Modeling and Control of Thermal Microsystems a Case Study

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1. Introduction

The miniaturized processes integrated with microreactors, microsensors and microactuators using semiconductor fabrication technologies can realize high efficiency and high throughput operation as well as surprising reduction of reagents, cost, reaction time, power etc. because they have characteristics of extremely high reaction surface-to-volume ratio, very fast mass/heat transfer, tiny total mass/volume. The thermal microsystem is one of the most typical miniaturized processes. In particular, it is useful for DNA polymerase chain reaction (PCR) that requires a rapid temperature control to shorten the total running time and a precise temperature control for high efficiency. Consider Figure 1 to understand the mechanism of PCR. PCR reaction is composed of three steps: denaturation, annealing and extension. If we heat the reactor up to about 95℃, the double stranded DNA separates to single stranded DNA in the denaturation step. Next, the primer would move to the right position of the single strand DNA where duplication starts if we cool the reactor down to about 55℃. The third (extension) step is to duplicate the single strand, resulting in two-times double stranded DNA. If we repeat the whole procedure 20-30 times, we would obtain 2^{20}-2^{30} times amplification of DNA. In this repetitive reaction, fast and accurate temperature control is important. If the temperature control is slow, the total reaction time may be long and also unspecific (side) reactions may occur. Accurate temperature control is also important to obtain desired amplification rate.

Conventional thermal systems suffer from very low heating/cooling rate (about 1℃/sec) and high power consumption because the total mass of the reactor is huge. Also, they cannot do real-time monitoring of PCR. Many types of thermal microsystems have been proposed to overcome the problems. Belgrader et al. (2001) developed a compact, battery-powered fluorometric thermal cycler that consisted of two reaction modules for multiplex real-time PCR. Northrup et al. (1988) designed a portable thermal cycle system including silicon-based reaction chambers with integrated heaters for efficient temperature control and optical windows for real-time fluorescence monitoring. Lao et al. (2000) fabricated a silicon-based thermal microsystem and demonstrate its precise temperature control, rapid heating and cooling. They used a gain-scheduling algorithm for the proportional-integral (PI) controller to incorporate the nonlinearity of the thermal cycler.

In this article, we mainly focus on a systematic modeling and control of the thermal microsystem in the hope that the system level analysis and optimization would contribute to maximizing the performance of the thermal microsystem and provide some insights on the optimal operation. We will demonstrate how to fabricate a silicon-based microreactor integrated with a platinum sensor/heater and hardware/software for data acquisition, control and power supply. The dynamic thermal characteristics of the thermal microsystem have been analyzed especially, in the control and modeling point of view. We propose an appropriate model structure on the basis of the dynamics analysis and estimate the model parameters using the prediction error identification method. Requirements for the high performance operation are discussed and a nonlinear control strategy linearizing the nonlinear dynamics of the thermal microsystem is proposed. We use the optimal tuning method to obtain the adjustable parameters of the controller. Finally, we will raise some important issues to improve thermal microsystems.

