

Adaptive Two-Stage Fuzzy Temperature Control for an Electroheat System

Chih-Hu Wang, Chun-Hung Lin, Bore-Kuen Lee, Chien-Nan Jimmy Liu, and Chauchin Su

Abstract

In this paper, we construct a simple adaptive two-stage fuzzy temperature tracking controller for a commercial electroheat system. Being not well isolated from the environment, it is hard to build an analytical model for the system due to heat convection caused by a fan for heat mixing in the chamber, heat leakage to the environment, variation of the environment temperature, and uncertain nonlinear heating dynamics. Also, as a commercial product by using cheap heater coils and without equipping a cooling system, this system usually has a bad transient response such as a long rise time, a large overshoot, and a long settling time. Moreover, temperature tracking at the steady-state phase is not easy to maintain due to heat interaction with the environment. Here, in the presence of the unknown system dynamics, we use a two-stage fuzzy controller to improve the transient response. Furthermore, a simple fine-tuning adaptive control scheme is proposed to overcome environmental influence and ensure tracking of the temperature setting. Simulation study and experimental results show good performance of the adaptive fuzzy temperature control system.

Keywords: adaptive fuzzy control, temperature controller.

1. Introduction

Temperature control has been widely studied for various thermal systems. The most ordinary model of thermal systems is established by the general energy balance equation [1] with which the entire heated chamber is considered as a lumped unit and the distribution of the heat is uniform. Hence, this model has been applied

to many temperature analyses as a result of its simplicity. In [2], a PID controller is used for temperature control of a 20 KW industrial electric resistance furnace where the plant is modeled by a first-order transfer function with a time delay. Temperature control of a heated barrel with electric heaters and water coolers was proposed in [3] which used the discrete-time variable structure system (VSS) control scheme.

It is noted that a model based on the general energy balance equation does not have a good fit for a large chamber, because the distribution of heat is radiating to the space. With the model-free approach, fuzzy temperature controllers were introduced in [4][5] which utilize two inputs (error, error change) to infer the fixed fuzzy rules and produce an output (duty cycle) to actuate the process. For crown temperature control of a TV glass furnace, a combination of PI control and fuzzy logic control has been proposed in [6] where the fuzzy system is used to determine the crown temperature setting. For superheated steam temperature of a power plant, a nonlinear generalized predictive controller based on a neuro-fuzzy network, which consists of local GPCs models of the plant, is proposed in [7]. A neural fuzzy inference network is proposed in [8] to construct a water-bath temperature control system which can automatically generate the fuzzy rules. The work in [8] is further improved in [9][10] by adopting a recurrent fuzzy network for improvement of the learning rate of the neural network.

An industrial heat process such as discussed in [2]-[7], usually has a cooling system and a good isolation from the environment so that a better control configuration can be maintained. However, this is not the case for a commercial product. In this paper, we shall implement a cheap but efficient temperature controller for a commercial electroheat system as shown in Figure 1. In the presence of heat convection in the chamber, irregular heat leakage to the environment, variation of the environment temperature, and uncertain heating dynamics, it is harder to analytically design a temperature controller based on a physical model. With operating experiences of the electroheat system in the transient and steady-state phases, a two-stage fuzzy temperature controller will be proposed to attain a good transient performance including fast system response and small overshoot. Moreover, a simple adaptive scheme, which is more effective

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than the adaptive schemes in [9] and [10], will be considered to counteract the disturbing effects of the environment so as to ensure temperature tracking at the steady state. This adaptive two-stage fuzzy temperature controller is built in a cheap 8051-based microprocessor system. Several experiments will be conducted to show the satisfactory efficiency and accuracy of the proposed temperature control system.

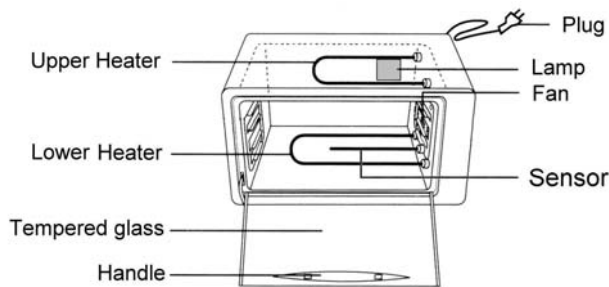


Fig. 1. Configuration of the heater RB-6240.

