Front. Electr. Electron. Eng. China 2010, 5(2): 218–223
DOI 10.1007/s11460-010-0002-5

RESEARCH ARTICLE

Minghui HU, Fuzhen XUAN, Huihe SHAO

A novel measurement method of temperature model for bioreactor

Abstract A novel measurement method of temperature model for bioreactor has been proposed. Temperature is the key parameter in monitoring the bioreactor operation. However, the system input signal of bioreactor is delayed, and model parameters are uncertain, so the output of temperature is non-steady-state. Many dynamic measurements are not steady so that it cannot be described by variables constant in time. In this paper, we adopt the monopulse signal as input so that the output of the bioreactor system is steady. This method has a powerful ability to steady the output of the bioreactor. In view of the measurement results, it can be seen that the model dynamic measurement approaches the real process. The analytical expression of the monopulse response for the temperature model of the bioreactor is obtained. The novel measurement approach is simple and can be easily adopted by industry.

Keywords measurement method, temperature model, monopulse response, time-variant, bioreactor

1 Introduction

Many dynamic measurements are not stationary and cannot be described by variables constant in time. Rather, they are made in a transient state defined by a substantial variation of the level of excitation of the system. Sharp, irregular or rapidly varying details of the output as well as its maxima/minima are often difficult to measure accurately. Nevertheless, detecting such transient and complex features is usually the primary reason for making a dynamic experiment [1]. The control of bioreactors was restricted to the regulation of variables, such as temperature and potential hydrogen (pH), for optimizing the microbial growth [2]. These were the ideal variables to control since they often have negligible perturbations [3,4]. However, in many practical control applications, a mathematical description of the bioreactor is not available, and a controller has to be designed on the basis of measurements.

The availability of continuous information on the essential variables of a process allows one to monitor and operate the process effectively. However, in many cases, such process variables cannot be measured or are measured at infrequent and/or irregular times and with significant time delays. This measurement problem is a consequence of the inadequacy of available sensors or operational limitations/concerns, such as the higher possibility of the contamination of the media in bioreactors when more samples are taken for off-line analysis. The measurement of temperature is of considerable interest [5]. Many techniques are based on different sensitivities to temperature or combining different types of sensors. Temperature measurement of bioreactors is to maintain the process outputs close to their desired values in the presence of various uncertainties, including external disturbances and time-varying parameters [6]. In the absence of frequent measurements of the essential variables, continuous estimates of these variables can be obtained from available frequent and/or infrequent measurements by a model of the process under consideration. Examples of measurements are those of temperature, pressure, dissolved oxygen concentration, and density that are usually available at high sampling rates and with almost no delays. A paper describes the design and implementation of a multi-rate nonlinear state observer [7] to estimate a parameter and the state variables of a batch biochemical reactor.

Received September 7, 2009; accepted January 6, 2010

Minghui HU (✉), Fuzhen XUAN
Key Laboratory of Safety Science of Pressurized System, Ministry of Education, School of Mechanical and Power Engineering, East China University of Science and Technology, Shanghai 200237, China
E-mail: agile_hu@ecust.edu.cn

Huihe SHAO
School of Electronic, Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

Many investigations related to the effect of temperature on anaerobic digestion show a very strong negative effect on the metabolic activity of the anaerobic microorganisms with temperature decrease [8] because like other biological processes, anaerobic digestion depends strongly on temperature. Generally speaking, the higher the temperature leads, the higher the microbial activity up to an optimum temperature [9]. The effect of temperature on biological activity is related to cell retention time in the digesters which should be superior at decreasing temperature. Although anaerobic microorganisms can be acclimated to operation temperatures outside the optimum range, biomass activity and digester performance may be adversely affected [10].