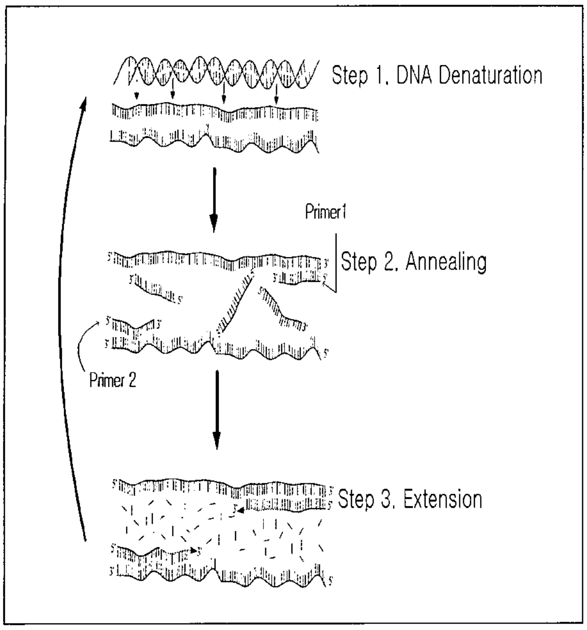
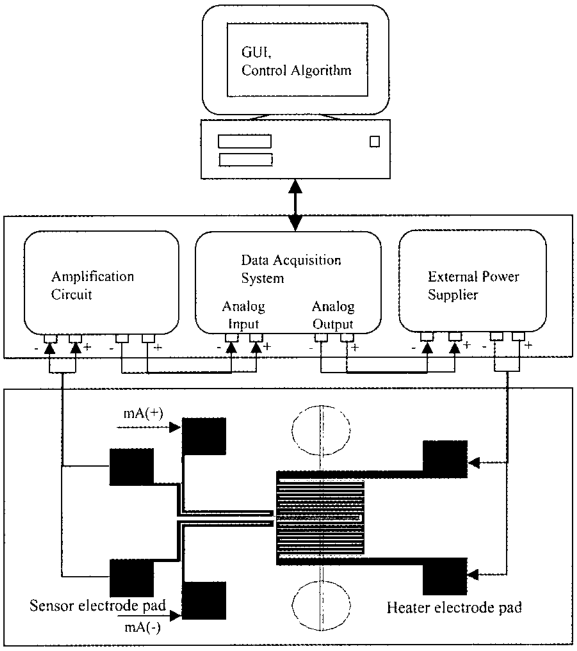
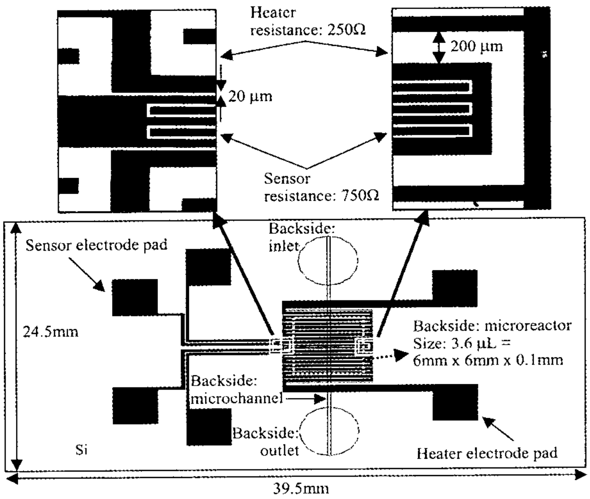


Figure 1. DNA amplification by Polymerase Chain Reaction (PCR).



(a) Over-all scheme



(b) Top view of the microreactor.

Figure 2. Thermal microsystem : (a), (b)

2. Construction of Thermal Microsystem

We manufactured the thermal microsystem as shown in Figure 2(a). It is composed of six parts : silicon-based microreactor, cooling fan, amplification circuit, data acquisition, external power supplier, software for the automatic control algorithm and graphic user interface. The control signal of the thermal microsystem flows like the following: The amplification circuit amplifies the voltage of the platinum sensor (equivalently, the temperature of the microreactor) and transfers the amplified voltage to the analog input of the data acquisition system as shown in Figure 2(a). Then, the automatic control algorithm adjusts the analog output to control the temperature as fast and precisely as possible and the graphic user interface graphically displays the temperature and the analog output on screen. Subsequently, the external power supplier powers the platinum heater in proportion to the analog output of the data acquisition system. Then, the voltage of the platinum sensor (equivalently, the temperature of the microreactor) changes and passes through the amplification circuit again. The whole procedure is repeated for every sampling time.

The silicon-based microreactor was integrated with thin-film platinum sensor and heater. The microchip in Figure 2(b) is fabricated through several steps as shown in Figure 3. At step 4, the silicon is etched to 100μm depth with tetramethylammoniumhydroxide (TMAH) for the microreactor and the microchannel. The thermal oxide film at step 5 serves as an electrical insulation layer. At step 7, titanium (Ti) film and platinum (Pt) film are deposited by dc off-axis magnetron sputtering.