The remainder of this paper is organized as follows. In Section 2, both the electroheat system and the implementation of the temperature controller are described. The dynamics and operating experience of the plant are discussed in Section 3. The proposed two-stage adaptive fuzzy temperature controller is presented in Section 4. Performance comparison with some related temperature control schemes is made in Section 5. Experimental results are shown in Section 6. Finally, conclusions are drawn in Section 7.

2. Description of The System

A. The Electroheat System

In this section, we shall introduce the instrumental settings in our experiment. The electroheat system, RB-6240, produced by Cook Power Co., Ltd. is of iron construction throughout. The purpose of the electroheat system is to bake bread and cake at home. It contains two heaters (one in the top and the other in the bottom), a fan, and a lamp. The configuration of RB-6240 is shown in Figure 1. The fan is used to stir the air in the chamber to make the temperature distribution more uniform. However, since the chamber is not perfectly sealed, cool air is also drawn into the chamber from the environment. Injection of cool air by the fan leads to undesired heat convection which is a significant disturbance for temperature control.

There is a transparent glass in the front side of the electroheat system for observation purpose. This provides a way of severe heat leakage to the environment. The rate of heat leakage also depends on the environment temperature which can vary with weather in a do-

mestic environment. Lastly, the resistance of the heater do vary with the temperature of the chamber so that the rate of supplied heat energy is not constant. It is also observed the heater is a nonlinear component in that the maximum temperature driven by the heater is saturated at about 250°C .

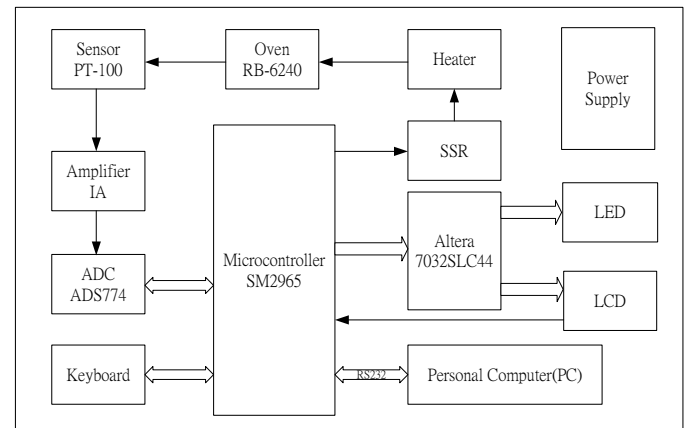


Fig. 2. Block diagram of the temperature controller.

B. The Temperature Controller

The temperature controller contains two principal parts: the analog part and the digital part. The analog part consists of a power supply, a temperature sensor (PT-100), an instrumentation amplifier (IA), a solid state relay (SSR), and two heaters. The digital part mainly includes the microcontroller AT89C51 and the analog-to-digital converter ADS774. The block diagram of our temperature controller is shown in Figure 2.

a) Temperature Sensor: The input signal of the analog part is from a platinum sensor which changes its resistance according to temperature variation. In our experiment, a platinum sensor PT-100 is used to detect the present temperature. It is a long stick which is installed at the bottom of the electroheat system shown in Figure 1. The operation curve of temperature vs. resistance of the platinum sensor PT-100 is shown in Figure 3. Obviously, we can observe that the curve is linear especially in the temperature range (less than 600°C) in our experiment. Therefore, its high linearity is very useful as a good temperature sensor.

b) Instrumentation Amplifier: The instrumentation amplifier (IA) is a very popular voltage amplifier used in many kinds of the meters for signal measurement and conditioning. This IA together the platinum sensor PT-100 form a Wheatstone resistive bridge sensor for temperature. A resistor in the IA is calibrated so that the output voltage V_o of the instrumentation amplifier is set to zero at 0°C . The analog signal V_o is then converted into binary data using the ADC ADS774. The reading of the binary data output of the ADS774 is calibrated so

that the binary output N is in the range $0 \leq T \leq 4000$ corresponding to $0^\circ\text{C} \leq T \leq 400^\circ\text{C}$, which implies that the sensor resolution is 0.1°C .

