

一类非线性系统的快速鲁棒故障诊断

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摘要: 结合在线估计器和滑模观测器方法, 基于所给出的一种新的自适应学习算法, 提出了一种针对非线性不确定系统的鲁棒故障诊断方法. 滑模观测器可以消除建模不确定性的影响以得到准确的状态估计, 而在线估计器可以实时估计故障的大小. 在此, 基于李亚普诺夫函数, 在理论上证明了所给出的状态和参数估计误差都是一致有界的; 针对三容水箱 DTS200 所做的仿真实验, 其结果验证了该方法的可行性. 研究结果表明, 由于滑模项的引入, 使得该方法的故障检测时间大大缩短, 其性能比 Polycarpou 所提出的在线估计器方法的性能要好.

关键字: 非线性系统; 故障诊断; 自适应; 滑模观测器

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为了研究具有建模不确定性的非线性系统故障诊断即非线性鲁棒故障诊断, J. Chen 等提出了未知输入观测器方法^[1], 将建模不确定项都视为未知输入, 在观测器设计时使其对未知输入解耦从而达到鲁棒性的要求, 但该方法只能应用于线性系统或可在平衡点附近线性化的非线性系统, 不是通用的非线性故障诊断方法; M. A. Demetriou 等基于自适应学习方法对非线性不确定系统进行故障检测和估计, 通过构造一个自适应观测器用于故障检测^[2], 其核心是用在线估计器估计故障大小, 从理论上给出了死区阈值, 保证其鲁棒性, 并证明了系统的稳定性. 基于 M. A. Demetriou 的参数估计思想^[2], 在此通过引入滑模观测器, 并基于所给出的新的自适应学习算法, 提出一种新的故障诊断方法.

($i = 1, \dots, n$) 为单位阶跃函数; $f(x, u, t) \in \mathbf{R}^n$ 为故障项.

假设 1 建模不确定项有界, 即 $|\varphi_i(x, u)| \leq \bar{\varphi}_i$ ($i = 1, \dots, n$). 其中, $\bar{\varphi}_i$ 为给定正数.

构造如下变结构自适应观测器:

$$\dot{\hat{x}} = -\Lambda \hat{x} + \xi(x, u) + M(\tilde{x}) + f(x, u, \theta). \quad (2)$$

其中: $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$, $\lambda_i > 0$; $f(x, u, \theta) = [f_1(x, u, \theta_1), \dots, f_n(x, u, \theta_n)]^T$, 为在线估计器; $\theta_i \in \mathbf{R}^{p_i}$, 为参数; $\tilde{x} = x - \hat{x}$, 为状态估计误差; $M(\tilde{x}) = [M_1(\tilde{x}_1), \dots, M_n(\tilde{x}_n)]^T$, 为滑模项. 为了防止高频振颤, 对滑模项引入如下边界层控制:

$$M_i(\tilde{x}_i) = \begin{cases} \text{sign}(\tilde{x}_i) \bar{\varphi}_i, & \text{if } |\tilde{x}_i| > \eta_i; \\ \frac{\tilde{x}_i}{\eta_i} \bar{\varphi}_i, & \text{if } |\tilde{x}_i| \leq \eta_i. \end{cases} \quad (3)$$

其中: $i = 1, \dots, n$; η_i 为边界层阈值, 通常为很小的正实数, 一般地, $\eta_i \ll \bar{\varphi}_i$.

为保证故障检测的鲁棒性, 要求在故障发生前 (即 $B(t-T) = 0$), 有 $f(x, u, \theta) \equiv 0$, 即参数的自适应学习算法不工作: $f(x, u, \theta(t_0)) = 0$ 且 $\dot{\theta} \equiv 0$.

定理 1 若 $\tilde{x}_i(t_0) = 0$ (由全状态可测), 则故障发生前观测器的状态估计误差满足: $|\tilde{x}_i| < \varepsilon$ ($i = 1, \dots, n$). 其中: $\varepsilon = \min \left[\frac{1}{2} \sqrt{\frac{\eta_i \bar{\varphi}_i}{\lambda_i}}, \eta_i \right]$.