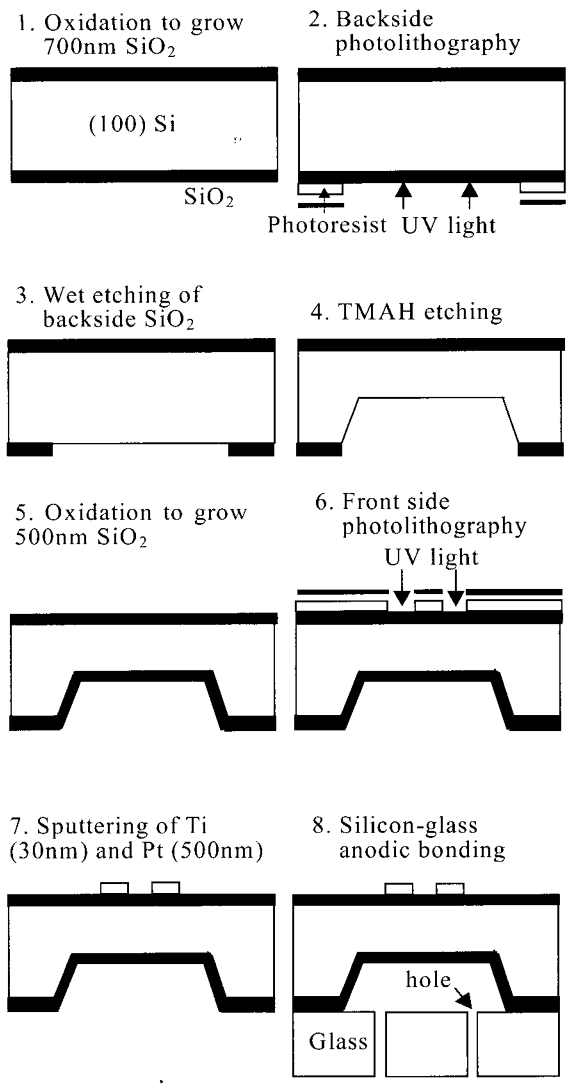


Figure 3. Fabrication steps of the microreactor.

3. Modeling of Thermal Microsystem

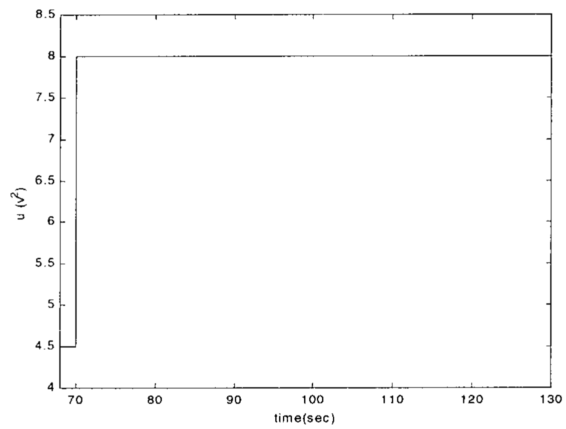
In this section, we will exemplify the development of a mathematical model to represent the dynamics between the reactor temperature and the voltage applied to the heater and estimate the model parameters using the prediction error identification method and demonstrate the model performances.

3.1 Determining Model Structure

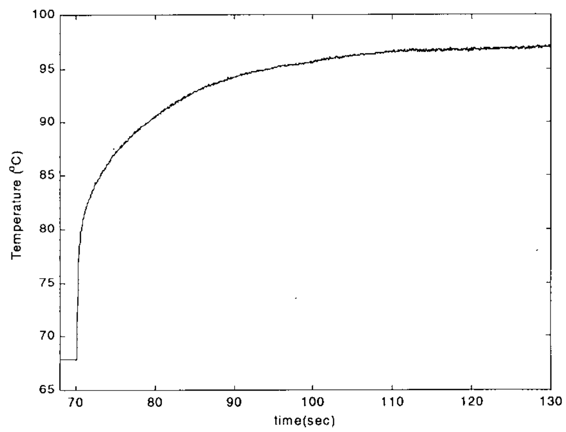
Before we estimate the model parameters, we should construct the model structure. The following five items are considered for the best model structure selection.

1) For electrical heating systems like thermal microsystems, the voltage has been frequently chosen as the input of the model. However, the choice is not good because the temperature is in proportion to the electrical power rather than the voltage. So, we should choose the square of the voltage (v^2)as the model input to avoid the nonlinearity.

