Hybrid Algorithm With Fuzzy System and Conventional PI Control for the Temperature Control of TV Glass Furnace

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***Abstract*—This paper presents a practical application of fuzzy logic to the temperature control of glass melting furnace for television picture tube. Because of the complexity and nonlinearity, temperature control of glass melting furnace is still delegated to human operators. Though the overall characteristics of glass melting furnace are complex and nonlinear, one part of the furnace characteristics can be modeled as a linear system. The linear part of the furnace dynamics is modeled with a first-order-plus-dead-time (FOPDT) system and a proportional integral (PI) controller is applied to the FOPDT model. The remaining complex and nonlinear part of the furnace dynamics is covered by the fuzzy system, i.e., rules of human experts. The PI controller and fuzzy system are combined in cascade. The PI controller is applied to maintain the left-right symmetric operation of the furnace, and a linear regression is used for the temperature trend to determine input to the fuzzy system in order to overcome the high frequency disturbance. The proposed hybrid controller is implemented in Samsung–Corning Company to demonstrate the effectiveness of the proposed control algorithm.**

***Index Terms*—Cascade control, first-order-plus-dead-time (FOPDT) System, fuzzy systems, glass furnace, temperature control.**

I. Introduction

THE MAIN idea of fuzzy logic control is to use the control ability of human being which includes experience and intuition of human experts. From this perspective, the temperature control of glass melting furnace can be a good application area for fuzzy logic control. Deviation of furnace temperature from a desirable condition should be kept to be within an operation tolerance so as to prevent impairment in the quality of molten glass. However, all of the phenomena that occur in the glass melting furnace have not been explained fully because of their complexity. This kind of furnace management is still delegated to a furnace operator.

Haber *et al.* [1] presented a modeling and control of a glass melting furnace. They elaborated a three input and output model with experimental data and applied a self-tuning regulator to the glass level control. Aoki *et al.* [2] proposed two application methods of fuzzy logic control to a glass melting furnace. They used the estimated plant output in the fuzzy PI controller and modified the fuzzy control action based on the estimated plant output to overcome the dead time characteristics of the furnace. Hadjili *et al.* [3] presented the identification of fuzzy models for a glass furnace process. They investigated three approaches, where the basic structures are Takagi–Sugeno fuzzy system for the gas input to the molten glass temperature. The main theme of this paper is to combine the benefits of both the conventional control and the fuzzy logic control. This kind of integrating approach which combines the fuzzy control with conventional control has been made by several researchers. Kim *et al.* [4] proposed a method where the setpoint of a conventional proportional integral derivative (PID) controller is precompensated by a fuzzy system to achieve better performance. They successfully applied the precompensation algorithm to control a dc servomoter. Wu and Liu [5] proposed a method for fuzzy control design with sliding modes. They used the fuzzy rule of Takagi–Sugeno type, and determined the parameters of fuzzy rules to satisfy both reaching and sliding conditions. And, they applied it to an inverted pendulum hinged to a rotating disk. Lin and Gau [6] proposed a hybrid approach integrating feedback linearization and fuzzy control for conical magnetic bearings. They presented the simulation results where the hybrid controller improves the transient performance and robustness better than the feedback linearization controller alone. Recently, Dussud *et al.* [7] presented another integrating approach of fuzzy controller and conventional PID controller for casting mold level control. The PID controller and fuzzy controller evaluate the control action simultaneously, and under normal condition the PID controller is activated while the fuzzy controller is activated under abnormal conditions.

In this paper, we present an integrating approach of fuzzy control and conventional proportional integral (PI) control, in order to take advantage of the characteristics of the furnace dynamics. Although the overall characteristics of glass melting furnace is complex and nonlinear, crown temperature of the furnace can be modeled as a linear system. If a system is a well behaving linear system, then the conventional controller is very effective and easy to implement. Therefore, the dynamics of the furnace is divided into linear and nonlinear parts. The crown temperature is controlled by the conventional PI controller. On the other hand, the remaining complex and nonlinear part of the furnace is controlled by the fuzzy system, i.e., the rules of human experts.

The organization of this paper is as follows: an overview of the TV glass furnace operation and temperature control is presented

Manuscript received October 29, 1999; revised August 9, 2002. Manuscript received in final form February 17, 2003. Recommended by Associate Editor K. Hunt. This work was supported in part by the Information and Telecommunication Research Institute (ITRI), Chung-Ang University, Seoul, Korea.