Presently, some methods are presented in the measurement system [11–15]. In Ref. [11], a model was presented, which was based on frequency response approach for thermal radiation microsensors. A basic model for the prediction of the dynamic response of complex pneumatic line systems is presented in Ref. [12], which is able to reproduce the physics of the problem correctly and deal with any complex network of lines and cavities. In Ref. [13], a novel method is proposed for evaluating the uncertainty associated with the output of a discrete-time infinite impulse response (IIR) filter when the input signal is corrupted by additive noise, and the filter coefficients are uncertain. A method is presented how the principle-related response time of temperature-modulated direct thermoelectric gas sensors can be reduced [14]. In Ref. [15], a sensing scheme is used to measure temperature and strain simultaneously by multiplexing a section of the multimode fiber. Because temperature strongly affects the rate of conversion processes, some essential improvements are required in conventional temperature measurement to enable application at sub-optimal temperatures [9].

In this paper, a novel measurement method is developed to determine the temperature model of the bioreactor. The measurement method uses monopulse response when the input signal is delayed and model parameters are uncertain. The output of the temperature measurement system is non-steady-state. A method based on monopulse input will be utilized to the unsteady process. We adopt the monopulse signal as input so that the output of the process is steady. The analytical expression for the monopulse response of the temperature model is obtained. The main objective of this paper is to show the derivation of the temperature model of the bioreactor. Finally, simulation results are given to show the effectiveness of the measurement method. The novel method given in this paper is simple and can be easily adopted by industry.

2 Structures of bioreactor

The temperature model of the bioreactor used in this paper was originally studied in our laboratory. Basically, a bioreactor is a tank in which several biological reactions occur simultaneously in a liquid medium. To provide suitable conditions for growth and production, it is common to monitor and control the essential cultivation variables, as shown in Fig. 1, where T_j and T are the sheath and tank temperature, respectively. As shown in Fig. 1, we can see that the range of T is from 0°C to 100°C; if 50°C $< T <$ 100°C, the heater operates; if 0°C $< T <$ 50°C, the valve of cooling water opens and the heater stops; if $T =$ 50°C, the valve of cooling water closes and the heater stops. The dissolved temperature is the variable that is normally measured on-line.

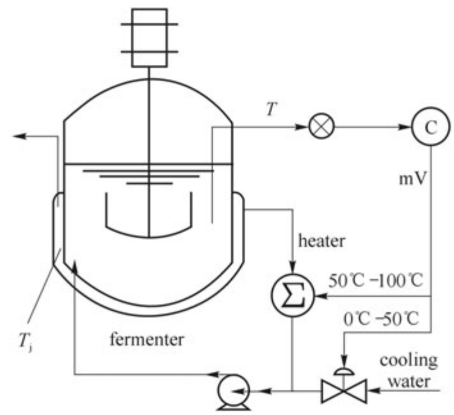

Fig. 1 Control scheme of bioreactor temperature process

In this section, a mathematical model describes the temperature of the bioreactor as follows:

$$\frac{\mathrm{d}}{\mathrm{d}t}\begin{bmatrix} T \\ T_\mathrm{j} \end{bmatrix} = \begin{bmatrix} -a_1(T-T_\mathrm{j}) \\ a_2(T-T_\mathrm{j})+a_3(T_0-T_\mathrm{j}) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} U, \quad (1)$$

$$Y = T, \quad (2)$$

where T_j is the sheath temperature; T is the temperature of the tank-side; T_0 is the room temperature; Y is the output; U is the input; a_1, a_2, and a_3 are the thermal conductivity coefficients of the tank from inner to external, respectively. Because a_1 and a_2 are the thermal conductivity coefficients of the reactant in the tank from inner to external, $a_1 = a_2$; thus, Eqs. (1) and (2) can be written as

$$T(s) = \frac{a_1}{s+a_1} T_\mathrm{j}(s), \quad (3)$$

$$(s+a_2+a_3)T_\mathrm{j}(s) = a_2 T(s) + U(s) + a_3 T_0, \quad (4)$$

where s is an s-function.

