Pergamon

Control Eng. Practice, Vol. 4, No. 11, pp. 1511-1520, 1996

0967-0661/96 $15.00 + 0.00

PII:S0967-0661(96)00165-7

ADAPTIVE FUZZY CONTROL OF THE MOLTEN STEEL LEVEL IN A STRIP-CASTING PROCESS

D. Lee*, J.S. Lee* and T. Kang**

**Department of Electrical and Electronic Engineering, Pohang University of Science and Tehnology, Pohang, 790-784, Korea*
(jsoo@vision.postech.ac.kr)
***Research Institute of Industrial Science and Tehnology, Pohang, 790-784, Korea*

(Received December 1995; in final form September 1996)

Abstract. This paper presents an adaptive fuzzy controller with nonlinear compensation and a switching control strategy to regulate the molten steel level of a strip-casting system. The proposed controller adopts an adaptive fuzzy control structure which is reported to be superior in performance to neural-network control techniques. The adaptive fuzzy controller is robust due to its fuzzy representation of the controller, and is adaptive due to its training capability. In order to compensate for the inevitable model-estimation error, the controller introduces an additional fixed gain switching control term. Additionally, a nonlinear compensation term is used in this system to eliminate disturbances due to variations in gap and speed. Combining all these terms, the proposed controller is able to achieve zero steady-state error asymptotically, with robustness and an adaptation capability inherent in the adaptive fuzzy controller.

Keywords. Strip-casters, molten steel level, roll gap, rolling force, adaptive fuzzy control, switching control, nonlinear compensation, model error compensation

1. INTRODUCTION

Recently, the research and development of strip-casting system technology has gained much interest as a new type of casting method for the 21st century's steel-making process. The idea of strip-casting has emerged from the constant desire to produce hot-rolled thin steel strip directly from the molten steel, thereby simplifying the steel-making process. The method renders unnecessary the separate reheating and hot rolling processes, which require tremendous energy and operating costs (Hlinka, *et al.*, 1988; Shim, *et al.*, 1993). The original idea of strip-casting can be traced back to the 19th century, when Sir Henry Bessemer suggested a twin-roll strip-casting technology. His idea was not realized then, because many key technical components, such as measurement devices and computer control technology, were not available at that time (Pitler, 1988). Thanks to the phenomenal growth of steelmaking and its relevant technologies, however, the efforts to implement strip-casting technology have recently been revived, and several countries are already actively involved in the development of full-sized strip-casting systems. No commercial strip-caster plant has yet been announced, but this will happen soon.

Fig.1 shows the pilot strip-caster plant that has been constructed by Pohang Iron & Steel Co. (POSCO) and DAVY International Co. based on a twin-roll system which is similar to Bessemer's (Shin, *et al.*, 1995; Edwards and Willis, 1992). The pilot plant is about 60 m in length, and is designed to produce 2 - 6 mm thick steel plates. Naturally, this complex system is equipped with many control units such as the mill drive control unit, the cooling control unit, the discharge control unit, the coiler control unit, etc. Among them, the most important control unit is the mill drive control unit (Fig. 2), which produces thin solidified steel strip from the molten steel. In this unit, the outflow of molten steel from the tundish is