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Digital Object Identifier 10.1109/TCST.2003.813385

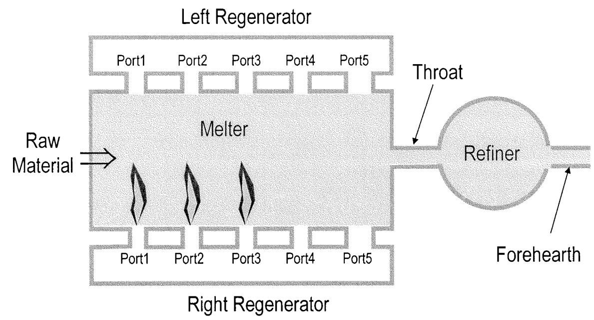

Fig. 1. Birdseye section structure of a glass melting furnace.

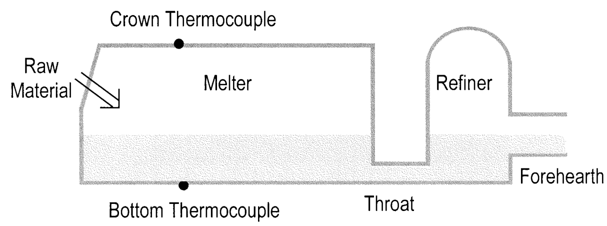

Fig. 2. Longisection structure of glass melting furnace.

in Section II. The overall concept of the hybrid temperature control, crown temperature controller design and the design of fuzzy system to generate setpoint for the crown temperature are presented in Section III. The hybrid temperature controller was implemented in a 300-ton/24-h glass melting furnace in Samsung–Corning Company, Suwon, Korea, and compared with the manual operation in Section IV. Finally, conclusions are drawn and a recommendation for future research is given in Section V.

II. Temperature Control of a TV Glass Furnace

Figs. 1 and 2 show a structure of a furnace, from birdseye section and longisection, respectively. In the figures, the gray regions represent the molten glass. The raw material fed into the melter is changed in its chemical characteristics to become molten glass and flows into the direction of refiner. Two regenerators are connected with a melter. In Fig. 1, ports 1–3 are heating ports which supply the fuel and combustion air. The firing and air flow directions are reversed form right to left in the next half cycle. The reversal takes place usually in every 20 min. For example, the right regenerator supplies the fuel and the air in the first 20 min, while the left regenerator is extinguished, and in the next 20 min, the left regenerator supplies the fuel and air while the right regenerator is extinguished. In the refiner, the temperature of molten glass is adjusted to a suitable temperature and impurities in the molten glass are settled to the bottom for product forming.

Temperature control problem in a glass melting furnace is to maintain the temperature of molten glass by adjusting the amount of fuel to ports 1–3. However, all of the phenomena that occur in the glass melting furnace have not been explained fully because of their complexity and various disturbances [1]–[3]. Some of the disturbances are the changes in the composition of raw materials and additional additives for glass coloring. The change in the glass melting load influences the temperature control. Since outside air is directly injected into the melter as combustion air, weather conditions, i.e., atmospheric temperature and humidity, affect the temperature in the melter. Another difficulty is the internal stream lines of molten glass in the melter. The heat supplied through the surface of molten glass causes a three-dimensional convection current. This convection current represents a very complex behavior as a result of the molten glass flowing toward the refiner. These kinds of disturbances result in the variations in the steady-state fuel consumption. Though the effect of each disturbance is not quantitatively analyzed, the maximum variation reaches to about 25% in fuel consumption in maintaining a constant molten glass temperature. When the furnace operation is not proper, it results mostly in the fluctuation of the furnace temperature which increase the number and size of impurities in the molten glass.

Many thermocouples are installed in the roof (or crown) and bottom of a melter to estimate its thermal condition. The crown thermocouples are installed beneath the roof to sense the atmospheric temperature inside of the melter due to the radiation energy. The bottom thermocouples are installed beneath the bottom of the furnace to measure the temperature of the molten glass. The furnace is kept to maintain the highest temperature around port 2 which is called hot spot of the melter. The raw material is changed to molten glass around the port 2 area. Therefore, the most important thermocouples are the crown and bottom thermocouples installed around port 2 of the melter in Fig. 2.