Under the condition of neglecting the loss of thermal, $a_3 = 0$. Combining Eqs. (3) and (4), $T(s)$ can be described as

$$T(s) = \frac{a_1 U(s)}{s^2 + 2a_1 s} = \frac{K_\mathrm{m}}{s(T_\mathrm{m}s+1)} U(s), \quad (5)$$

where K_m is a coefficient, and $T_\mathrm{m}=\dfrac{1}{2a_1}$. Considering the time delay, Eq. (5) can be simply described as

$$T(s)=\frac{K_\mathrm{m}\mathrm{e}^{-L_\mathrm{m}}}{s(T_\mathrm{m}s+1)}U(s), \tag{6}$$

where L_m is the time delay.

3 Model dynamic measurement

A model of the measurement can be determined by parametric system identification of a calibration experiment. Here, a complete dynamic model and its uncertainty are defined in Eq. (6). All aspects of dynamic characterization and system identification will thus be excluded. However, the temperature model expressed as in Eq. (6) is integrating the process with the time delay. The transfer function has one or more poles in the imaginary axes of the complex plane. The output of the temperature measurement system is non-steady-state. We adopt the monopulse signal as input so that the output of the process is steady.

For the temperature model which is described in Eq. (6), we adopt the monopulse signal as input, so the output response of the temperature process of the bioreactor can be presented as follows:

$$Y(s)=\frac{K_\mathrm{m}}{s(T_\mathrm{m}s+1)}\mathrm{e}^{-L_\mathrm{m}s}U(s). \tag{7}$$

In zero initial state, applying the inverse Laplace transformation to the output response of Eq. (7), an algebraic equation in the transform variable t is obtained:

$$T_\mathrm{m}y''(t)+y'(t)=K_\mathrm{m}u(t-L_\mathrm{m}). \tag{8}$$

Equation (8) can be represented as follows:

$$T_\mathrm{m}y(t)+\int_0^t y(\tau)\mathrm{d}\tau=K_\mathrm{m}\int_0^t\int_0^\tau u(\tau_1-L_\mathrm{m})\mathrm{d}\tau_1\mathrm{d}\tau. \tag{9}$$

We adopt the monopulse signal as input so that the output of the process is steady. The monopulse signal can be described as

$$u(t)=h[1(t)-1(t-T_\mathrm{d})], \tag{10}$$

where

$$1(t)=\begin{cases}0, & \text{if } t<0,\\ 1, & \text{if } t\geqslant 0;\end{cases} \tag{11}$$

h is the monopulse amplitude; T_d is the monopulse duration. The monopulse signal can be expressed as

$$\int_0^t\int_0^\tau u(\tau_1-L_\mathrm{m})\mathrm{d}\tau_1\mathrm{d}\tau$$

$$=\begin{cases}0, & 0<t<L_\mathrm{m},\\ \dfrac{1}{2}(t-L_\mathrm{m})^2h, & L_\mathrm{m}\leqslant t<L_\mathrm{m}+T_\mathrm{d},\\ -\dfrac{1}{2}T_\mathrm{d}^2h+T_\mathrm{d}th-T_\mathrm{d}L_\mathrm{m}h, & t\geqslant L_\mathrm{m}+T_\mathrm{d}.\end{cases} \tag{12}$$

Obviously, Eq. (12) is a piecewise continuous function. For finding the delay, the model of measurement temperature can be determined by parametric system identification of the third expression of Eq. (12). Substituting the third expression of Eq. (12) into Eq. (9), the following equation can be obtained:

$$\begin{aligned}y(t)&=-\frac{1}{T_\mathrm{m}}\int_0^t y(\tau)\mathrm{d}\tau-\frac{1}{2}\frac{K_\mathrm{m}}{T_\mathrm{m}}T_\mathrm{d}^2h+\frac{K_\mathrm{m}}{T_\mathrm{m}}T_\mathrm{d}th-\frac{K_\mathrm{m}}{T_\mathrm{m}}T_\mathrm{d}L_\mathrm{m}h\\ &=\left[-\int_0^t y(\tau)\mathrm{d}\tau,\quad -\frac{1}{2}T_\mathrm{d}^2h+T_\mathrm{d}th,\quad -T_\mathrm{d}h\right]\\ &\quad\cdot\left[\frac{1}{T_\mathrm{m}},\quad \frac{K_\mathrm{m}}{T_\mathrm{m}},\quad \frac{K_\mathrm{m}L_\mathrm{m}}{T_\mathrm{m}}\right]^\mathrm{T}.\end{aligned} \tag{13}$$