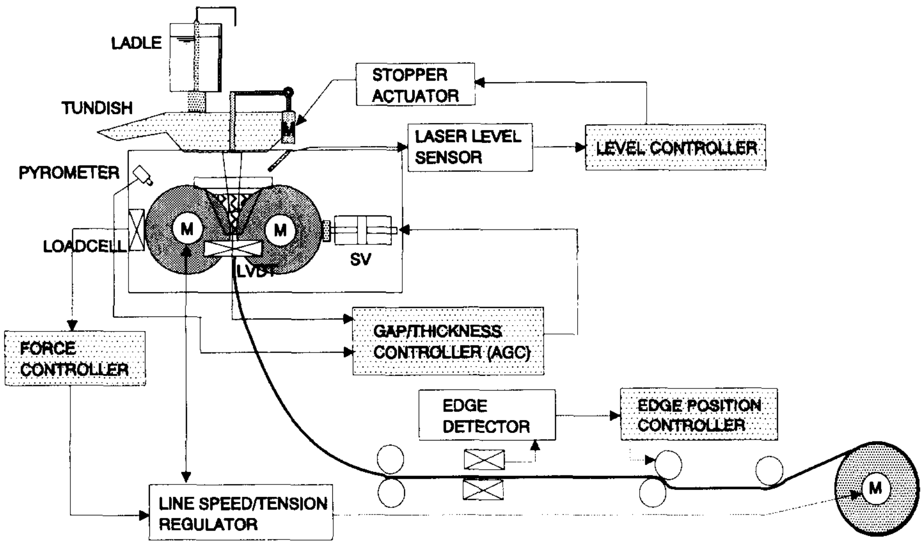

Fig. 1. Schematic layout of strip-caster pilot plant constructed in POSCO

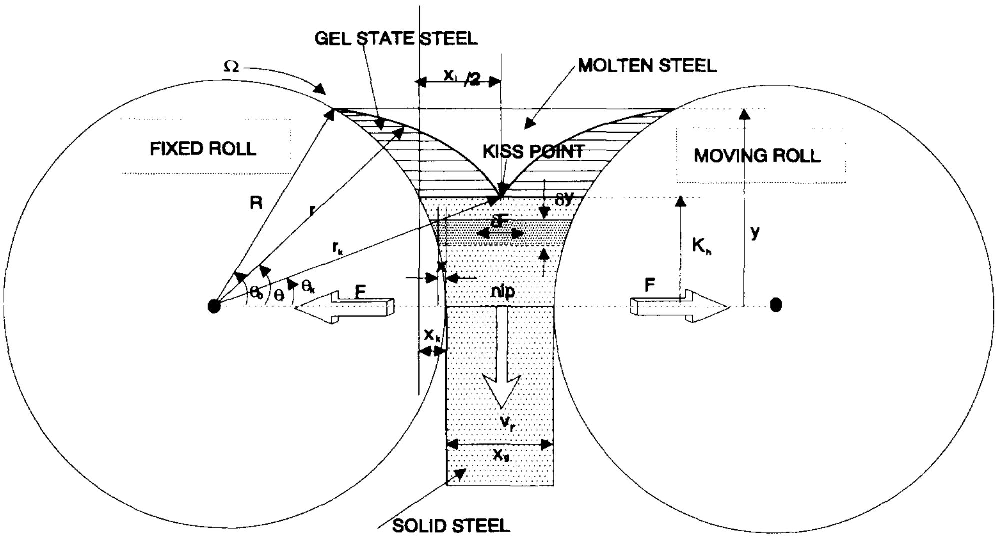

Fig. 2. Mill drive control unit

regulated either manually or automatically by the electrically controlled flow-control device to keep the height of the molten steel filled between the roll cylinders to a desired value. The molten steel then solidifies rapidly from the bottom, and at the same time is hot rolled by the gap positioning system. The mill drive control unit itself consists of three control subunits: the molten steel level control unit, the roll gap control unit, and the force control unit. During normal operation, the level control unit regulates the height of the molten steel at a fixed preset value in order to guarantee good-quality solidification. The roll gap control unit regulates the thickness of the steel strip at the desired preset value. The force control unit regulates the roll force at a preset value to keep the molecular structure of the solidified steel uniform. These three control units are in fact in a coupled form, and are described as a coupled nonlinear system corrupted by various types of disturbances such as roll eccentricity, roll expansion by heating, oil film compression changes in the roll axes, roll crown bending effects, measurement delay, sensor noises, etc. It is clearly a challenging task to control the system in its coupled nonlinear form.

As a first step to tackle the strip-caster control problem, this paper focuses on the molten steel level control. This is considered the most critical to the production of high-quality solidified steel strip. It is difficult to control in itself, since it has high nonlinearities in its dynamics, is under various process-parameter changes and disturbances, and is coupled with other control loops. The main sources of disturbances are the variations in flow rate, roll gap, and roll rotation speed. The variation in flow rate results mainly from hardware wear, whereas the variation in roll gap results from roll eccentricity. The coupling with other control loops introduces yet another source of disturbances. Under these conditions, it is extremely difficult to control the molten steel level accurately, using only a conventional PI algorithm.

In order to achieve high performance regulation, even under various disturbances and nonlinearities, this paper presents a fuzzy control technique with an adaptation capability, coupled with nonlinear compensation and switching control techniques.

The concept of fuzzy logic theory was introduced by L. A. Zadeh (1965), and the first application of fuzzy logic theory to process control was initiated by Mamdani (1974). Subsequently, many other experts in this field have successfully applied various fuzzy control techniques to many different application areas (Mamdani and Gaines, 1981; Takagi and Sugeno, 1985; Andersen and Nielsen, 1985; Ying, *et al.*, 1990; Lee, 1990; Tseng and Hwang, 1993; Wang and Mendel, 1992; Carli, *et al.*, 1994; Zeng and Singh, 1995). These results are, however, mostly experimental in nature and have not been determined with rigorous mathematical analysis. In addition to these, other related topics are referenced in (King and Mamdani, 1977; Narendra and Partharathy, 1990; Levin and Narendra, 1993; Raju, 1993; Rovithakis and Christodoulou, 1993).

Recently, a considerable amount of research effort has been directed to stability analysis and the convergence proofs of fuzzy control systems, and some results are beginning to appear in the literature. Motivated by the work of Polycarpou and Ioannou (1991) who developed adaptive controllers by using neural networks, Wang has developed similar adaptive controllers in a fuzzy logic system framework (Wang, 1993). However, he could not prove that the output error converges to zero unless the model approximation error is L_2-bounded, which is not clear to hold in a real situation. On the other hand, inspired by the work of Sanner and Slotine (1992) who proposed a direct adaptive controller by using the Gaussian radial basis functions and sliding-mode control techniques, Su and Stepanenko (1994) developed an adaptive fuzzy controller by using the fuzzy basis functions, and proved that the error converges to zero by using the switching controller with time-varying gain. However, their controller applies only to a rather restricted class of nonlinear systems that does not include strip-caster systems as a subset.

The proposed adaptive fuzzy controller adopted Wang's fuzzy control structure as one of its components. This is reported to be superior in performance to neural-network control techniques. In order to prove convergence of output error to zero, the controller introduces yet another fixed gain switching control term that compensates for model approximation error. The technique is similar to that of Su and Stepanenko, but has been extended to a wider class of nonlinear systems which includes strip-caster systems as a subset. Additionally, a nonlinear compensation term is used in this paper to eliminate disturbances due to gap and speed variations. Combining all these terms, the proposed controller is able to achieve zero steady-state error asymptotically, with robustness and an adaptation capability inherent in the adaptive fuzzy controller.

