves. The water level in the mold is measured by an ultrasonic sensor. The appearance of the H/W simula-
tor is given in Figs. 11, 12, 13, 14.

The input side of the H/W simulator consists of the slide gate velocity (Analog signal from the VME system), bulging motor velocity (Analog signal from the VME system), and emergency button (Digital signal from the emergency stop button). The output side of the simulator consists of the mold level (Analog signal from the ultrasonic sensor), slide gate position (Encoder pulse from the motor amps), limit sensors (Analog and digital signals from the proximity sensors).

A servo motor was used for the slide gate for level control and two servo motor were used for the bulging genera-
tor. There is a manual valve under the H/W simulator to control the outgoing flow from the mold to the water tank and the amount of the outgoing flow is sent to the user with an electric signal.

MoldView is an MMI (Man Machine Interface) for monitoring and shows the level value, slide gate position, FFT value of the level, statistics analysis and animated molten steel level control system. In addition, it is possible to save the value of the level and slide gate position for a preset time. MoldView is described in Fig. 15.

6. Simulation Results

In order to demonstrate the feasibility and features of the developed controller, computer simulations have been performed first. The reference mold level is 80 mm and the casting speed is 3 mm/s. Simulation was performed for two cases. The first case is for a single sinusoidal bulging and the second is for a two sinusoidal bulging. The single sinusoidal bulging frequency is 0.118 Hz, and its amplitude is peak to peak 11 mm. The two bulging disturbance frequencies are 0.121 Hz and 0.134 Hz respectively and their amplitudes are peak to peak 11 mm. All bulging disturbances have a phase of 0 degrees.

In order to show the efficiency of the adaptive scheme, the simulation tests for the proposed controller without
adaptation have been performed. Figures 16, 17 show the performance of the proposed controller without adaptation. They show the performance of the PID controller with no bulging disturbance, PID controller with bulging disturbance and PID controller with fuzzy estimator without adaptation with bulging disturbance. From 0 to 150 s, the PID controller is operating without bulging disturbance and from 150 to 300 s, the PID controller is working with bulging disturbance. From 300 s, the proposed adaptive fuzzy estimator without adaptation is activated along with the PID controller.

Figures 18, 20 show the performance of the PID controller with no bulging disturbance, PID controller with bulging disturbance and PID controller with adaptive fuzzy estimator with bulging disturbance. Figures 19, 21 show the slide gate position for the above three situations. From 0 to 300 s, the results are the same as those of Figs. 16, 17. But from 300 s, the proposed adaptive fuzzy estimator is applied in Figs. 18, 20 to compensate for the bulging disturbance. Comparing Figs. 18, 20 with Figs. 16, 17, from 300
to 450 s, we see that the performance with adaptation scheme is better in mold level performance.

When the proposed controller is used, the level error decreased from over $\pm 6$ mm to about $\pm 1.5$ mm. The adaptive fuzzy estimator generated the estimated bulging compensation signal within 10 s and it shows a good performance.

### 7. Experimental Results

In order to compare the control performance between the PID controller and the PID controller with adaptive fuzzy estimator, we configured one and two bulging disturbances cases and compared the performance of the bulging rejection. In the single sinusoidal case, the bulging frequency is 0.118 Hz. In the two bulging case, we experimented for the two cases. The first test bulging has frequencies of 0.121 Hz and 0.134 Hz, has the amplitude of peak to peak 11 mm. The second test bulging has frequencies of 0.121 Hz and 0.140 Hz, has the amplitude of peak to peak 11 mm. Figure 22 is the bulging that is generated in the H/W simulator. It has the form of a composition of two sine waves and has amplitude of peak to peak 11 mm. All bulgings have a phase of 90 degrees.

The result of the H/W simulator tests with one and two bulging disturbances are given in Figs. 23, 24, 25. Figures 23, 24, 25 show the comparison of 3 situations, PID control with no bulging, PID control with bulging, PID control with adaptive fuzzy estimator. The first row indicate the mold level when the reference is 80 mm and the second row indicate the slide gate position. The PID controller is operating without bulging disturbance from 0 to 150 s and from 150 to 300 s, the PID controller with bulging disturbance is introduced. From 300 s, the proposed adaptive fuzzy estimator based PID controller is operating with bulging disturbance. We can recognize that the controller with adaptive fuzzy estimator shows better performance than the PID controller when the bulging disturbance exists. When there is no bulging disturbance, level error is almost within $\pm 1$ mm but if the bulging occurs, level error raises up to $\pm 5$ mm but the proposed controller reduces the level error to almost within $\pm 3$ mm.

Table 2 was organized to compare the reduction degree of the bulging. There are two tables in Table 2, the first column shows which controllers were used. The first row shows categories with level error within $\pm 3$ mm, over $\pm 3$ mm and under $\pm 5$ mm, over $\pm 5$ mm and under $\pm 10$ mm, over $\pm 10$ mm. In the column, PID means that only PID controller was used to maintain the water level even under the bulging, PID+EST means that PID controller with adaptive fuzzy estimator was used to maintain the water level under bulging. These data are statistics of the water level in the mold for 4 min. The reason why $\pm 3$ mm swing is a standard is because the quality of the slab is considered to be satisfied when the molten steel level swing is within $\pm 3$ mm in the field. In Table 2(a), if the PID+EST was used, water level degree within the under $\pm 3$ mm is 97.60%. So Table 2 shows that PID with adaptive fuzzy estimator stabilizes the level up to 98% within $\pm 3$ mm.
Fig. 23. Mold level comparison (experiment result for 0.118 Hz single sinusoidal bulging).

Fig. 24. Mold level comparison (experiment result for 0.121 Hz, 0.134 Hz bulging).

Fig. 25. Mold level comparison (experiment result for 0.121 Hz, 0.141 Hz bulging).
In a high speed casting process, the bulging disturbance is expected to be much faster than the current simulation. So we tested for the very fast bulging disturbance. The bulging disturbance is a single sinusoidal and has a 0.118 Hz frequency and 11 mm peak to peak amplitude. Previous bulging with composition of two sine waves has a period about 1 min. Therefore the biggest amplitude comes up once every minute but this single sinusoidal bulging disturbance has a 0.118 Hz frequency, so the 11 mm amplitude comes up once every about 8.5 s. Figure 23 shows that the PID with adaptive fuzzy estimator has almost the same performance although the bulging disturbance frequency was very fast. Table 3 shows that the proposed controller has a very good performance.

8. Conclusions

In this paper, we reduced the effect of the bulging disturbance to the molten steel level by using an adaptive fuzzy estimator and the PID controller. We first derived the specific modeling of the bulging disturbance and then the molten steel level system. Then assuming that the bulging frequencies, phases, and time delay are known, we proposed an adaptive fuzzy estimator to create a bulging compensation signal that is used to cancel the actual disturbance at the molten steel level. Time delay, which turns out to be very important for control, is compensated in generating the bulging compensation signal. The computer simulation is performed and the experiment is performed with the presented H/W simulator and VME system. As a result, we showed that the proposed controller reduced the bulging disturbance effectively. Recently 1:1 H/W simulator has been manufactured by POSCO, and the proposed system is expected to be applied to this system in the future.

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