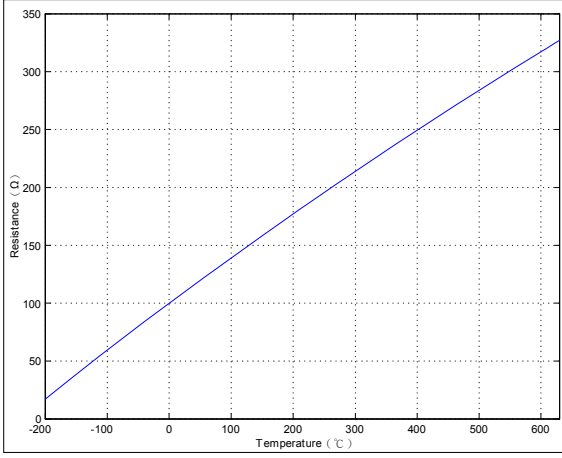


Fig. 3. Operation curve (temperature vs. resistance) of the platinum sensor PT-100.

It is worth noting that the current, passing through the platinum sensor PT-100, should be well processed. Due to thermal noise in a high-temperature chamber, the signal-to-noise ratio (SNR) of the measured signal is not good. To solve this problem, temperature measurement and heater actuation are operated at different sampling rates. Temperature measurement is operated at a higher sampling rate so that an average of a segment of temperature measurement is provided to calculate a heater actuation signal, which is operated at a lower sampling rate. Since the heating dynamics has a slow time response, this window-average method can improve the SNR of temperature measurement.

3. System Equation and Operating Experience

In this section, the characteristics of heat transfer will be studied from a lumped parameter perspective. The general energy balance equation [1] is given by

$$\text{Rate of accumulation of energy} = \text{Rate of energy input} - \text{Rate of energy output} \quad (1)$$

For the considered electroheat system shown in Figure 1, we have

$$\text{Rate of accumulation of energy} = \rho c V \frac{dT(t)}{dt} \quad (2)$$

$$\text{Rate of energy input} = \omega(t) \quad (3)$$

$$\text{Rate of energy output} = hA [T(t) - T_\infty] + f(T(t), t) \quad (4)$$

where ρ and c are the density and the specific heat of the air contained in the chamber, respectively,

and V the volume of the chamber. Assume the entire chamber is considered as a lumped unit with temperature $T(t)$. Let constant h be the heat transfer coefficient, T_∞ the temperature of the environment, and A the external area surrounded by the temperature T_∞ . The term $f(T(t), t)$ accounts for the drawn heat power by using the fan, heat leakage to the environment, the effect of convection, and other uncertain terms.

We now turn to discuss the energy input rate $\omega(t)$ for heating process. In our experiment, two heaters are supplied with a AC voltage $V_{ac}(t)$:

$$V_{ac}(t) = V_m \cos(2\pi f_0 t + \phi) \quad (5)$$

where V_m is the amplitude, $f_0 = 60$ Hz is the frequency, and ϕ is the phase angle of $V_{ac}(t)$, respectively. However, the actual voltage $V(t)$ applied to the heaters are controlled by the SSRs with variable firing angles, i.e.,

$$V^2(t) = \begin{cases} 0, & \text{for } 0 \leq t \leq (1-x(t))\frac{T}{2} \\ V_{ac}^2(t), & \text{for } (1-x(t))\frac{T}{2} < t \leq \frac{T}{2} \end{cases}$$

where $T = 1/f_0$ and $x(t)$, with $0 \leq x(t) \leq 1$, is the duty ratio controlled by the SSRs. Note that due to cost concern, the SSR device is used instead of using the industrial standard PWM scheme. Therefore, the instantaneous power, denoted as $P(t) = V^2(t)/R(T(t))$, where $R(T(t))$ is the resistance of the heater, is a periodic truncated signal. A periodic signal can be represented by a Fourier series which contains two parts, one is called the DC (average) component and the other one includes the harmonic components. As the electroheat system can be regarded as a low pass filter, the effect of the harmonic components can be ignored and only the average power signal is effective to the heater. This is why the average power of the heater is used in the following analysis. The average applied power to the heater is given by

$$P_{ave}(t) = \frac{2}{T} \int_{(1-x(t))\frac{T}{2}}^{\frac{T}{2}} \frac{V_{ac}^2(t+\tau)}{R(T(t+\tau))} d\tau$$