1 鲁棒故障检测及估计

1.1 非线性不确定系统

考虑如下全状态可测的非线性不确定系统:

$$\dot{x} = \xi(x, u) + \varphi(x, u) + B(t-T)f(x, u, t). \quad (1)$$

其中: $x \in \mathbf{R}^n$, 为状态变量; $u \in \mathbf{R}^m$, 为控制量; $\xi(x, u) \in \mathbf{R}^n$, 为非线性系统的标称模型; $\varphi(x, u) \in \mathbf{R}^n$, 为建模不确定项; $B(t-T) = \text{diag}\{\beta_1(t-T_1), \dots, \beta_n(t-T_n)\}$, 代表第 i 个子系统的故障发生时间为 T_i ; $\beta_i(\tau)$

证明 故障发生前,由式(1)和(2)得如下误差动态方程:

$$\dot{\tilde{x}} = -\Lambda\tilde{x} + \varphi(\mathbf{x}, \mathbf{u}) - \mathbf{M}(\tilde{x}). \quad (4)$$

考虑其中第 i 个误差子系统($i = 1, \dots, n$):

$$\dot{\tilde{x}}_i = -\lambda\tilde{x}_i + \varphi_i(\mathbf{x}, \mathbf{u}) - \mathbf{M}_i(\tilde{x}_i). \quad (5)$$

取 Lyapunov 函数为 $V_i = \frac{1}{2}\tilde{x}_i^2$, 则:

$$V_i = \tilde{x}_i\dot{\tilde{x}}_i = -\lambda\tilde{x}_i^2 + \tilde{x}_i(\varphi_i(\mathbf{x}, \mathbf{u}) - \mathbf{M}_i(\tilde{x}_i)). \quad (6)$$

a. 当 $|\tilde{x}_i| > \eta$ 时,

$$V \leq -\lambda\tilde{x}_i^2 + |\tilde{x}_i| \bar{\varphi}_i - |\tilde{x}_i| \bar{\varphi}_i = -\lambda\tilde{x}_i^2 < 0. \quad (7)$$

b. 当 $|\tilde{x}_i| \leq \eta$ 时,

$$\begin{aligned} V_i &\leq -\lambda\tilde{x}_i^2 + |\tilde{x}_i| \bar{\varphi}_i - \frac{|\tilde{x}_i|^2}{\eta} \bar{\varphi}_i \\ &- \lambda\tilde{x}_i^2 - \bar{\varphi}_i \left[\frac{|\tilde{x}_i|^2}{\eta} + |\tilde{x}_i| + \frac{\eta}{4} \right] + \frac{\eta \bar{\varphi}_i}{4} \\ &\leq -\lambda\tilde{x}_i^2 + \frac{\eta \bar{\varphi}_i}{4}. \end{aligned} \quad (8)$$

若 $\eta > \frac{1}{2} \sqrt{\frac{\eta \bar{\varphi}_i}{\lambda}}$, 则当 $\frac{1}{2} \sqrt{\frac{\eta \bar{\varphi}_i}{\lambda}} < |\tilde{x}_i| \leq \eta$ 时, 有 $V_i < 0$;

若 $\eta \leq \frac{1}{2} \sqrt{\frac{\eta \bar{\varphi}_i}{\lambda}}$, 则当 $|\tilde{x}_i| > \eta$ 时, 有 $V_i < 0$.

综上分析可知: 当 $|\tilde{x}_i| > \varepsilon$ 时, 有 $V_i < 0$. 又 $\tilde{x}_i(t_0) = 0$, 因此, 第 i 个误差子系统在故障发生前总有 $|\tilde{x}_i| < \varepsilon$ (通常, 由于 $\eta \ll \bar{\varphi}_i$, 故 $\varepsilon = \eta$).

1.2 鲁棒故障检测策略

$|\tilde{x}_i| > \varepsilon$ ($i = 1, \dots, n$) 之前, 系统无故障; 若第 1 次检测到 $|\tilde{x}_s| > \varepsilon$, 则判定第 s 个子系统发生故障; 并启动参数估计算法对故障幅值进行估计^[3].