Define

$$\begin{cases}\varphi^\mathrm{T}(t)=\left[-\displaystyle\int_0^t y(\tau)\mathrm{d}\tau,\quad -\dfrac{1}{2}T_\mathrm{d}^2h+T_\mathrm{d}th,\quad -T_\mathrm{d}h\right],\\ \theta^\mathrm{T}=\left[\dfrac{1}{T_\mathrm{m}},\quad \dfrac{K_\mathrm{m}}{T_\mathrm{m}},\quad \dfrac{K_\mathrm{m}L_\mathrm{m}}{T_\mathrm{m}}\right],\end{cases} \tag{14}$$

and

$$\begin{cases}\psi=[\varphi(t_1),\varphi(t_2),\ldots,\varphi(t_N)]^\mathrm{T},\\ \Gamma=[y(t_1),y(t_2),\ldots,y(t_N)]^\mathrm{T},\end{cases} \tag{15}$$

where t_i, $i=1,2,\ldots,N$, and $L_\mathrm{app}+T_\mathrm{d}\leqslant t_1<t_2<\cdots<t_N$.

Combining Eqs. (14) and (15), we can get the following form:

$$\Gamma=\psi\theta, \tag{16}$$

where column vector groups of ψ are independent. Thus, $\psi^\mathrm{T}\psi$ is a nonsingular matrix. Applying the least-squares method to the matrix, we can deduce the equation as follows:

$$\hat{\theta}=(\psi^\mathrm{T}\psi)^{-1}\psi^\mathrm{T}\Gamma. \tag{17}$$

To simplify the operation, we can obtain K_m by steady-state output $y(\infty)$ of the process. Adopting monopulse signal as input, when the process reaches steady state, the terminal value theorem of the process can be presented as

$$\begin{aligned}&y(\infty)-y(0)\\ &=\lim_{s\to 0}\left[s\frac{K_\mathrm{m}}{s(T_\mathrm{m}s+1)}\mathrm{e}^{-L_\mathrm{m}s}\frac{h}{s}(1-\mathrm{e}^{-T_\mathrm{d}s})\right]\\ &=K_\mathrm{m}T_\mathrm{d}h,\end{aligned} \tag{18}$$

where $y(0)$ is the steady-state value of the process without the input monopulse signal. Thus, K_m can be presented as follows:

$$K_m = \frac{y(\infty) - y(0)}{T_d h}. \quad (19)$$

Thus, Eq. (14) can be represented as

$$\begin{cases} \varphi^T(t) = \left[-\int_0^t y(\tau)d\tau - \frac{1}{2}K_m T_d^2 h + K_m T_d th, \quad -K_m T_d h \right], \\ \theta^T = \left[\frac{1}{T_m}, \ \frac{L_m}{T_m} \right]. \end{cases} \quad (20)$$

Thus, model parameters can be written in the following form:

$$\begin{bmatrix} K_m \\ T_m \\ L_m \end{bmatrix} = \begin{bmatrix} \frac{\bar{y}(\infty) - \bar{y}(0)}{T_d h} \\ \frac{1}{\theta_1} \\ \frac{\theta_2}{\theta_1} \end{bmatrix}. \quad (21)$$

In the practical process control, it is difficult to avoid measurement noise [16]. Thus, we cannot obtain the consistent estimation of the system parameter by Eq. (17). To solve the problem, we adopt the instrument variable method. The instrument variable can be presented as follows:

$$\Lambda = \begin{bmatrix} \frac{1}{t_1} & 1 \\ \frac{1}{t_2} & 1 \\ \vdots & \vdots \\ \frac{1}{t_N} & 1 \end{bmatrix}. \quad (22)$$

Thus, the consistent estimation of the system parameter can be obtained by the follow equation:

$$\hat{\theta} = (\Lambda^T \psi)^{-1} \Lambda^T \Gamma. \quad (23)$$

The consistent estimation of the model parameters of continuous systems with dead time has been proved in Ref. [17]. Similarly, we can obtain the consistent estimation of system parameters by Eq. (23).