The temperature characteristics in the two sensors are quite different. The crown temperature directly reacts to fuel consumption, because it senses the atmospheric temperature in the melter, while the bottom temperature reacts through the molten glass. Disturbances such as atmospheric temperature, surface condition of the molten glass and the mixing condition of raw materials also quickly affect the crown temperature [1]. On the other hand, the bottom temperature shows the complex behavior of nonlinear and time-varying characteristics due to the transport delay and the internal flow of the molten glass and various kinds of disturbances [2]. The final goal of the temperature control problem is to maintain the glass temperature, i.e., the bottom temperature by adjusting the amount of fuel into ports 1–3.

III. Design of Hybrid Control Algorithm

A. *Overall Concept of the Hybrid Temperature Control*

The basic concept of the proposed controller is to implement the control ability of human experts in automatic control. Therefore, understanding control strategy of human operator is very important. Human operators control the furnace based on the observation of furnace temperatures, the crown and bottom temperatures, simultaneously. They observe the bottom and the crown temperatures, and with the two readings adjust the amount of the fuel consumption.

Fuel is distributed among ports with predefined ratios as follows:

$$\begin{aligned}\Delta u_1 &= r_1 \Delta u_t \\ \Delta u_2 &= r_2 \Delta u_t \\ \Delta u_3 &= r_3 \Delta u_t \qquad (1)\end{aligned}$$

where r_1, r_2, and r_3 are the fuel ratio constants such that $r_1 + r_2 + r_3 = 1$; Δu_1, Δu_2, and Δu_3 are the fuel changes in ports

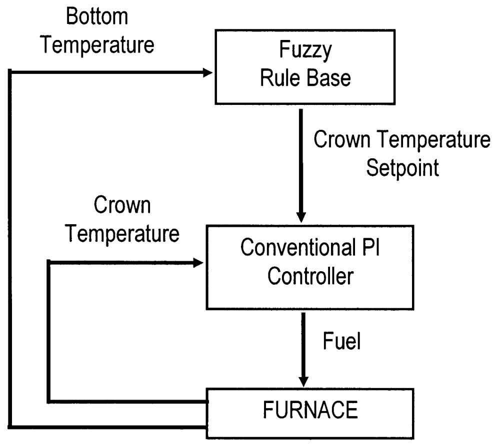

Fig. 3. Hybrid fuzzy-PI controller.

Fig. 4. Comparison of the FOPDT model with real crown temperature data.

1, 2 and 3, respectively; and Δu_t is the total fuel change. When a furnace is newly installed, the furnace operator tests various ratio constants. Typical initial values for r_1, r_2, and r_3 are 0.3, 0.4, and 0.3, respectively. From these initial values, fine tuning is done around those values by trial and error until good quality of molten glass is produced consistently for several days. Since port 2 is the hotspot with the highest temperature in the melter, r_2 should be larger than r_1 and r_3. After the ratio constants are determined, they are not changed much during the life of the furnace. Thus, the furnace can be regarded as a single input system with the total fuel u_t as the input, while the real plant has three inputs, i.e., the fuel into ports 1–3.

In this paper, an attempt is made to combine the benefits of both the conventional PI controller and the fuzzy logic controller. It can be shown that the dynamics of the crown temperature with respect to fuel can be modeled simply as a linear first-order-plus-dead-time (FOPDT) system [9]. The time constant of the crown temperature is 5–8 min [1]; however, the dynamics of the bottom temperature with respect to the crown temperature and fuel is not linear and is difficult to model. Though the bottom temperature is roughly increased (decreased) as the crown temperature is increased (decreased), it is difficult to model with simple fixed dead time, time constant, or gain. The bottom temperature typically showed a dead time of 1 h and the time constant of 1–5 h [2], [3]. Since the dynamics of the crown temperature is fast, it is not easy to maintain it manually. However, its control can be effectively achieved by a conventional PI controller based on the FOPDT model [8], [9]. Although the fuzzy logic controller shows good performance in many applications, it can be successfully applied, especially to an ill-defined system. For a well-defined linear system, however, the conventional linear controller is more effective and easier to implement.

Fig. 3 shows the hybrid structure of the proposed controller. Two controllers, fuzzy system and PI controller, are connected in cascade. The bottom temperature is fed back to the fuzzy system, then an appropriate setpoint for the crown temperature that will maintain the bottom temperature is set by the fuzzy system. The crown temperature is then controlled by the PI controller which is designed based on the FOPDT model. In Fig. 3, the fuzzy rule base is obtained from human experts. After implementing the PI controller first, the human operator sets the crown temperature setpoint based on the experience of manual operation. The linguistic information of this semiautomatic operation is formed as a fuzzy rule base.