2) A step test is one of the simplest techniques to detect the dynamic characteristics of the process. Figure 4 shows the step response of the thermal microsystem. It should be noted that there is a sudden jump from the initial temperature (67.9℃) up to around 80℃ at the instance of the input change. This is a strong evidence that the transfer function from the input (i.e., the square of the voltage) to the output (i.e., the temperature) includes a small negative 'zero' (here, 'zero' is defined as the solution that makes the transfer function zero).



(a) step input



(b) temperature

Figure 4. Step response of the thermal microsystem: (a), (b)

3) We also recognize from the step response of Figure 4b that there is nearly no time delay between the input and the output. The existence of time delays seriously deteriorates the maximum achievable control performance of the feedback control system (Sung and Lee, 1996). So, this observation of nearly zero time delay is very favorable for us to design a high performance feedback controller.
4) Another dynamic characteristic of the step response is that the jump is not a vertical line and the transition from the initial jump to the next dynamic response of the temperature is smooth rather than clearly separated. This means that the order of the dynamic system is at least two.
5) Finally, it should be noted that there is always a small input nonlinearity because of various causes like the resistance variation of the heater during heating, nonlinear characteristic of the data acquisition system and the power supplier etc.

Putting it all together, we should consider the following model requirements to choose an appropriate model structure for the thermal microsystem:

1. The input and output of the dynamic model should be the square of the voltage and the microreactor temperature, respectively.
2. The dynamic model should contain a small negative zero.
3. The time delay can be chosen as zero.
4. The order of the dynamic thermal microsystem is at least two.
5. Input nonlinearity should be included.

Especially, if the model does not satisfy the first and second requirement, we cannot achieve acceptable model performances in a way of increasing the model parameters.

We suggest the following nonlinear model structure that satisfies the above model requirements.

$$u(t) = v(t)^2 \tag{1}$$

$$q(t) = u(t) + p_1 u^2(t) + \cdots + p_{m-1} u^m(t) \tag{2}$$

$$\frac{dx(t)}{dt} = Ax(t) + Bq(t) \tag{3}$$

$$y(t) = Cx(t) + e(t) \tag{4}$$

Where $u(t)$ and $y(t)$ denote the model input (the square of the voltage) and the model output (the temperature), respectively. $e(t)$ is a white measurement noise $x(t)$ is the n-dimensional state. Sys tem matrices A and B have the following respective forms:

$$A = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 & -a_n \\ 1 & 0 & 0 & \cdots & 0 & -a_{n-1} \\ 0 & 1 & 0 & \cdots & 0 & -a_{n-2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 & -a_2 \\ 0 & 0 & 0 & \cdots & 1 & -a_1 \end{bmatrix} \tag{5}$$

$$B = [b_n \quad b_{n-1} \quad b_{n-2} \quad \cdots \quad b_2 \quad b_1]^T \tag{6}$$

$$C = [0 \quad 0 \quad 0 \quad \cdots \quad 0 \quad 1] \tag{7}$$

Here, (2) is the nonlinear static function and the system of (3) and (4) is the linear dynamic system. For readers who are familiar with time series expression, (3) and (4) can be rewritten equivalently like the following continuous-time output error (OE) model.

$$\begin{aligned} & z^{(n)}(t) + a_1 z^{(n-1)}(t) + \cdots + a_{n-1} z^{(1)}(t) + a_n z(t) \\ & = b_1 q^{(n-1)}(t) + b_2 q^{(n-2)}(t) + \cdots + b_{n-1} q^{(1)}(t) + b_n q(t) \end{aligned} \tag{8}$$

$$y(t) = z(t) + e(t) \tag{9}$$

Where $z^{(i)}(t)$ denotes the i-th derivative of the continuous-time signal $z(t)$

The chosen dynamic model of (1)-(9) satisfies the model requirements as follows : (1) is to satisfy the first requirement. If we do not fix $b_i, i = 1,2,\cdots,n-1$ at zeros, the second requirement would be satisfied. Because (3) does not include time delay, the third requirement is satisfied. The process order of the dynamic system composed of (3) and (4) is n So, it should be $n \geq 2$ to satisfy the fourth requirement. The fifth requirement is incorporated by the nonlinear equation of (2).