By assuming that $R(T(t+\tau)) = R(T(t))$ for $0 < \tau \leq \frac{T}{2}$, it is easy to obtain

$$P_{ave}(t) = \frac{V_m^2}{R(T(t))} g(x(t))$$

where

$$g(x(t)) = x(t) - \frac{1}{4\pi} \sin(2\pi x(t))$$

Then the input power given by the two heaters can be expressed by

$$\omega(t) = 2c_0 P_{ave}(t)$$

where c_0 is a constant that transforms electric energy to

heat energy. The approximated overall heat dynamics can be rewritten by

$$\frac{dT(t)}{dt} = -my(T(t) - T_\infty) + Q \left(2c_0 \frac{V_m^2}{R(T(t))} g(x(t) - f(T(t), t)) \right) \quad (6)$$

where $m = \frac{hA}{\rho c V}$ and $Q = \frac{1}{\rho c V}$. With the overall plant dynamics in (6) with the control input being the duty cycle $x(t)$ and the control output being the chamber temperature $T(t)$, we can see that this is a nonlinear system with several uncertainties.

For baking purpose, the desired setting temperature T_r of the chamber is usually between 100°C to 200°C . For this operating range, it is observed from experiments that if we set $x(t) = x^*$, then there exist T^* , δ^* , and t^* such that

$$|T(t) - T^*| \leq \delta^* \quad (7)$$

for $t \geq t^*$. The fluctuation of $T(t)$ around T^* is due to the effect of the term $f(t)$, i.e., the drawn heat power by using the fan, heat leakage to the environment, the effect of convection, and other miscellaneous uncertain terms. The deviation amplitude δ^* can be larger than 10°C . The corresponding value T^* also varies with the environment temperature T_∞ . Furthermore, the response of the electroheat system is very slow, e.g. $t^* \geq 20$ minutes, and a large overshoot, about 30%, usually occurs. It is noted that as without equipping a cooling system, the overshoot is hard to decay.

4. Two-Stage Fuzzy Temperature Controller

Based on the previously mentioned operating experiences, the duty ratio $x(t)$ will be adjusted by an adaptive two-stage fuzzy control law based on the zero-order Sugeno fuzzy model [11]. The two-stage fuzzy control scheme is proposed so that rise time is improved and the overshoot is decreased. Moreover, by adding a simple adaptive fine tuning scheme, steady-state temperature tracking is ensured and the disturbing effects of the environment can be overcome.

A. Strategy for transient phase

Given a temperature setting value T_r , we shall first set $x(t) = 1$, i.e., use full power, to heat up the chamber. Once if the chamber temperature $T(t)$ exceeds some threshold value βT_r with $0 < \beta < 1$, we set $x(t) = x_2$, with $0 < x_2 \leq 1$. The value β must be suitably chosen in order to reduce overshoot of $T(t)$ and the value x_2 is determined to drive $T(t)$ to approach to the setting value T_r . Note that both the values β and x_2 de-

pend on the temperature setting T_r , and x_2 , in addition, also depends on the environment temperature T_∞ . Usually several suitable pairs (β, T_r) and (x_2, T_r) can be determined through experiments. Then, for arbitrary T_r , its corresponding β and x_2 can be calculated by fuzzy interpolation. We shall carefully design the fuzzy rules such that there exists a time instant t_c with $T(t_c) = T_r$.

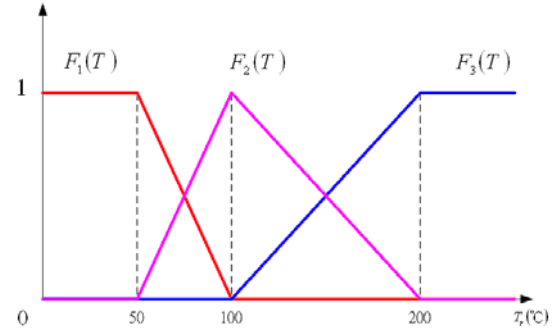


Fig. 4. Membership functions of fuzzy sets F1, F2, and F3.