This paper is organized as follows. Section 2 introduces the strip-caster model that is to be used mainly for molten steel level control. Section 3 presents an adaptive fuzzy controller and its parameter update laws, and proves the stability of the overall closed-loop system by using the Lyapunov stability method. Section 4 shows simulation results, and Section 5 concludes the paper.

2. MOLTEN STEEL LEVEL MODEL AND OPERATION IN THE STRIP-CASTING PROCESS

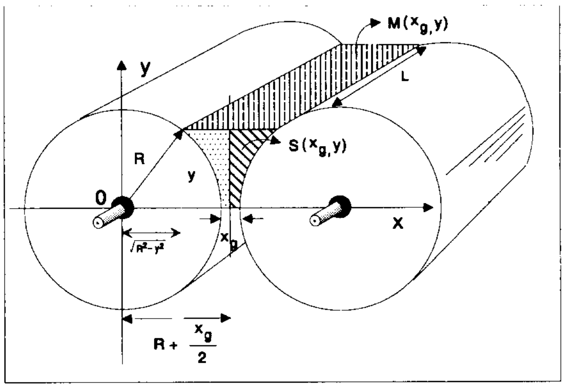

Fig. 3. Volume of molten steel filled between the twin roll cylinders.

This section develops a simple mathematical model for molten steel level control of the twin-roll strip-caster system that has been implemented in POSCO. In the development of the mathematical model, it was assumed that the molten steel is incompressible. The continuity equation of liquid steel is then described as

$$Q_{in} - Q_{out} = \frac{dV}{dt}, \tag{1}$$

where Q_{in} is the input flow into the space between roll cylinders, Q_{out} is the output flow from the roll cylinders, and V is the volume of the molten steel stored between the twin roll cylinders.

The volume V between the roll cylinders is $2SL$, where S is the shaded area as shown in Fig. 3 and L is the length of the roll cylinder.

The shaded area S is given by

$$S = \int_0^y \left[\frac{x_g}{2} + R - \sqrt{R^2 - y^2} \right] dy \tag{2}$$

where x_g is the roll gap and R is the radius of the roll cylinder.

Then the volume V is

$$V = 2\,S\,L \qquad (3)$$

and

$$\frac{dV}{dt} = \left[(x_g + 2R) - 2\sqrt{R^2 - y^2}\right] \frac{dy}{dt} L.$$

If $A_r(x_g, y)$ is defined as $[(x_g + 2R) - 2\sqrt{R^2 - y^2}]$, then eq. (1) becomes

$$\frac{dy}{dt} = \frac{1}{A_r(x_g, y)\,L}(Q_{in}(h) - Q_{out}(x_g, v_r)), \quad (4)$$
$$= \frac{1}{M(x_g, y)}(Q_{in}(h) - Q_{out}(x_g, v_r)),$$

where $M(x_g, y) = A_r(x_g, y)\,L$ and h is the opening length of the flow-control device.

Q_{in} here is proportional to the opening length h and Q_{out} is determined by using the Bernoulli equation as :

$$Q_{out}(x_g, v_r) = L\,x_g\,v_r, \qquad (5)$$

where L is the length of the roll cylinder and v_r is the roll rotation speed (Miraveto, 1988; Edwards and Willis, 1992; D'Souza, 1992).

The objective of the molten steel level control system is to regulate the molten steel-height y at the preset desired value y_d. Of course, the level y must be in $[0,\ R]$ in order not to cause any overflow above the roll cylinders, or any molten steel to pass through the roll gap unsolidified. Actual operation of a strip-caster system consists of two modes: startup operation and normal operation. The startup operating mode is the initial operating period when the molten steel starts to flow into the twin roll cylinders. During this period, the level-control algorithm is inactive and the molten steel continues to fill in the space between the roll cylinders until y reaches certain level that is close to y_d. As soon as y reaches the inside of $U_y = [y_d - \delta_y, y_d + \delta_y]$ for some small $\delta_y > 0$, then the control mode switches to normal operation and the level-control algorithm becomes active. In practice, it is important to guarantee that once the control mode is in normal operation, it continues to stay in that mode all the way to the end of the casting. In fact, when the control algorithm proposed in the next section is employed, not only is this boundedness requirement maintained, but also the level y converges to y_d asymptotically. Another important aspect of U_y is that it provides the fuzzy logic system with a compact region in which the fuzzy logic system can approximate any nonlinear function with arbitrary accuracy.

3. ADAPTIVE FUZZY CONTROL ALGORITHM FOR MOLTEN STEEL-LEVEL REGULATION

This section presents a stable adaptive fuzzy controller that regulates the height of the molten steel filled between the roll cylinders of the strip-caster mill drive system. As derived in the previous section, the basic mathematical model that describes the molten steel level y to the inflow rate Q_{in} is

$$\dot{y} = \frac{1}{M(x_g, y)}(Q_{in}(h) - Q_{out}(x_g, v_r)). \qquad (6)$$

In the discussion that follows, M is used for $M(x_g, y)$, Q_{in} for $Q_{in}(h)$, and Q_{out} for $Q_{out}(x_g, v_r)$ to simplify the notation.