4 Simulations

Simulations are performed to examine the performance of the proposed model dynamic measurement. Figures 2 and 3 show the model dynamic measurement result for a higher order integrating process with time delay which is generally applied in industrial and chemical practice. Consider the process $P(s)$ presented as

$$P(s) = \frac{0.01e^{-11s}}{s(10s+1)(3s+1)}. \quad (24)$$

Under the white Gaussian noise with maximum amplitude 0.05 and 0.1, respectively, we can obtain the measurement result using the least-squares method. Respectively, the measurement results can be written in the following form:

Model 1

$$P_m(s) = \frac{0.0086e^{-15.1621s}}{s(21.5267s+1)}. \quad (25)$$

Model 2

$$P_m(s) = \frac{0.092e^{-14.8739s}}{s(22.5916s+1)}. \quad (26)$$

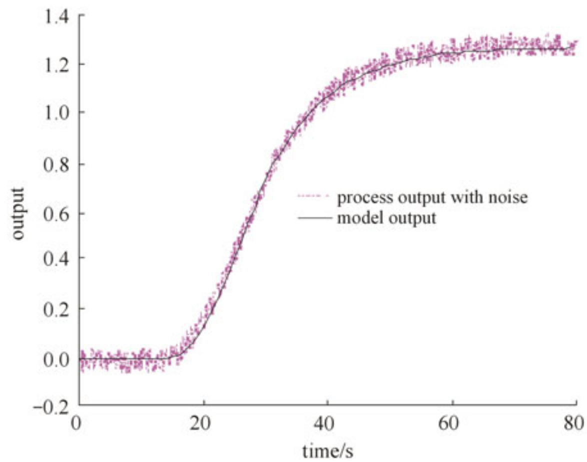

Fig. 2 Measurement result when amplitude of white Gaussian noise is 0.05

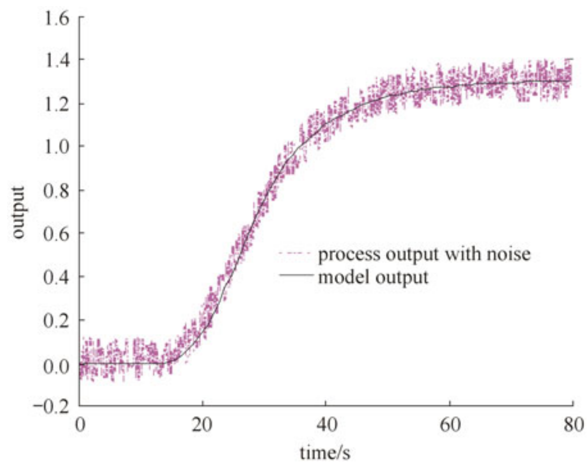

Fig. 3 Measurement result when amplitude of white Gaussian noise is 0.1

In the frequency domain, the Nyquist curves of the model measurement and exact process are shown in Fig. 4 under the different white Gaussian noises.

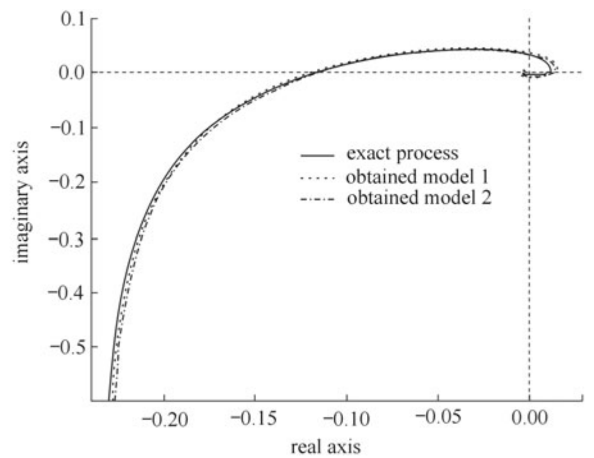

Fig. 4 Nyquist curves of model dynamic measurement and exact process

From Figs. 2–4, it can be seen that the model dynamic measurement approaches the real process. The effect of the maximum amplitude of white Gaussian noise can be neglected for the model dynamic measurement.