3.2 Estimating Model Parameters

We did itemize the model requirements for the thermal microsystem and established the model structure that satisfies the requirements. In this section, we use the prediction error identification method (Sung et al., 2001) to estimate the model parameters by minimizing the following cost function as follows.

$$\min_{\hat{P},\hat{A},\hat{B}}\left[V(\hat{P},\hat{A},\hat{B}) = \frac{0.5}{N}\sum_{i=1}^{N}(y(t_i) - \hat{y}(t_i))^2 \right] \tag{10}$$

subject to

$$u(t) = v^2(t) \tag{11}$$

$$\hat{q}(t) = u(t) + \hat{p}_1 u^2(t) + \cdots + \hat{p}_{m-1} u^m(t) \tag{12}$$

$$\frac{d\hat{x}(t)}{dt} = \hat{A}\hat{x}(t) + \hat{B}\hat{q}(t) \tag{13}$$

$$\hat{y}(t) = C\hat{x}(t) \tag{14}$$

$$t_0 = 0 < t_1 < \cdots < t_{N-1} < t_N \tag{15}$$

where, $y(t)$ and $\hat{y}(t)$ denote the measured process output and the predicted model output, respectively. (11)-(14) are the optimal predictor for the process of (1)-(4). To solve the optimization problem, we use the Levenberg-Marquardt optimization method because its convergence rate is fast and robust. All equations to calculate the derivatives of the cost function in the Levenberg-Marquardt method can be easily derived from (10)-(14) as done in Sung et al. (2001).

Table 1. Estimated model parameters and the modeling error (ISE-integral of the square error).

Model structure	Model parameters						ISE
	a_1	a_2	b_1	b_2	p_1	p_2	
$n=2$, $b_1=0$, $u(t)=v^2(t)$, $m=1$	177.4	-	84.98	-	-	-	1232.4
$n=2$, $u(t)=v(t)$, $m=1$	5.972	1.028	56.70	27.92	-	-	1464.5
$n=2$, $u(t)=v^2(t)$, $m=1$	2.246	0.195	9.090	1.666	-	-	122.7
F $n=2$,igure 5: $u(t)=v^2(t)$, $m=2$	2.657	0.281	9.781	2.236	0.0129	-	18.43
$n=2$, $u(t)=v^2(t)$, $m=3$	2.604	0.272	9.790	2.194	0.0142	0.0010	17.83

3.3 Model Performances

We activated the thermal microsystem using roughly tuned PI controller to generate the test data. Table 1 shows the model performances of three linear model types : the simple linear second order model with $v^2(t)$ as the model input ($n=2, b_1=0, u(t)=v^2(t), m=1$), the linear second order model which has a zero and the voltage as the model input ($n=2, u(t)=v(t), m=1$), the linear second order model which has a 'zero' and $v^2(t)$ as the model input ($n=2, u(t)=v^2(t), m=1$), respectively. These estimation results are consistent with the expected results from the model requirements in Subsection 3.1. That is, the simple linear second order model cannot well describe the dynamics because the model has no zero. Because the voltage is chosen as the model input, the model performance is inevitably poor due to the nonlinearity of the square function. The linear second order model which has a negative zero and the square of the voltage as the model input can describe the dynamics more precisely than other cases. According to the remaining fifth model requirement, we can improve the model performance further by introducing the nonlinear polynomial to incorporate the nonlinear dynamics. Table 1 and Figure 5 show the model performance of the second order model with the second order nonlinear polynomial function ($n=2, u(t)=v^2(t), m=2$), and the third order nonlinear polynomial function ($n=2, u(t)=v^2(t), m=3$), respectively. Both show satisfying identification results. We identified the third order model also. Its performance is revealed almost the same with the second order model. We finally choose the model of Figure 5 because it is simple while its performance is close to the best.

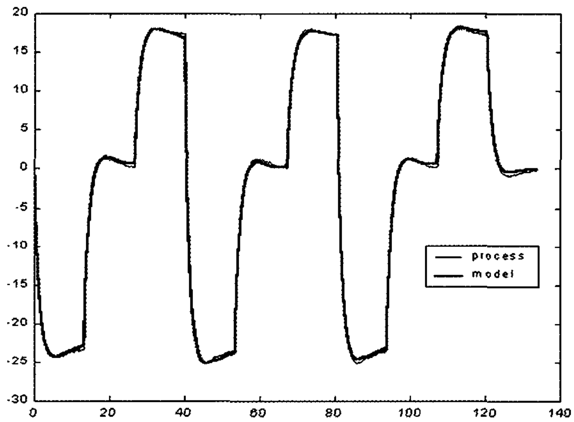
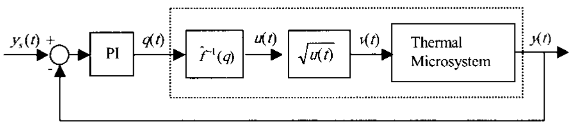