If M and Q_{out} were completely known, a natural candidate for control input Q_{in} would be $Q^*_{in} = M\,K_p\,e + Q_{out}$. Substituting Q^*_{in} for Q_{in} in eq. (6), would give $\dot{e} + K_p e = 0$ where $e = y_d - y$ and $e \to 0$ as $t \to \infty$ as long as $K_p > 0$. Note here that $\dot{y}_d = 0$ since y_d is constant and K_p is a design parameter that determines the exponential convergence rate of output error $e(t) = e(0)\,exp(-K_p t)$. This type of control strategy is what is called the "feedback linearizing control strategy". However, since Q_{out} and M are not completely known in reality due to various disturbances and uncertainties, Q^*_{in} is not physically realizable. A physically realizable control input Q_{in} that is close to Q^*_{in} can be formulated when the estimated values $\hat{Q}_{out}$ and $\hat{M K_p e}$ are used for Q_{out} and $M K_p e$ respectively. Good estimates $\hat{Q}_{out}$ and $\hat{M}$ can be found when they are calculated either at the desired values (y_d, x_{gd}, v_{rd}) or at the measured values (y, x_g, v_r). In this paper, the measured values are used to get $\hat{Q}_{out}$ and $\hat{M}$. Then $\hat{Q}_{in} = \hat{Q}_{out} + \hat{M} K_p e$ would make a good controller for Q_{in} with reasonable control performance. However, in order to compensate for system nonlinearities and various disturbances that inevitably exist in the strip-caster system, an additional fuzzy control term $\tilde{M}_c K_p e$ is added to Q_{in}, where $\tilde{M}_c$ is an adaptive fuzzy logic term that approximates $\tilde{M} = M - \hat{M}$. Still, due to the estimated error $\tilde{Q}_{out} = Q_{out} - \hat{Q}_{out}$, the above $\hat{Q}_{in}$ plus a fuzzy control term is not enough to make the output error converge to zero. Thus, a switching control term u_s is added to Q_{in} to achieve $e \to 0$ as $t \to \infty$. Combining all these terms, the control input Q_{in} that is proposed in this paper becomes

$$Q_{in} = \hat{Q}_{out} + \hat{M} K_p e + u_c + u_s, \qquad (7)$$

where $u_c = \tilde{M}_c K_p e$.

3.1 *Adaptive Fuzzy Controller with Switching Control Strategy*

The fuzzy logic system used in this paper is formulated by using the singleton fuzzifier, the center-average defuzzifier, and the product inference rule. Combining all these pieces, it is of the form (Wang, 1994):

$$f(y) = \sum_{l=1}^{n_r} \theta_l \frac{\prod_{i=1}^{n} \mu_{F_i^l}}{\sum_{k=1}^{n_r} \prod_{i=1}^{n} \mu_{F_i^k}}, \tag{8}$$

where n_r is the number of linguistic rules, n is the number of states, $\mu_{F_i^l}$'s are the membership functions of input fuzzy sets and θ_l's are the values in the output universe of discourse at which the membership functions of output fuzzy sets attain their maximum values.

It is known from the Universal Approximation Theorem that for any given real continuous function $F(y)$ on a compact set $U \subset R$ and arbitrary $\epsilon > 0$, there exists a fuzzy logic system f in the form of eq. (8) such that $\sup_{y \in U} |F(y) - f(y)| \leq \epsilon$. Also, the fuzzy logic system (8) can be viewed as the fuzzy basis function expansion $f(y) = \sum_{l=1}^{n_r} \theta_l \xi_l(y) = \theta^T \xi(y)$, where $\xi_l(y) = \frac{\prod_{i=1}^{n} \mu_{F_i^l}}{\sum_{k=1}^{n_r} \prod_{i=1}^{n} \mu_{F_i^k}}$ is the fuzzy basis functions, $\theta^T = (\theta_1, \ldots, \theta_{n_r})$, and $\xi^T = (\xi_1(y), \ldots, \xi_{n_r}(y))$. When the parameters are all fixed in $\xi_l(y)$, then the fuzzy logic system is in the regressor form, which is linear with respect to θ, and an appropriate parameter update law can be designed to estimate θ. Thus $\xi_l(y)$ will be selected a priori and the fuzzy basis function approach will be used in this paper.

Assuming that the Q_{out} term is effectively canceled by the compensation term $\hat{Q}_{out}$, the role of $\tilde{M}_c(y|\theta)$ here is to estimate $\tilde{M}$ as closely as possible. Then, the adaptive fuzzy control term $\tilde{M}_c(y|\theta)$ is defined as $\theta^T \xi(y)$ with an appropriate fuzzy basis function vector $\xi(y)$ which is determined from a reasonable number of fuzzy rule-bases. If the number of fuzzy rule-bases is too high, then the classical Gram-schmidt orthogonal least-squares approach can be used, for example, to select the most significant fuzzy basis functions.

If the optimal parameter vector θ^* is defined as the vector θ that makes $|\tilde{M}_c(y|\theta) - \tilde{M}|$ minimum in the compact set U_y, then it is known from the Universal Approximation Theorem that there is an upper bound ϵ such that $|\tilde{M}_c(y|\theta^*) - \tilde{M}| \leq \epsilon$ uniformly in the compact set U_y. Let $\Delta\tilde{M} = \tilde{M} - \tilde{M}_c(y|\theta^*)$. Then clearly $|\Delta\tilde{M}| \leq \epsilon$.

Substituting (7) into (6) and noting that $\dot{y} = -\dot{e}$,

$$\dot{y} = \frac{1}{M}(Q_{in} - Q_{out}) \tag{9}$$

$$= \frac{1}{M}\left(\hat{Q}_{out} + \hat{M}K_p e + \tilde{M}_c K_p e + u_s - Q_{out}\right)$$

and

$$\dot{e} = -\frac{\hat{M} + \tilde{M}_c}{M} K_p e + \frac{1}{M}(\tilde{Q}_{out} - u_s). \tag{10}$$

Now, let $u_s = w\, sgn(e)$, where $sgn(e)$ is 1 when $e > 0$ and -1 when $e < 0$ and w is an upper bound of $|\tilde{Q}_{out}| = |Q_{out} - \hat{Q}_{out}|$. In practice, since Q_{out} can be estimated accurately from the geometry of the roll cylinders, it is appropriate to assume that there exists $w \geq 0$ which is very small.