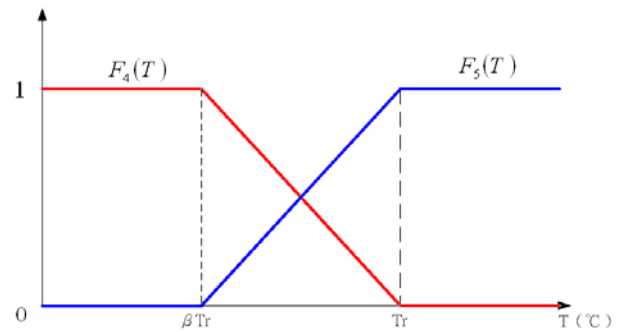


Fig. 5. Membership functions of fuzzy sets F4 and F5.

The values x_2 and β are calculated by inferring the following fuzzy Rules 1~3:

Stage 1:

Rule 1: IF T_r is F_1 , THEN $\beta = \beta_1$ and $x_2 = c_1$.

Rule 2: IF T_r is F_2 , THEN $\beta = \beta_2$ and $x_2 = c_2$.

Rule 3: IF T_r is F_3 , THEN $\beta = \beta_3$ and $x_2 = c_3$.

The fuzzy sets F_1 , F_2 , and F_3 represent low, middle, and high temperature settings, respectively. Membership functions of these fuzzy sets are shown in Figure 4. Then by using the product reference engine, singleton fuzzier, and center average defuzzifier [11], the values of β and x_2 are given by

$$\beta = \beta_1 F_1(T_r) + \beta_2 F_2(T_r) + \beta_3 F_3(T_r)$$

$$x_2 = c_1 F_1(T_r) + c_2 F_2(T_r) + c_3 F_3(T_r)$$

In this paper, for simplicity, we use the symbol $F_i(\cdot)$ to represent the membership function of the fuzzy set F_i . The calculated values of x_2 and β will be used in Rules 4 and 5 in the following to determine the duty ra-

tio $x(t)$ in the transient phase for $T(t) \geq \beta T_r$. For $\beta T_r \leq T(t) \leq T_r$, the duty ratio $x(t)$ is determined based on Rules 4 and 5:

Stage 2:

Rule 4: IF $T(t)$ is F_4 , THEN $x(t)$ is 1.

Rule 5: IF $T(t)$ is F_5 , THEN $x(t)$ is x_2 .

Membership functions of these fuzzy sets are shown in Figure 5. After $T(t) \geq \beta T_r$, the output of the fuzzy temperature controller is given by

$$x(t) = 1 \times F_4(T(t)) + x_2 F_5(T(t)) \quad (8)$$

The purpose of the fuzzy rules at stage 1 is to heat up the chamber as fast as possible, and that of the fuzzy rules at stage 2 is to decrease overshoot as much as possible by suitably controlling the input heat energy. Note that the fuzzy rules at stage 2 are necessary since the electroheat system does not have a cooling system. Otherwise, we usually have a large overshoot which is hard to decay.

Remark 1: Note that the value β determined from Rules 1~3 is implicitly used in the membership functions $F_4(T(t))$ and $F_5(T(t))$ and the value x_2 also appears in the THEN part of Rule 5. Therefore we have a two-stage cascade fuzzy inference engine. At the stage 1, according to the temperature setting value T_r , the two values β and x_2 are generated by inference Rules 1~3. These two values are then fed into stage 2 in order to calculate the duty ratio $x(t)$ by inference Rules 4~5. The cascade structure of the fuzzy inference engine not only reflects our control strategy but can also effectively reduce the number of rules.

B. Strategy for steady-state phase

At the time instant t_c , the system has been brought around the desired operating point $T(t) = T_r$. However, due to uncertain environment temperature, heat leakage to the environment, the effect of heat convection caused by the fan, and other miscellaneous uncertain terms, $T(t)$ will fluctuate around the set point at the steady state. To reduce the fluctuation and obtain the desired steady-state tracking accuracy, after $t = t_c$, the duty ratio $x(t)$ will be adjusted by an adaptive scheme.