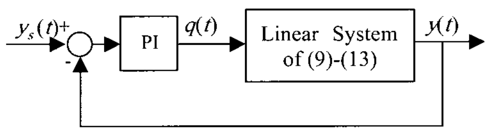
Figure 5. Model performances when the model has a second order nonlinear polynomial.

4. Control Strategy

In the previous section, we identified the nonlinear second order model, which has the square of the voltage for the model input, a small negative zero to incorporate the initial jump in the step test and the second order nonlinear polynomial to describe the input nonlinearity. In this section, we will establish an automatic control strategy using the nonlinear proportional-integral (PI) controller as shown in Figure 6 on the basis of the identified nonlinear model. It satisfies the following three control requirements for high performance thermal microsystem.



(a) The proposed nonlinear control strategy



(b) Equivalent control system

Figure 6. Linearizing the nonlinear dynamics of the thermal microsystem : (a), (b)

4.1 Linearization

It should be noted that because the PI controller is a linear one, the corresponding process also should be linear to achieve the full performance of the PI controller. To satisfy the requirement, the proposed control strategy linearizes the nonlinear dynamics of the thermal microsystem using the identified nonlinear model as shown in Figure 6(a), where the dotted-line-box is equivalent to the linear process of (3)-(4) if the model is perfect. That is, the linear PI controller controls the linear process as shown in Figure 6(b), which makes the tuning of the PI controller easier as well as guarantees high performances as in the linear case.

4.2 Tuning of the PI Controller

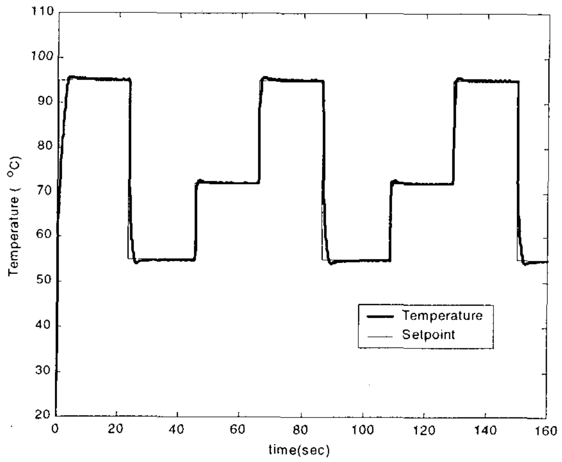
For the tuning of the proposed controller in Figure 6(a), we dont have to consider the nonlinear parts of (11) and (12) because Figure 6(a) is essentially equivalent to Figure 6(b). That is, we can tune the PI controller for the linear model of (13)-(14). To tune the PI controller, we estimate the tuning parameters by minimizing the integral of the time-weighted square value of the error (ITSE) for the unit step set point change (Sung et al. (2002)).

4.3 Integral Windup

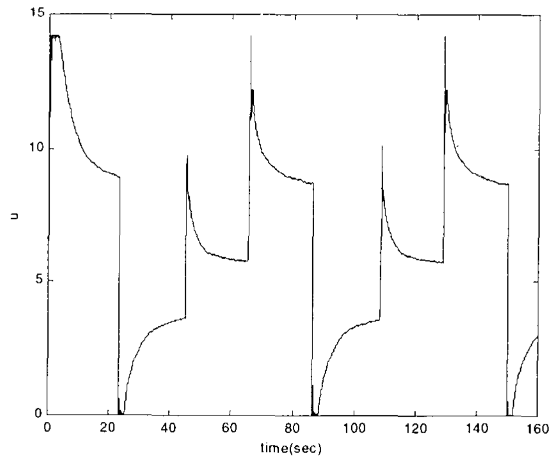
The maximum achievable control performance for the thermal microsystem is very high because it has almost negligible time delay and no unstable 'zeros' (Morari and Zafiriou, 1983). This means that we can raise the temperature up to the desired temperature within very short time only if we can afford to apply high voltage. But, we cannot increase infinitely the maximum voltage because of the limited resolution of the data acquisition system (note that the resolution decreases as the maximum voltage increases) and cost problems. Then, the control output may be initially saturated at the maximum value for a large set point change (for example, from room temperature to 95℃). The same situation happens in the cooling process. We should initially enter the minimum control output (i.e., zero voltage) for a while to drop the temperature as fast as possible. It is clear from the above argument that there should be inevitably actuator saturation for high performance operation. Then, the integral part of the PI controller accumulates too much when the control output is saturated, resulting in a large overshoot in the heating process and a large undershoot in the cooling process (Seborg et al., 1989). The situation is called "integral windup". In this research, when the control output is saturated, we stop the integral action of the PI controller to prevent the integral windup phenomenon.