Then, since $\hat{M} = M - \tilde{M}$, equation (10) becomes

$$\begin{aligned}
\dot{e} &= -K_p e + \frac{1}{M}(\tilde{Q}_{out} + \tilde{M}K_p e - \tilde{M}_c K_p e \\
&\quad -w\, sgn(e)) \\
&= -K_p e + \frac{1}{M}(\tilde{Q}_{out} + \Delta\tilde{M}K_p e + \tilde{M}_c(y|\theta^*)K_p e \\
&\quad -\tilde{M}_c K_p e - w\, sgn(e)) \\
&= -K_p e + \frac{1}{M}(\tilde{Q}_{out} + \Delta\tilde{M}K_p e + \phi^T \xi K_p e \\
&\quad -w\, sgn(e)),
\end{aligned} \tag{11}$$

where $\phi = \theta^* - \theta$ and ξ is the fuzzy basis function vector.

Choosing a Lyapunov function candidate

$$V = \frac{M}{2}e^2 + \frac{1}{2\gamma}\phi^T \phi, \tag{12}$$

gives

$$\begin{aligned}
\dot{V} &= \frac{\dot{M}}{2}e^2 + M e\dot{e} + \frac{1}{\gamma}\phi^T \dot{\phi} \\
&= \frac{\dot{M}}{2}e^2 - MK_p e^2 + \tilde{Q}_{out}\, e + \Delta\tilde{M}K_p e^2 \\
&\quad +\phi^T \xi K_p e^2 - w|e| + \frac{1}{\gamma}\phi^T \dot{\phi} \\
&= \frac{\dot{M}}{2}e^2 - (M - \Delta\tilde{M})K_p e^2 + \frac{\phi^T}{\gamma}(\gamma \xi K_p e^2 + \dot{\phi}) \\
&\quad +\tilde{Q}_{out}\, e - w|e|.
\end{aligned} \tag{13}$$

By choosing the adaptive law $\dot{\theta} = -\dot{\phi} = \gamma \xi K_p e^2$,

$$\begin{aligned}
\dot{V} &= -(M - \Delta\tilde{M} - \frac{\dot{M}}{2K_p})K_p e^2 \\
&\quad +\tilde{Q}_{out} e - w|e| \\
&\leq -(M - \Delta\tilde{M} - \frac{\dot{M}}{2K_p})K_p e^2.
\end{aligned} \tag{14}$$

Note here that $\dot{M}$ is bounded because y and $\dot{y}$ are bounded. y is bounded since $y \in U_y$, and $\dot{y}$ is bounded since Q_{in} is bounded due to the geometric constraints of the tundish and the flow-control device. Therefore, by choosing K_p and the fuzzy rule bases appropriately in (8), $(M-\Delta\tilde{M}-\frac{\dot{M}}{2K_p}) \geq 0$. In fact, it follows that

$$\dot{V} \leq -\kappa e^2 \leq 0, \quad (15)$$

where $\kappa = (M^L - \epsilon - \frac{\dot{M}^U}{2K_p})K_p \geq 0$,
$M^L = \min_{y\in U_y}|M|$, and $\dot{M}^U = \sup_{t\geq 0}|\dot{M}|$.

The asymptotic convergence of the tracking error e can be given by applying the Barbalat's lemma (Slotine and Li, 1991) to the continuous and non-negative function $V_1(t)$ as follows :

$$V_1(t) = V(t) - \int_0^t (\dot{V}(\tau) + \kappa e^2(\tau))d\tau, \quad (16)$$

with $\dot{V}_1(t) = -\kappa e^2 \leq 0$. It can easily be shown that every term in the right-hand side of (11) is bounded, hence $\dot{e}(t)$ is bounded and $V_1(t)$ is uniformly continuous. Since $V_1(t)$ is bounded below by 0 and $\dot{V}_1(t) = -\kappa e^2 \leq 0$ for all t, the use of Barbalat's lemma proves that $\dot{V}_1(t) \to 0$ and $e \to 0$ as $t \to \infty$ (Slotine and Li, 1991).

Remark 1: From the twin roll geometry of the strip-caster system, the incremental upper surface area $\tilde{M}$ is bounded above and below as long as $y \in U_y$. Thus, it is reasonable to limit θ in some compact region set U_θ. In case θ tries to pass outside U_θ, the projection operator is used to keep θ in U_θ. Taking the projection operator into account, the update algorithm for θ is modified as:

$$\dot{\theta} = \begin{cases} \gamma\xi K_p e^2 & \text{if } (\theta \in U_\theta) \text{ or if } (|\theta| = U_\theta \\ & \text{and } \theta^T\xi \leq 0) \\ P\{\gamma\xi K_p e^2\} & \text{if } (|\theta| = U_\theta \text{ and } \theta^T\xi > 0), \end{cases}$$

where the projection operator $P\{*\}$ is defined as

$$P\{\gamma\xi K_p e^2\} = \gamma\xi K_p e^2 - \gamma K_p e^2 \frac{\theta\theta^T\xi}{|\theta|^2}.$$

Even for this parameter-update law, the same asymptotic stability conclusion can be drawn by using a similar procedure to that of Wang (1994).