This proposed control structure is more or less equivalent to cascade control structure [9]. The inner or slave loop is the PI controller, and its input is crown temperature and its output is the fuel. The outer or master loop is the fuzzy system, and its input is bottom temperature and its output is the setpoint of the crown temperature. However, a good quality of transfer function model from crown temperature to bottom temperature is necessary to apply the conventional cascade control to the furnace. Though it is possible to use an approximate model, it is more reliable to use the experience of the furnace operator than to use a poor quality model, especially in a production plant.

B. Design of a Crown Temperature Controller

A conventional PI controller is designed base on the linear model of the crown temperature y_c. It can be shown that the crown temperature can be adequately modeled with a FOPDT system as follows [9]:

$$G(s) = \frac{Yc(s)}{U(s)} = \frac{Ke^{-Ts}}{\tau s + 1} \tag{2}$$

where

- y_c crown temperature;
- u total amount of fuel;
- K steady-state gain;
- T process dead time;
- τ time constant.

Then, the modeling problem is to determine the model parameters, K, T, and τ. In this paper, an *ad hoc* offline trial and error approach was performed to determine the model parameters. At first, the values of the three parameters are assumed. Then, it is possible to compare the crown temperature data with model output using the same input u. Based on the physical understanding of K, T, and τ, the parameter values can be updated manually to match the model output to the real crown temperature data. This parameter update is done iteratively with many fuel-crown temperature data sets.

Fig. 4 shows a comparison between the plant output (real crown temperature data) and the model output data. In Fig. 4, the solid line is the real crown temperature data and the dashed line is the output of the FOPDT model for the same fuel input. The valleys at every 20-min interval represent the reversal of the left-right firings. That is, during the first 20 min the left flames heat the crown temperature while the right flames are extinguished. On the other hand, during the second 20 min the right flames heat the crown temperature while the left flames are extinguished. This process is repeated in every 40 min. Normally, there is a 6–9-min interval from the time that the flames of the left (right) regenerator are extinguished to the time that the flames of the right (left) regenerator supply the heat. This reversal of the flames can be regarded as a step test input to determine the steady-state gain, process dead time and the time constant. From the temperature rise curve, the rise time and steady-state gain of the FOPDT model can be determined, and using the time when the temperature starts to drop, the dead time of the FOPDT model can also be determined appropriately. Fig. 4 shows that the crown temperature can be modeled adequately with the FOPDT system.

Since the dead time is smaller than the time constant, the FOPDT system can be controlled effectively by a PI controller [8], [9]. Another reason to use PI control is that the PI controller can be easily understood by the furnace operators because of its simple structure. Usually the furnace operator is not a control engineer. However, with simple education, the operator can easily understand and predict the control action of the PI controller. The PI controller is tuned by minimizing Integral of the time-weighted absolute value of the error (ITAE) [8], [9]. The PI controller is described as follows:

$$G_c(s) = K_c\left(1 + \frac{1}{\tau_i s}\right) \tag{3}$$

where K_C is the proportional gain and τ_i is the reset time. The proportional gain and the reset time are determined by minimizing the ITAE performance index

$$\text{ITAE} = \int_0^\infty t|e(t)|\,dt \tag{4}$$

where $e(t) = y_{\text{setpoint}} - y(t)$. Calculation shows the following results for the system in (2) [9]:

$$K_c = \frac{0.859}{K}\left(\frac{T}{\tau}\right)^{-0.977} \tag{5}$$

$$\tau_i = \frac{\tau}{0.674}\left(\frac{T}{\tau}\right)^{0.686}. \tag{6}$$

One of the difficulties in the control of a furnace is the left-right symmetric operation of the furnace firing system to maintain the heat energy supply from the left and the right flames to be the same. If not controlled properly, the molten glass flows in an asymmetric manner, resulting in undesired effects in the furnace operation and in the quality of the molten glass. For example, a simple burner tip change in the left or in the right side could cause an asymmetric problem. When the tip angle of a replaced burner is changed from the previous position, the three-dimensional (3-D) flame angle to the melter is changed, and the crown temperature is influenced directly. Because the setpoint of the crown temperature in automatic control is fixed for both the left and right firings, this results in an asymmetric heat energy supply in an effort to maintain the crown temperature uniform. Therefore, its sustained operation could stress the furnace severely.