For $t > t_c$, the value x_2 in the THEN part of Rule 5 is updated according to following the discrete-time adaptive control law:

$$x_2((k+1)T_s) = \begin{cases} x_2(kT_s), & \text{if } |e(kT_s)| > \delta_d \\ x_2(kT_s) + k_c \operatorname{sgn}(e(kT_s)), & \text{if } |e(kT_s)| \leq \delta_d \end{cases} \quad (9)$$

where k is the sampling time index, T_s is the sampling time, $e(kT_s) = T_r - T(kT_s)$ is the temperature

tracking error, δ_d the desired accuracy, and k_c the adaptation gain. Therefore the fuzzy interpolation of the

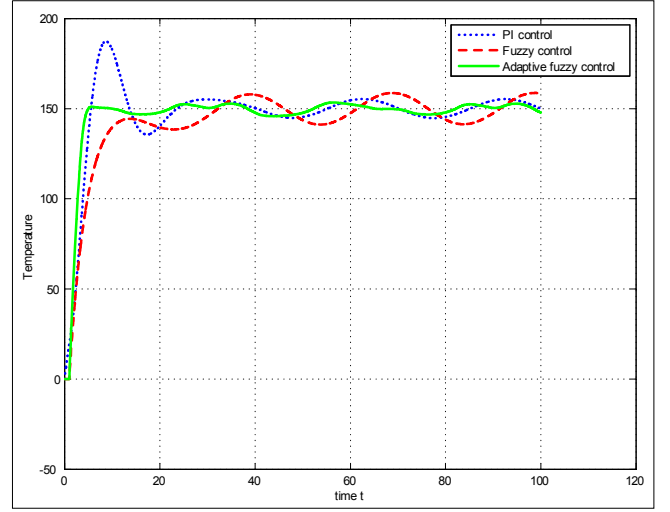


Fig. 6. Performance comparison of our scheme with the PI and fuzzy control schemes.

duty ratio $x(t)$ in the steady-state phase is given by

$$x(kT_s) = 1 \times F_4(T(kT_s)) + x_2(kT_s) F_5(T(kT_s)) \quad (10)$$

Note that as the step response of the open-loop electroheat system has a slow transient response and a large overshoot, the bandwidth of the system is not wide and the phase margin can be poor. Therefore, the adaptation gain k_c should be small, and on the contrary, the sampling time T_s of the digital temperature control system should not be short.

5. Simulation Study

In this section, the performance of our proposed scheme will be compared with the conventional PI control as discussed in [2] and the conventional fuzzy control scheme in [4][5]. To make a fair comparison, we consider the heating process [2][5] which is modeled by $\dot{T}(t) = -0.3T(t) + 250x(t-1) + f(t)$, $f(t) = 10\sin(2\pi t/30) - 10$ where the disturbance $f(t)$ is used to represent the disturbing effects such as heat convection and heat leakage. This process has a slow step response and a time delay. The control objective is to shorten the rise time, reduce the overshoot, and counteract temperature fluctuation at the steady state due to the disturbance $f(t)$.

Performance comparison of our scheme with the PI control and the fuzzy control is shown in Fig. 6. The control schemes to be compared are discussed in the following.

a) *The PI control scheme:* The PI controller in the unit feedback control system is given by $\frac{1}{250}(0.5 + \frac{0.5}{s})$ which is chosen so that the closed-loop system has a fast

response. However, applying a PI controller to a time-delay system usually results in a closed system with

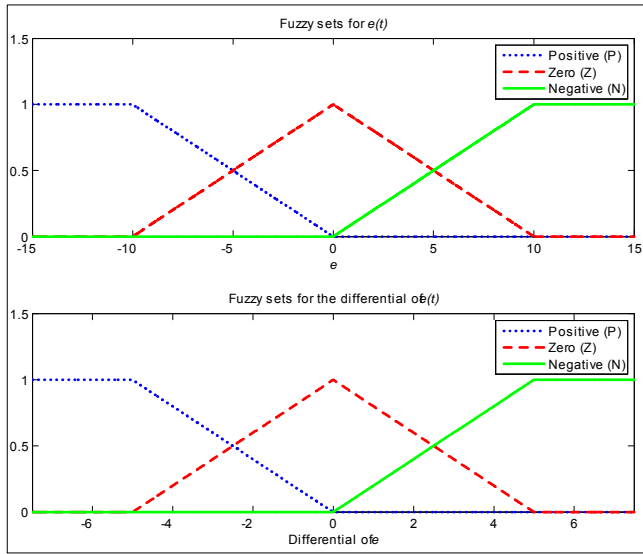


Fig. 7. The fuzzy sets used in the conventional fuzzy control schemes.