Remark 2:
The adaptive fuzzy controller is derived, based on the premise that $y \in U_y$ and $|\tilde{M}_c(y|\theta^*) - \tilde{M}| \leq \epsilon$ continues to hold by the Universal Approximation Theorem. Thus, it is important to make sure that y stays in U_y all the time. From eq. (12) and eq. (15),

$$\frac{M}{2}e^2 \leq V(t) \leq V(0) = \frac{M}{2}e^2(0) + \frac{1}{2\gamma}\phi^T(0)\phi(0),$$

where $V(0)$ is the value of V at $t = 0$, and

$$|e(t)| \leq \sqrt{e^2(0) + \frac{1}{\gamma M^L}\phi^T(0)\phi(0)}.$$

Thus, the molten steel level y always stays within $y_d \pm \sqrt{e^2(0) + \frac{1}{\gamma M^L}\phi^T(0)\phi(0)}$.

Remark 3:
$u_s = w\,sgn(e)$ is a switching controller action which changes its sign according to that of e to eliminate the effect of the approximation error $\tilde{Q}_{out}$. Since $\hat{Q}_{out}$ is calculated from the measured roll gap and the roll rotation speed values, $\tilde{Q}_{out}$ is usually very small, and its upper bound w can be made very small. In cases where $\hat{Q}_{out}$ computes Q_{out} precisely and $\tilde{Q}_{out} = 0$, u_s can be set equal to zero, leading to the same asymptotic stability conclusion as derived above. If u_s is not used even if $\tilde{Q}_{out} \neq 0$, a reasonable result is still obtained: $|e(t)| \leq (1+\epsilon)\varrho w$ for some $\varrho > 0$ and $\epsilon > 0$ (Su and Stepanenko, 1994; Slotine and Li, 1991). This time, however, the asymptotic stability cannot be guaranteed theoretically.

4. SIMULATION

In order to demonstrate the feasibility and features of the developed controller, several simulations have been performed, and are described in this section. First of all, the adaptive fuzzy control law $\tilde{M}_c(y|\theta)$ is designed, based on the following seven linguistic rules initially set up either from the geometry of the twin roll system or from the off-line fuzzy rule-generation method. The initial rules are:

(1) If level error is negative big, then output is θ_1,
(2) If level error is negative medium, then output is θ_2,
(3) If level error is negative small, then output is θ_3,
(4) If level error is zero, then output is θ_4,
(5) If level error is positive small, then output is θ_5,
(6) If level error is positive medium, then output is θ_6, and
(7) If level error is positive big, then output is θ_7,

where the θ_l's are to be updated by the adaptation algorithm. The membership functions that have been employed in each rule are shown in Fig. 4.

In the simulations, it was assumed that the gap and the velocity disturbance signals are periodic because the common roll eccentricity disturbance that occurs in the rolling process is nearly periodic. The proposed controller is tested on the strip-caster model described in Section 2 and compared with the conventional PI controller. Fig. 5 shows the architecture of the proposed controller.

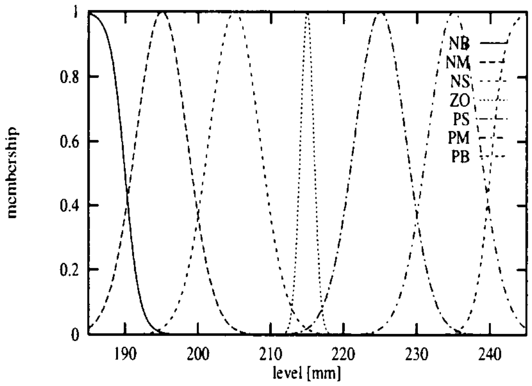

Fig. 4. Adaptive fuzzy membership function

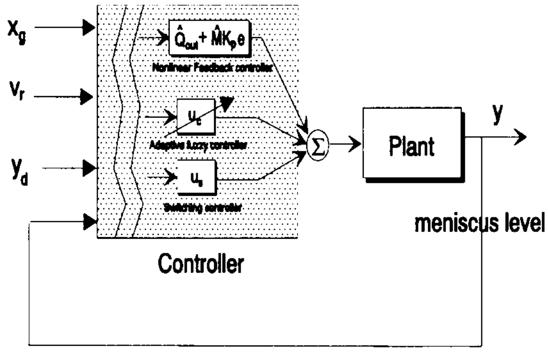

Fig. 5. Adaptive fuzzy control system

The gap disturbance that has been employed in the simulations is shown in Fig. 6, which reflects the roll eccentricity effects and contains up to the third harmonics of the roll rotating frequency.

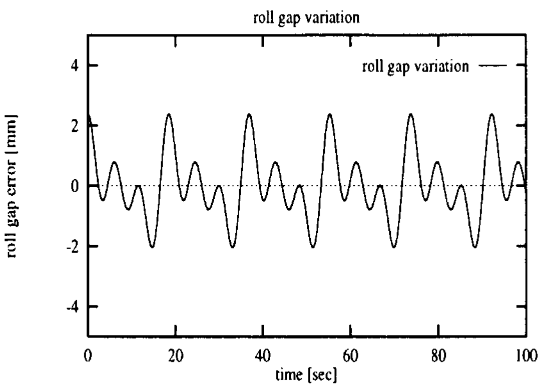

Fig. 6. Roll gap variation

The angular speed disturbance is set up as $sin(2\pi t/3)$, which simulates the control-loop actions of the rolling force. The sampling time is chosen as 1 ms. The desired values of gap, level, and velocity were chosen as 3 mm, 215 mm, and 13 mpm, respectively. The proportional and integral gains of the conventional PI controller are given as 2 and 0.0013, respectively. The performance of the controller with these gains is nearly optimum with the PI control structure. In the figures, PI denotes a conventional PI controller, Wang's denotes Wang's adaptive fuzzy controller and Proposed denotes the proposed adaptive fuzzy controller respectively. PI plus Compensation denotes the PI controller with nonlinear compensation $\hat{Q}_{out}$. The model errors represent the estimation errors $\tilde{M}$ and $\tilde{Q}_{out}$ of M and Q_{out} respectively.