4.4 Control Results

We choose $\tau = 0.2$ sec as the time constant of the desired trajectory and the sampling time is $\Delta t = 0.055$ sec. The estimated optimal tuning results for the desired trajectory are $k_c = 0.2107$ and $k_i = 0.2107/0.2242$ We use the anti-windup technique. The control performance is excellent as shown in Figure 7. It shows remarkable heating and cooling rates of approximately 36℃/sec and 22℃/sec, about 15 times faster than commercial PCR machines. The overshoot was not over 0.8℃ and the steady state error is less than i‡0.1℃. Figure 8 shows what happen if we dont use anti-windup techniques. There are a big overshoot and a big undershoot because the integral part of the PI controller becomes too big when the control output is saturated. We strongly recommend using the anti-windup function for the high-performance thermal microsystem. Figure 9 demonstrates what happen if we use only linear PI controller without linearizing the nonlinear dynamics of the thermal microsystem. The linear PI controller is tuned for the operating region of 55℃. As a result, it shows acceptable performance for the corresponding region. But, it shows poor control performances for the other operating regions of 72℃ and 95℃ because the linear controller cannot remove the nonlinear dynamics.

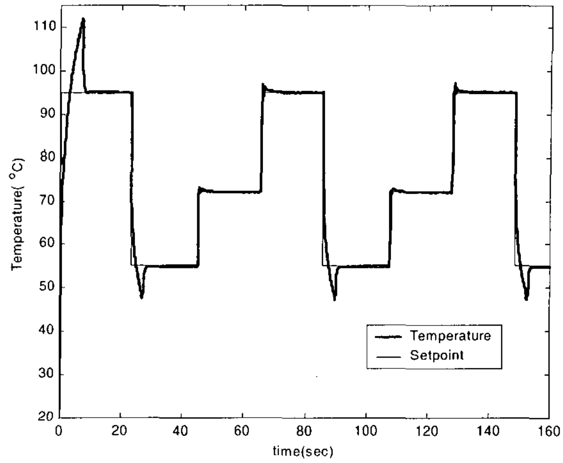


(a)



(b)

Figure 7. Control performances of the proposed control strategy.



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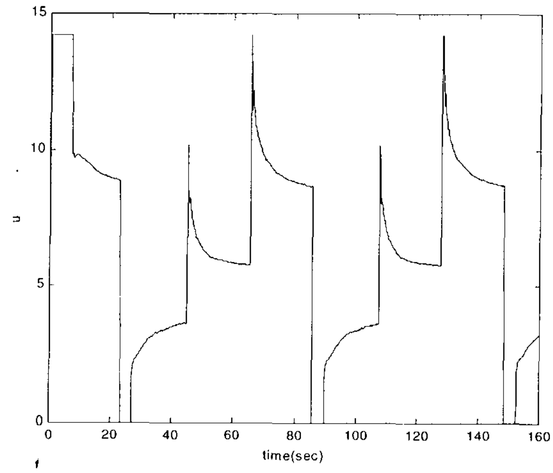
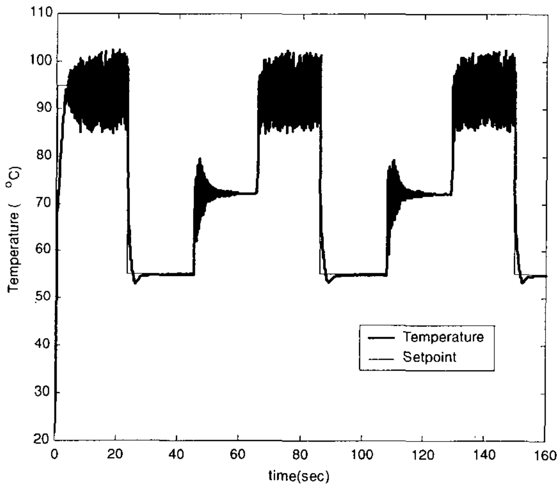