Because of the symmetric structure of the furnace, the dynamics of crown temperature from left or right flames is identical as can be seen in Fig. 4, and the PI controller (3) can be applied to both left and right flames. In practice, however, the PI controller is applied only to control flames in one side of the furnace to minimize the asymmetric furnace operation, and a fixed controller with constant input is applied in the opposite side. The constant value is the average of the PI controller input applied during the immediate past half cycle. Because of the left-right reversal, each controller is activated only for half cycle alternately, and when one controller is activated the other controller is at rest. When the PI controller is applied to the left side, for example, the control action for a cycle, 40 min or 2400 s, can be described as follows:

$$u_{\text{left}}(t) = \begin{cases} K_c\left(e(t) + \dfrac{1}{\tau_i}\displaystyle\int e(t)\,dt\right), \\ \quad \text{for } 0 \le t < 1200 \text{ s} \\ 0, \qquad \text{for } 1200 \le t < 2400 \text{ s} \end{cases} \tag{7}$$

$$u_{\text{right}}(t) = \begin{cases} 0, \qquad \text{for } \le t < 1200 \text{ s} \\ \text{displaystyle}\frac{1}{1200}\displaystyle\int_0^{1200} u_{\text{left}}(t)\,dt, \\ \qquad\qquad \text{for } 1200 \le t < 2400 \text{ s} \end{cases} \tag{8}$$

where u_{left} and u_{right} are the amounts of fuel to the left and right sides, respectively. In this operation, the heat energy in both sides do not deviate too much from each other and this one-side control can maintain the symmetric flow of molten glass in the long-term operation of the furnace. The one-side control can be applied to either side, left or right, because of the symmetric structure of the furnace. When the flame condition of a controlled side changes, though it is not usual, the operator can switch the side on-line without stopping the automatic controller.

C. Design of Fuzzy System

The role of the fuzzy system is to generate the setpoint for the crown temperature, which reflects the bottom temperature. We first implemented the crown temperature controller (7) and (8), inner loops, to the furnace. Then, the furnace operator observes the bottom temperature and manipulates the setpoint for the crown temperature instead of the amount of fuel. From the experience of this semiautomatic operation and the manual operation of human operator, a linguistic information is formed as a fuzzy rule base.

In a cascade control structure, an important consideration is that the outer loop must be slower than the inner loop [9]. In our case, the crown temperature setpoint should be updated after the inner loop compensates for a disturbance to the crown temperature. Therefore, considering the fact that the time constant of the crown temperature is 5–8 min, the sampling time of fuzzy system is 10 min, i.e., the crown temperature setpoint is fixed for 10 min.

The fuzzy controller follows a classic pattern. The inputs to the fuzzy inference system are the bottom temperature error

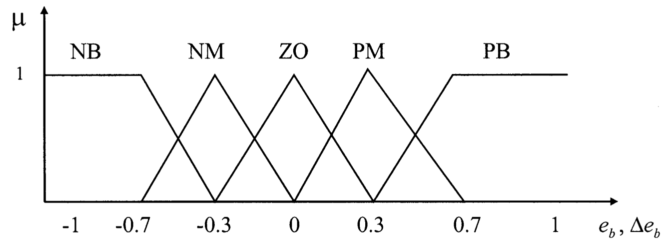

Fig. 5. Membership function for the bottom temperature error and its change.

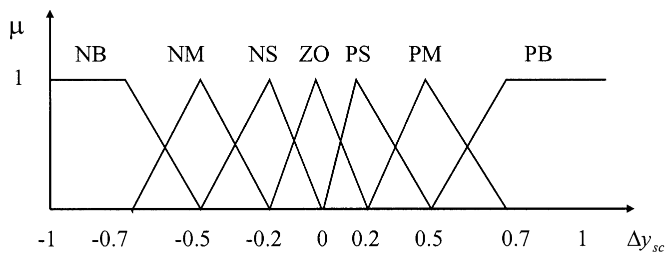

Fig. 6. Membership function for the crown temperature setpoint change Δy_{sc}.

(e_b), which is the bottom temperature minus the setpoint of the bottom temperature, and the change in the bottom temperature error (Δe_b). The output is the setpoint change for the crown temperature (Δy_{sc}).