Table 1. Rule table of the conventional fuzzy control scheme.

$\dot{e}(t) \backslash e(t)$	N	Z	P
P	Z	P	VP
Z	N	Z	P
N	VN	N	Z

a poor phase margin so that overshoot is inevitable as shown in Fig. 6. At the steady state, the temperature fluctuates around the setting point $T_r = 150^\circ C$.

b) *The conventional fuzzy control*: For the conventional fuzzy control scheme, the terms $e(t)$ and $\dot{e}(t)$ are used as the inputs to the zero-order T-S fuzzy controller in order to generate the output $\Delta x(t)$, the increment of the duty ratio $x(t)$. Since the inputs both have three fuzzy sets as shown in Fig. 7, there are nine rules in the fuzzy rule base as shown in Table 1.

In Table 1, the centers of $\Delta x(t)$ of the fuzzy sets VN, N, Z, P, and VP in the consequent parts are $-k_f$, $-k_f/4$, 0, $k_f/4$, and k_f , respectively, where $k_f = 0.01$. Being implemented as a digital control system, this increment is updated for every time interval $T_s = 1$ sec. After determining $\Delta x(kT_s)$, the integral control law is given by $x((k+1)T_s) = x_2(kT_s) + \Delta x(kT_s)$ which can be used for asymptotical tracking of step command and for asymptotical rejection of constant disturbance.

Table 2. Parameters in Rules 1~3.

Rule 1		Rule 2		Rule 3	
50°C		100°C		200°C	
β_1	c_1	β_2	c_2	β_3	c_3
0.2	50/250	0.4	100/250	0.6	200/250

In Fig. 6, this fuzzy control scheme has a smaller overshoot than the PI control scheme, but has a slower response. At the steady state, this fuzzy controller the worst fluctuation among the three schemes due to the sinusoidal component of $f(t)$. This is because rejection of such a component is not elaborately considered in the design of the conventional fuzzy control scheme.

c) *The proposed adaptive fuzzy control*: In the simulation study, the control sampling time for updating the actuation signal $x(t)$ at the steady state is 1 sec and the adaptation gain k_c is equal to 0.01. For the proposed adaptive two-stage fuzzy control scheme, the related parameters are shown in Table 2.

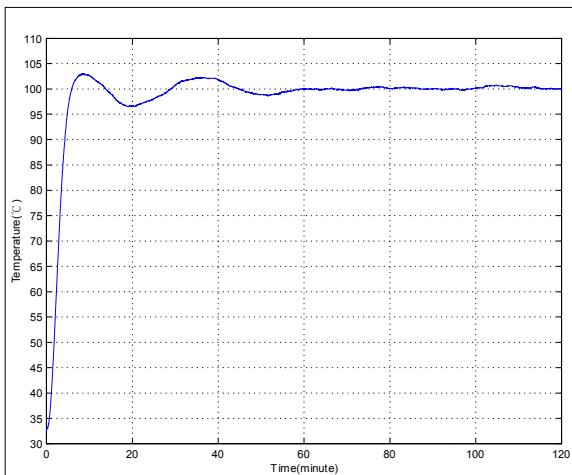
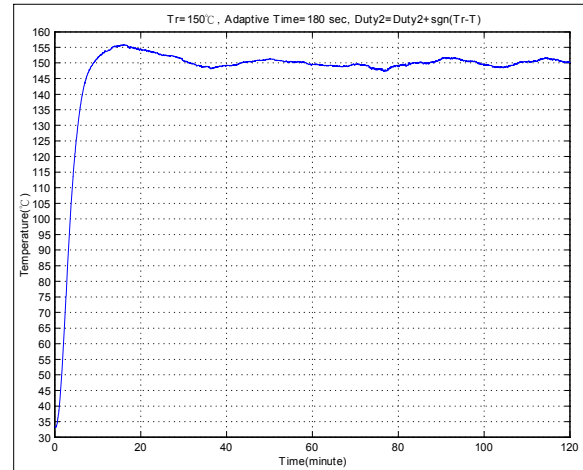
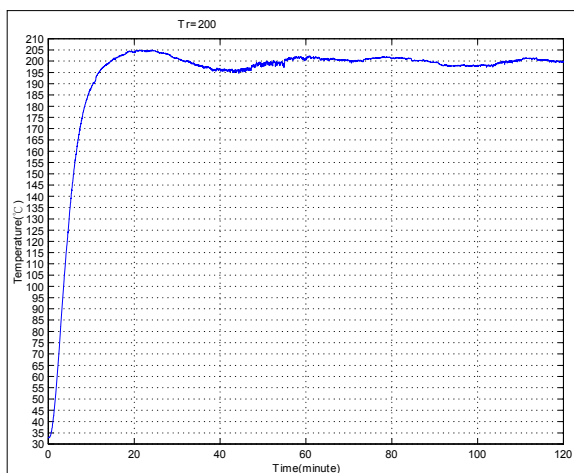
For tracking with respect to the setting $T_r = 150^\circ C$, it is obvious from Fig. 6 that this proposed control scheme attains the shortest time, the minimal overshoot, and the smallest mean root square tracking error at the steady state among the three control scheme. This performance is expected since the proposed scheme uses full power to heat up the process at the stage $T(t) \leq \beta T_r$ to reduce the rise time. Moreover, while operating at the range $\beta T_r \leq T(t) \leq T_r$, cautious control output is generated by the two-stage fuzzy inference system in order to reduce overshoot. Finally, at the steady state, the proposed adaptive integral control scheme can attain constant command tracking and lessen temperature fluctuation due to the disturbance.