To obtain the temperature model of the bioreactor, in normal state, the result of temperature model dynamic measurement based on monopulse response is shown in Fig. 5. It can be seen that the temperature model parameters $K_{\mathrm{m}} = 0.0006$, $T_{\mathrm{m}} = 134.5$, and $L_{\mathrm{m}} = 12.1$, so the temperature model of the bioreactor can be written as

$$P_{\mathrm{m}}(s) = \frac{0.0006}{s(134.5s+1)}\mathrm{e}^{-12.1s}. \tag{27}$$

From Fig. 5, it can be seen that the model output approaches the real process output. Thus, the model measurement results represent the real temperature model of the bioreactor.

Under proportion integration differentiation (PID) control, Fig. 6 describes the elimination of the steady-state error of the bioreactor process operation with 500-mL cold water injection at $t = 1200$ s, where PV is the process variable, and SP is the set point. The temperature comes to a steady state. From Fig. 6, the performance of temperature shows that the system has been successfully controlled to the set point.

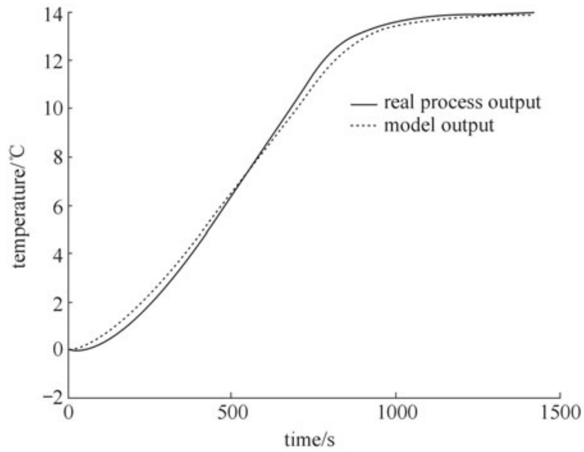

Fig. 5 Temperature model dynamic measurement for bioreactor (in normal state)

5 Conclusions

In this paper, a novel measurement method of the temperature model for the bioreactor has been proposed. The output of the temperature measurement system of the bioreactor is non-steady-state. When the input signal is delayed and the model parameters of the bioreactor are uncertain, the novel model dynamic measurement method based on monopulse input will be utilized to the bioreactor. Using the least-squares method and consistent estimation of the system parameter, in view of the measurement results under the white Gaussian noise with maximum amplitude 0.05 and 0.1, respectively, it can be seen that the model dynamic measurement approaches the real process. The effect of the maximum amplitude of white Gaussian noise can be neglected for the model dynamic measurement. Thus, the measurement results represent the real temperature model of the bioreactor.

We adopt the monopulse signal as input so that the

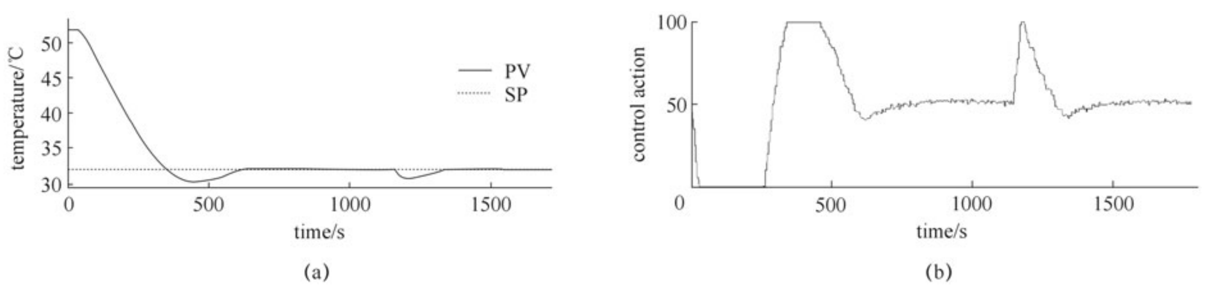

Fig. 6 Temperature and control action under PID control. (a) Temperature output; (b) control action under PID