Since there are random disturbances in the bottom temperature, it is difficult to measure its change (Δe_b). Interview with furnace operators reveals that the furnace temperature trend should include about 2 h of data in order to have a reasonable estimate of the change (Δe_b). This is to avoid the effect of the high-frequency noise and disturbances contained in the bottom temperature. In this paper, a simple linear regression [10] is used to model the trend of the bottom temperature. To consider the 2 h of bottom temperature data, 12 sampling data are used for regression since sampling time for the fuzzy system is 10 min. Using the data in the 2-h moving window, the slope is calculated at every sampling point and used as the change in the bottom temperature error (Δe_b).

The membership functions for e_b, Δe_b, and Δy_{sc} are assumed as triangular shapes, and the fuzzy partition of universe of discourse and the creation of the rule base were drawn from the criteria used by human operators. The inputs to the fuzzy inference system are e_b and Δe_b which are estimated with the linear regression, and the output is the setpoint change Δy_{sc}. The e_b and Δe_b are divided into five linguistic expressions, which are positive big (PB), positive medium (PM), zero (ZO), negative medium (NM), and negative big (NB). Fig. 5 shows the membership functions for e_b and Δe_b. The output of the fuzzy inference system, Δy_{sc}, is divided into seven linguistic expressions, which are positive big (PB), positive medium (PM), positive small (PS), zero (ZO), negative small (NS), negative medium (NM), and negative big (NB). Fig. 6 shows the membership function of Δy_{sc}.

The rule base is the linguistic expression of output Δy_{sc} as a function of e_b and Δe_b. The rule base is obtained from human

TABLE I
RULE TABLE FOR OUTPUT Δy_{sc} WITH TWO INPUTS e_b AND Δe_b

		e_b				
		NB	NM	ZO	PM	PB
Δe_b	NB	PB	PB	PM	PM	PS
	NM	PB	PM	PM	PS	PS
	ZO	PM	ZO	ZO	ZO	NM
	PM	NS	NS	NM	NM	NB
	PB	NS	NM	NM	NB	NB

experience of manual and semiautomatic operation. Examples of the rules are as follows.

$$\begin{array}{l}\text{Rule 1: IF } e_b \text{ is PB and } \Delta e_b \text{ is PB, THEN } \Delta y_{sc} \text{ is NB.}\\ \text{Rule 2: IF } e_b \text{ is PM and } \Delta e_b \text{ is ZO, THEN } \Delta y_{sc} \text{ is ZO.}\\ \text{Rule 3: IF } e_b \text{is NM and } \Delta e_b \text{is ZO, THEN } \Delta y_{sc} \text{ is ZO.}\\ \cdots\cdots\cdots\cdots\end{array} \tag{9}$$

Table I shows the rule table of the fuzzy system for the setpoint change of the crown temperature from two inputs, e_b and Δe_b. In Table I, the gray region represents the linguistic output variable of Δy_{sc}. The inference based on these rules is carried out by fuzzy inference, a kind of approximate reasoning technique. In practice, the inputs e_b and Δe_b, and the output Δy_{sc} are scaled with scaling factors, K_{eb}, $K_{\Delta eb}$, and $K_{\Delta ysc}$, respectively, and, the crisp inputs for fuzzy inference are represented as follows:

$$\begin{aligned} x_0 &= K_{eb} e_b(k) \\ y_0 &= K_{\Delta eb}\, \Delta e_b(k) \end{aligned} \tag{10}$$

where $e_b(k)$ and $\Delta e_b(k)$ are the inputs to the fuzzy system at the kth step, and x_0 and y_0 are the scaled values for $e_b(k)$ and Δe_b (k), respectively. The crisp inputs are fuzzified and the product inference is used. Let us express the fuzzy sets of e_b, Δe_b and Δy_{sc} of the ith rule as A_i, B_i and C_i, respectively, and the variables e_b, Δe_b, and Δy_{sc} as x, y, and z, respectively. Then, the truth value or firing strength of the ith rule at the kth sampling step is given by

$$\begin{aligned} \omega_i &= \mu_{A_i}(x) \wedge \mu_{B_i}(y)\big|_{x=x_0,\, y=y_0} \\ &= \mu_{A_i}(x_0) \wedge \mu_{B_i}(y_0) \end{aligned} \tag{11}$$