(b)

Figure 8. Control performances of the nonlinear control strategy without anti-windup technique.



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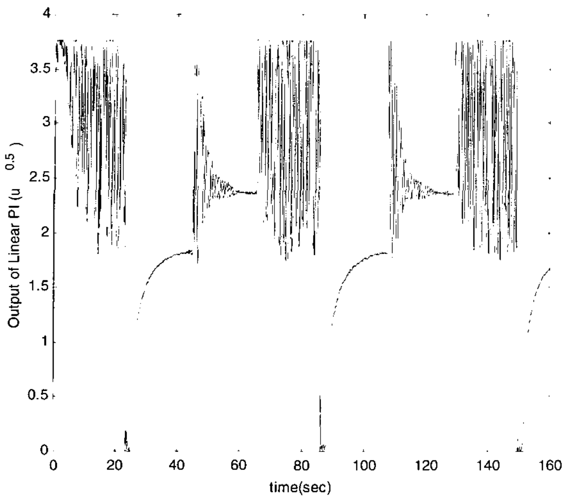

(b)

Figure 9. Control performances of the linear PI controller.

5. Future Issues

One of the most promising characteristics of microsystems is parallel processing of diversified reactants and materials. In the thermal microsystem, it is also important to operate simultaneously hundred PCR reactors in one array. Commercial PCR machines can do the parallel processing only if all temperature profiles for every reactor in the array are identical because they cannot control the reactor temperatures independently. We need to develop a new thermal microsystem that independently controls all PCR reactors in the array to follow each desired temperature profile. To realize the parallel processing, first, the PCR machines should be manufactured to minimize the temperature interactions between adjacent reactors so that the huge multi-input-multi-output control system is close to single-input-single-output control system. Second, an efficient and robust control algorithm to manipulate the interactions between the huge number of control loops. Third, much more compact/tiny/fast controller should be devised to manipulate more than hundred control loops.

Another interesting feature of the thermal system is the repetitive operation composed of three steps (denaturation, annealing and extension). Then, the dynamic behavior of the next cycle is predictable from that of the past cycle. So, we have a chance to achieve a better control performance each cycle based on the dynamic behavior of the previous cycle. We call it the repetitive learning control. It is expected that the learning control plays an important role in enhancing the performance of the thermalzt microsystem.

6. Conclusions

We exemplified the development of a thermal microsystem composed of a silicon-based microreactor and other equipments/software required for full automation. The dynamic characteristic of the thermal microsystem was analyzed and on the basis of the analysis, the model structure was determined. We identified the model parameters using the prediction error identification method and demonstrated its excellent model performances. A nonlinear control strategy was proposed to linearize the nonlinear dynamics of the thermal microsystem, which makes the tuning of the PI controller easier and guarantees high performances as in the linear case. We could demonstrate a high-performance operation with the anti-windup nonlinear PI controller tuned by the optimal tuning method. Finally, we raise several important issues to improve the thermal microsystems.

Acknowledgment

This work is supported by the BK21 Project and Center for Ultramicrochemical Process Systems sponsored by KOSEF

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명실상부한 산,학,연의 정보 교환의 장으로서 학회지가 회원님들에게 보다 도움이 되는 실질적인 정보를 제공하고자 아래와 같은 기사를 모집합니다. 회원님들의 적극적인 참여를 부탁드립니다.

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7) 공개 채용 안내를 위한 자료 (학회 홈페이지 및 학회지에 게재)
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   - 회원사의 사원 모집 공고, 회원 중에서 필요한 인력 채용 공고
   - 벤처 기업 및 중소 기업에서의 필요 인력 채용 공고
   - 기타 회원 대상 홍보 내용

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