output of the process is steady. The analytical expression of the monopulse response for the temperature model of the bioreactor is obtained. The main objective of this paper is to show the derivation of the temperature model. Simulation results are given to show the effectiveness of the measurement method. In particular, this applies to all the common time-variant and non-stationary transient dynamic temperature measurements of the bioreactor. The novel method given in this paper is simple and can be easily adopted by industry.

Acknowledgements This work was supported by the National High Technology Research and Development Program of China (No. 2004AA412050).

References

1. Hessling J P. A novel method of evaluating dynamic measurement uncertainty utilizing digital filters. Measurement Science and Technology, 2009, 20(5): 055106
2. Barrón M A, Aguilar R. Dynamic behaviour of a continuous stirred bioreactor under control input saturation. Journal of Chemical Technology and Biotechnology, 1998, 72(1): 15–18
3. Dondo R G, Marqués D. Optimal control of a batch bioreactor: a study on the use of an imperfect model. Process Biochemistry, 2001, 37(4): 379–385
4. Ziegler J G, Nichols N B. Optimum settings for automatic controllers. Transactions of the American Society of Mechanical Engineers, 1942, 64(11): 759–768
5. Kim D W, Shen F, Chen X, Wang A. Simultaneous measurement of refractive index and temperature based on a reflection-mode long-period grating and an intrinsic Fabry-Perot interferometer sensor. Optics Letter, 2005, 30(22): 3000–3002
6. Engin S N, Yildiz F, Ince M, Onkal Engin G, Keskinler B. Modeling and parameter identification of a jet-loop bioreactor. In: Proceedings of American Control Conference. 2007, 6122–6127
7. Tatiraju S, Soroush M, Mutharasan R. Multi-rate nonlinear state and parameter estimation in a bioreactor. In: Proceedings of the 1998 American Control Conference. 1998, 4: 2324–2328
8. Banik G C, Viraraghavan T, Dague R R. Low temperature effects on anaerobic microbial kinetic parameters. Environmental Technology, 1998, 19(5): 503–512
9. Lettinga G, Rebac S, Zeeman G. Challenge of psychrophilic anaerobic wastewater treatment. Trends in Biotechnology, 2001, 19 (9): 363–370
10. Bergamo C M, Monaco R D, Ratusznei S M. Effects of temperature at different organic loading levels on the performance of a fluidized-bed anaerobic sequencing batch bioreactor. Chemical Engineering and Processing, 2009, 48(3): 789–796
11. Kozlov A G. Frequency response model for thermal radiation microsensors. Measurement Science and Technology, 2009, 20(4): 045204
12. Antonini C, Persico G, Rowe A L. Prediction of the dynamic response of complex transmission line systems for unsteady pressure measurements. Measurement Science and Technology, 2008, 19(12): 125401
13. Link A, Elster C. Uncertainty evaluation for IIR (infinite impulse response) filtering using a state-space approach. Measurement Science and Technology, 2009, 20(5): 055104
14. Rettig F, Mpps R. Temperature-modulated direct thermoelectric gas sensors: thermal modeling and results for fast hydrocarbon sensors. Measurement Science and Technology, 2009, 20(6): 065205
15. Zhang J, Zhang Y, Sun W, Yuan L. Multiplexing multimode fiber and Fizeau etalon: a simultaneous measurement scheme of temperature and strain. Measurement Science and Technology, 2009, 20(6): 065206
16. Hu M H, Shao H H. Autoregressive spectral analysis based on statistical autocorrelation. Physica A: Statistical Mechanics and Its Applications, 2007, 376: 139–146
17. Wang Q G, Zhang Y. Robust identification of continuous systems with dead-time from step responses. Automatica, 2001, 37(3): 377–390