where "$\wedge$" is the minimum operator. Using the product operation rule of fuzzy implication, the output fuzzy set C is calculated as

$$\mu_C(z) = \bigcup_{i=1}^{m} \{\omega_i \cdot \mu_{Ci}(z)\} \tag{12}$$

where m is the number of rules. The defuzzification strategy chosen is the center of gravity, given by

$$z_0 = \frac{\int z\mu_C(z)\, dz}{\int \mu_C(z)\, dz} \tag{13}$$

where z_0 is the crisp result of the fuzzy inference. The output of fuzzy system is then scaled by

$$\Delta y_{sc}(k+1) = K_{\Delta ysc} z_0 \tag{14}$$

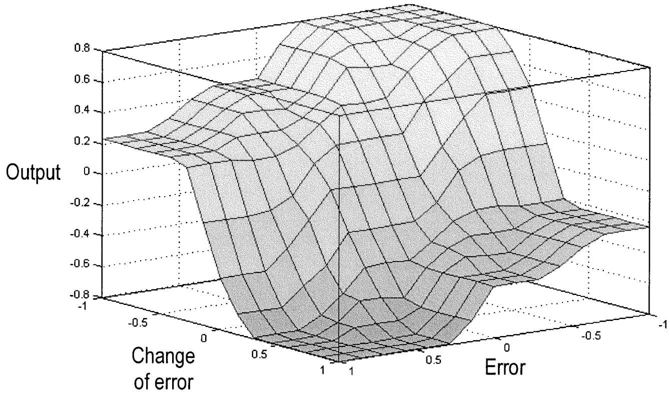

Fig. 7. Output mapping as a function of e_b and Δe_b.

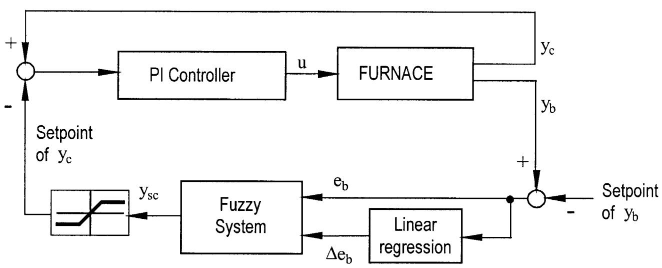

Fig. 8. Proposed hybrid fuzzy-PI controller for glass melting furnace.

and, at each sampling instance k, the setpoint for the crown temperature is updated as

$$y_{sc}(k+1) = \Delta y_{sc}(k+1) + y_{sc}(k). \tag{15}$$

Fig. 7 shows the output Δy_{sc} of fuzzy controller as a function of two inputs, e_b and Δe_b. This figure shows that the fuzzy controller is a nonlinear control. Fig. 8 shows the overall structure of the proposed control system for furnace control, where a limiter of y_{sc} is included in the figure. The role of this limiter is to avoid the crown temperature being too far from the normal operation range.

The proposed control structure can be compared with conventional cascade control structure. The reasons to use fuzzy system for outer or master loop instead of conventional PI controller are these: First, as mentioned in Section III-A, a good quality transfer function model from crown temperature to bottom temperature is necessary to apply the cascade control to the furnace. Though it is possible to use an approximate model, it is more reliable to use the experience of furnace operator than to use a poor quality model, especially in a production plant. Second, the proposed fuzzy system and the PI controller are not equivalent. This is because of the nonlinear characteristic of the fuzzy inference system as shown in Fig. 7 and the error trend calculation with 2-h regression. The nonlinear mapping with the error trend of 2 h cannot be replicated by a conventional PI controller.

IV. Implementation Results in a Real Furnace

The proposed hybrid algorithm has been applied to a 300-ton/24-h glass melting furnace in Samsung–Corning Company, Suwon, Korea. The Rosemount Distributed Control System (DCS) RS3 is installed in the furnace. The PI controller is implemented in the internal module of the DCS. The fuzzy system is developed with C-programming language and implemented in a Hewlett Packard (HP) Workstation J210. Rosemount Network Interface (RNI) is used for the real-time interface between the workstation and the DCS.