To check if the good results developed in the previous section are valid in a real situation, the following data were borrowed from POSCO's pilot strip-caster. The radius and width of the roll cylinder are 375 $[mm]$ and 350 $[mm]$ respectively. The desired molten steel level y_d is 215$[mm]$, and the radius of the compact set U_y is 30 $[mm]$. Thus, y_{min} = 185 $[mm]$ and y_{max} = 245 $[mm]$ in normal operation. $Q_{in,max} = 1e-3\,[m^3/sec]$ and $Q_{in,min} = 0\,[m^3/sec]$ by design of the tundish and the flow control device. When the roll gap varies by about 2 mm about the desired roll gap, the maximum and minimum values of Q_{out} are respectively $3.792e-4\,[m^3/sec]$ and $7.583e-5\,[m^3/sec]$. By using these data, the following values are obtained :

$$\dot{y}_{max} = 20\,[\frac{mm}{sec}], \quad \dot{y}_{min} = -8.4\,[\frac{mm}{sec}],$$
$$M_{max} = 0.0517\,[m^2], \quad M_{min} = 0.04514\,[m^2],$$
$$\dot{M}_{max} = 0.0288\,[\frac{m^2}{sec}], \quad \dot{M}_{min} = -0.0116\,[\frac{m^2}{sec}],$$
$$M_{min} - \epsilon - \frac{\dot{M}_{max}}{2K_p} \geq 0,$$
$$0.038 - \epsilon \geq 0,$$

where $K_p = 2$.

Therefore, the fuzzy logic system $\tilde{M}_c$ should be designed so as to satisfy $\epsilon \leq 0.038 = 38000\,[mm^2]$. This can easily be satisfied with the fuzzy logic system, since the value 0.038 is about 84% of M_{min}

Simulation 1: the system without disturbance (Fig. 7).

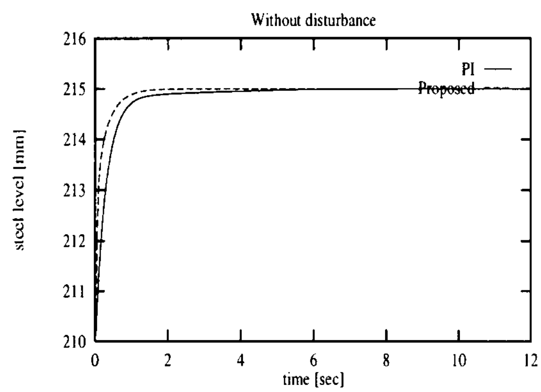

Fig. 7. Simulation without disturbance

In this case, the proposed controller achieves a shorter settling time than the conventional PI controller does.

Simulation 2: the system with a parameter change after some time (Fig. 8).
The parameter change could happen when the flow rate k_f changes. k_f is set up to change after 6 sec in the simulation. The value of k_f is changed 3 times larger than the original value. The simulation result shows that the proposed adaptive controller adapts to parameter changes much faster than the PI controller does.

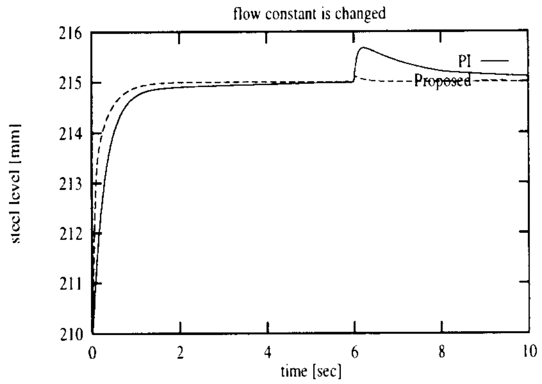

Fig. 8. Simulation with parameter change

Simulation 3: the system with disturbances (Figs 9 and 10).
In this case, the simulation results show that the adaptive fuzzy controller responds quickly to system variations, whereas the PI controller does not. Fig. 9 shows the performance of Wang's adaptive fuzzy controller, where the nonlinear compensation term and the switching control term do not exist, and Fig. 10 shows the performance of proposed controller. These two figures clearly show the effectiveness of the nonlinear compensation term and the switching control term.

Simulation 4: the system with disturbance plus 30% of system model errors (Fig. 11).
Fig. 11 shows the performance of the controllers when both the PI and adaptive fuzzy controller use nonlinear compensation term $\hat{Q}_{out}$ and there are 30% system model errors on $\tilde{M}$ and $\tilde{Q}_{out}$. Clearly, the proposed adaptive fuzzy controller compensates for the model errors very well.