6. Experimental Results

In this section, we shall demonstrate the experimental results of the proposed fuzzy temperature controller. The control sampling time for generating the actuation signal $x(t)$ is 3 minutes, the adaptation gain k_c is equal to 0.01, and the desired accuracy δ_d is $1^\circ C$. The temperature settings $50^\circ C$, $100^\circ C$, and $200^\circ C$ are tested to obtain control parameters β_i and c_i in fuzzy Rules 1~3 in advance. The testing results are summarized in Table 3.

Table 3. Parameters in Rules 1~3.

Rule 1		Rule 2		Rule 3	
50°C		100°C		200°C	
β_1	c_1	β_2	c_2	β_3	c_3
0	0.03	0.2	0.2	0.6	0.73

Fig. 8. Control for low temperature ($T_r = 100^\circ\text{C}$).Fig. 10. Control for middle temperature ($T_r = 150^\circ\text{C}$).Fig. 9. Control for high temperature ($T_r = 200^\circ\text{C}$).

In the following, we proceed to check the tracking capability of the proposed adaptive fuzzy temperature controller with respect to the temperature settings 100°C , 150°C , and 200°C . For the temperature setting $T_r = 100^\circ\text{C}$, the experimental result is shown in Figure 8 which shows an overshoot about 3°C and an average steady-state tracking error about 1°C . Next, tracking performance for the temperature setting $T_r = 200^\circ\text{C}$ is illustrated in Figure 9. In this figure, we can observe that the overshoot is about 5°C and the

average steady-state error is about 1°C . For the above two cases, overshoot of the temperature response is lessened by the suitably chosen parameters β_i and c_i in fuzzy Rules 1~3. On the other hand, fluctuation of chamber temperature $T(t)$ at the steady state is effectively reduced by the adaptive tuning law so that good tracking performance is attained.

Now we test the temperature setting $T_r = 150^\circ\text{C}$ which is not considered in the training phase of the fuzzy control system. Therefore, in this case, the duty ratio $x(t)$ is generated by fuzzy interpolation using the fuzzy rules which correspond to the temperature settings 50°C , 100°C , and 200°C , respectively. The experimental result is shown in Figure 10. From this figure, we can see that the overshoot is about 6°C , and the average steady-state error is about 1.5°C . The transient and steady-state responses are still satisfactory for a commercial heating product.

7. Conclusions

In this paper, we implement a simple adaptive two-stage fuzzy controller for temperature control of a commercial electroheat system which is not well isolated from the environment and is not equipped with a cooling system. With the two-stage fuzzy control scheme, system response time is improved and overshoot is decreased. Moreover, by using the adaptive fine tuning scheme, performance of the steady-state temperature tracking is ensured and the disturbing effects of the environment is reduced. Simulation study for performance comparison with some related temperature control schemes and experimental results verify the expected performance of the adaptive fuzzy temperature control system.

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