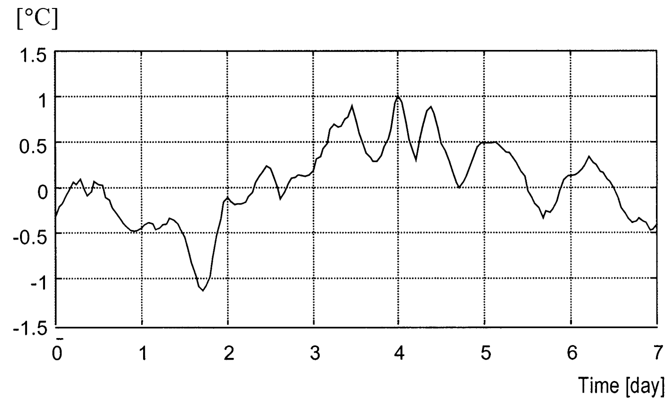

Fig. 9. Bottom temperature variation in the manual operation.

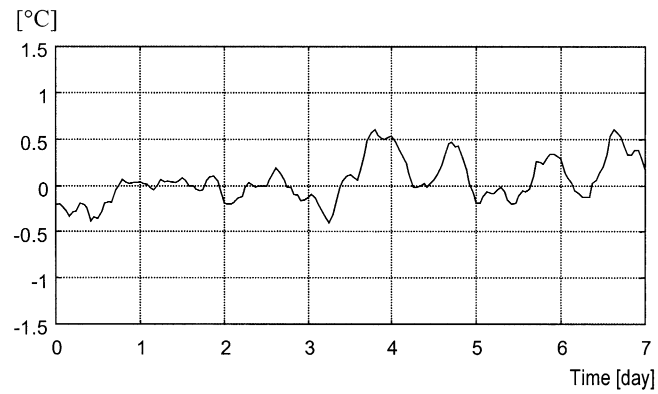

Fig. 10. Bottom temperature variation in the hybrid fuzzy control operation.

Fig. 9 shows a typical bottom temperature variation in the manual operation. The average experience of the operators is more than five years. Therefore, they are experienced enough with the furnace. The reference is zero in the figure. The variation range is ± 1 °C in a week, and the standard deviation is 0.43 for manual operation. Fig. 10 shows the bottom temperature variation in the hybrid fuzzy control operation. The reference is also zero in the figure. The variation range is ± 0.5 °C in a week, and the standard deviation is 0.23 for the hybrid fuzzy control operation. The standard deviation of the bottom temperature in the hybrid fuzzy controller is decreased to 53% from that in the manual control, and the variation range is reduced to the half of that in the manual control, resulting in a much smoother and tighter operation. The smoother and tighter operation makes less perturbation to the internal stream of molten glass, therefore decreases the number and size of impurities, such as blisters, stones, knots, and cords in the glass. Though the exact economic analysis of the temperature deviation is not done, the 53% reduction contributes significantly to the yield and quality of the final product.

The reason for better performance of the proposed control system than manual control can be explained from two points of view. First reason is that the crown temperature is too fast to be controlled manually, though human operators control the furnace based on both the crown and bottom temperatures, simultaneously. Second reason is the advantage of automation. Though the fuzzy system is designed to mimic the human operator, human operator is hard to concentrate on the job all day long, and is subject to error due to fatigue or interruptions.

V. Conclusion

An effective hybrid control algorithm for glass melting furnace is proposed which combines the benefits of both the conventional control and the fuzzy logic control. Although the overall characteristics of the glass melting furnace is complex and nonlinear, some parts of the furnace characteristics can be controlled by the conventional linear controller. Based on this concept, the crown temperature is modeled with the FOPDT system, and the conventional PI controller is implemented to control the crown temperature. The setpoint of the PI controller is determined by the fuzzy system, which in turn controls the trend of the bottom temperature. An application method of the PI controller is also proposed to keep the left-right symmetric operation of the furnace. This simple application can be applied to a similar control problem which needs the symmetric actuation. A linear regression is used for the temperature trend to compute an input to the fuzzy system in order to overcome the high-frequency disturbance effect in the data.

The proposed hybrid algorithm has been successfully implemented in a real manufacturing furnace in Samsung-Corning Company, Suwon, Korea. The proposed cascade structure with fuzzy and conventional controller can be applied to a similar plant for which the outer or master transfer function is hard to model.

This work has demonstrated that without knowing a complete model for a complex system, fuzzy logic control can improve the performance of industrial processes by supplementing conventional controls. For future research, further improvement can be achieved by expanding the fuzzy logic control to have a self-organizing capability [11].

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