Simulation 5: the system with disturbances, 30% of system model errors, k_f change, and sensor noise (Figs 12 and 13).
In this case, k_f, roll gap and speed variations, and sensor noise terms are simultaneously added. As the sensor noise, a white noise of variance 2 is added to the system. The sensor noise here reflects on the disturbances such as slugs and smoke that exist on the molten steel surface between the roll cylinders. Since a laser sensor is used for level measurement in POSCO's strip-caster plant, these disturbances are reflected as sensor noise on the input data.

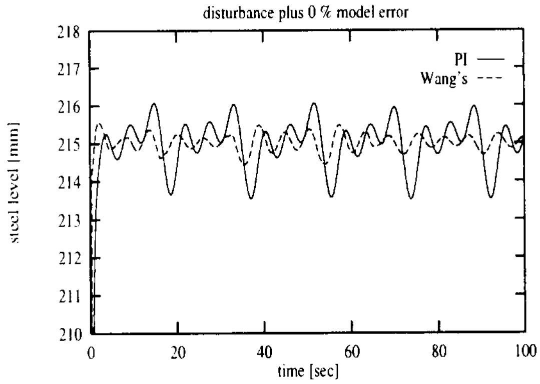

Fig. 9. Simulation with disturbances plus 0% model errors

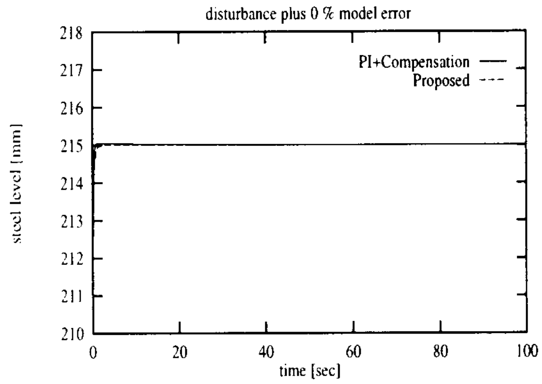

Fig. 10. Simulation with disturbance plus 0% model errors

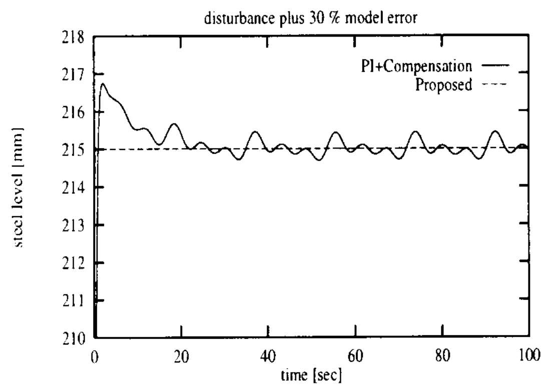

Fig. 11. Simulation with disturbance plus 30% model errors

Note that in Fig. 12, the conventional PI control has larger peak than the PI plus compensation.

Clearly, the proposed controller demonstrates much better performance than the PI-type controller. The PI controller performs well when there is no noise, and no parameter changes. Its performance degrades, however, when uncertainties and/or parameter changes are introduced in the system. Although the proposed adaptive fuzzy controller was designed using simple rules, it shows good results in all the simulation studies. Even with the large model errors, the proposed controller performs well.

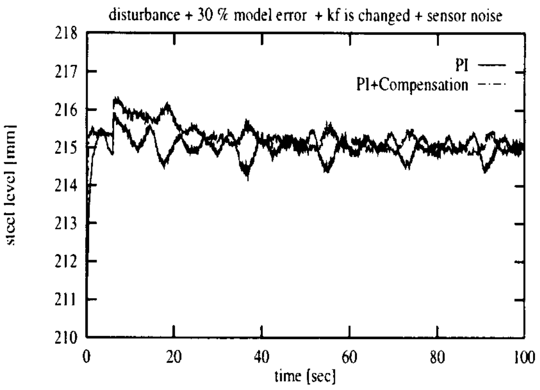

Fig. 12. Simulation with disturbance + 30% model errors + k_f change + sensor noise

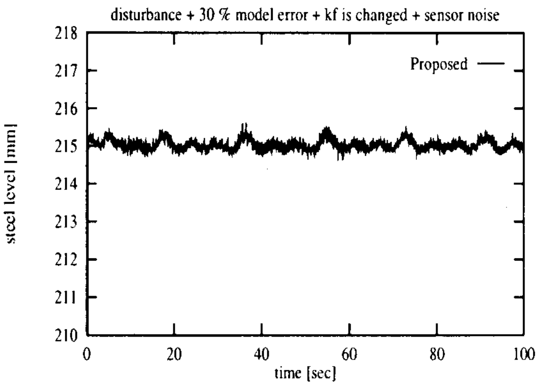

Fig. 13. Simulation with disturbance + 30% model errors + k_f change + sensor noise

5. CONCLUSION

An adaptive fuzzy controller with nonlinear compensation and a switching control strategy is presented, to regulate the molten steel level of a strip-caster system. The proposed controller is robust and adaptive, due to its fuzzy representation of the controller and its training capability. Further, the closed-loop system with the proposed controller guarantees that the molten steel level converges to the preset desired value asymptotically. A similar adaptive fuzzy control approach can be employed to regulate the roll gap in the gap positioning system, as well as the roll force in the force-control system. Since the three control units: level-control unit, gap positioning unit, and force-control unit are in fact a coupled nonlinear system, the design of an adaptive fuzzy controller applied to this coupled system would represent a challenging but rewarding task.

ACKNOWLEDGEMENTS

The authors wish to acknowledge the generous support from the Korea Science and Engineering Foundation through the Automation Research Center at POSTECH.

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