$f(\mathbf{x}, \mathbf{u}, \theta)$ 选用线性参数化估计器(如 RBF 神经网络), 即具有如下形式:

$$f_i(\mathbf{x}, \mathbf{u}, \theta_i) = \Omega_i^T(\mathbf{x}, \mathbf{u}) \theta_i. \quad (9)$$

其中: $i = 1, \dots, n$. 对 RBF 网络则有: $\Omega_i(\mathbf{z}) = \left[\exp\left[-\frac{\|\mathbf{z} - \mathbf{c}_{i1}\|^2}{\sigma_{i1}^2}\right], \dots, \exp\left[-\frac{\|\mathbf{z} - \mathbf{c}_{ip_i}\|^2}{\sigma_{ip_i}^2}\right] \right]^T$, $\theta_i \in \mathbf{R}^{p_i}$. 由于 RBF 神经网络具有通用逼近性, 因此, $f(\mathbf{x}, \mathbf{u}, \theta)$ 可以任意精度逼近 $f(\mathbf{x}, \mathbf{u}, t)$. 给定 p_i , c_{ij} 和 σ_{ij} , 令

$$\theta_i^* = \arg \min_{\theta_i \in \mathbf{R}^{p_i}} \sup_{\mathbf{x} \in B} |f_i(\mathbf{x}, \mathbf{u}, t) - f_i(\mathbf{x}, \mathbf{u}, \theta_i)|.$$

其中 B 是状态和控制变量的可行域, 则

$$f_i(\mathbf{x}, \mathbf{u}, t) = \Omega_i^T(\mathbf{x}, \mathbf{u}) \theta_i^* + v_i. \quad (10)$$

其中: $i = 1, 2, \dots, n$; v_i 为最优参数下 RBF 神经网络的建模误差.

假设 2 $|v_i| \leq \bar{v}_i$, $\|\theta_i^*\| \leq \bar{\theta}_i$ 且 $\|\theta_i^*\| \leq \bar{\theta}_i$

($i = 1, \dots, n$).

定理 2(稳定性) 若选取如下自适应学习算法:

$$\dot{\hat{\theta}} = \begin{cases} \Gamma_i(-k_i\hat{\theta}_i + \Omega_i\tilde{x}_i), & \text{if } |\tilde{x}_i| > \varepsilon, \text{ 且 } \theta_i(t_0) = 0; \\ 0, & \text{if } |\tilde{x}_i| \leq \varepsilon, \text{ 且 } \theta_i(t_0) = 0. \end{cases} \quad (11)$$

其中: $i = 1, 2, \dots, n$. $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$, 为参数估计误差; $\Gamma_i \in \mathbf{R}^{p_i \times p_i} > 0$, 为学习速率; $k_i > 0$, 为反馈系数. 则由式(2)和(11)给出的状态估计和参数估计误差都一致有界.

证明 第 i 个误差子系统在故障发生后可表示为:

$$\dot{\tilde{x}} = -\lambda\tilde{x}_i + \varphi_i(\mathbf{x}, \mathbf{u}) - \mathbf{M}_i(\tilde{x}_i) + \Omega_i^T(\mathbf{x}, \mathbf{u}) \tilde{\theta}_i + v_i. \quad (12)$$

取 Lyapunov 函数为 $V_i = \frac{1}{2}(\tilde{x}_i^2 + \tilde{\theta}_i^T \Gamma_i^{-1} \tilde{\theta}_i)$, 则

$$\begin{aligned} V_i &= \tilde{x}_i\dot{\tilde{x}}_i + \tilde{\theta}_i^T \Gamma_i^{-1} \dot{\tilde{\theta}} = \tilde{x}_i\dot{\tilde{x}}_i + \tilde{\theta}_i^T \Gamma_i^{-1} (\theta_i^* - \dot{\hat{\theta}}) \\ &= -\lambda\tilde{x}_i^2 + \tilde{x}_i(\varphi_i(\mathbf{x}, \mathbf{u}) - \mathbf{M}_i(\tilde{x}_i)) + \tilde{x}_i v_i + \\ &\quad \tilde{\theta}_i^T [\Gamma_i^{-1} \theta_i^* + k_i(\theta_i^* - \tilde{\theta}_i)]. \end{aligned}$$

令 v_i^m 为 Γ_i^{-1} 得最大特征值, 则由式(7)和(8)和假设 2 得:

$$\begin{aligned} V_i &\leq -\lambda\tilde{x}_i^2 + \frac{\eta \bar{\varphi}_i}{4} + \bar{v}_i |\tilde{x}_i| + \\ &(k_i \bar{\theta}_i + v_i^m \bar{\theta}_i) \|\tilde{\theta}_i\| - k_i \|\tilde{\theta}_i\|^2 \\ &\leq -\frac{1}{2}(\lambda\tilde{x}_i^2 + k_i \|\tilde{\theta}_i\|^2) + \\ &\left[\frac{\eta \bar{\varphi}_i}{4} + \frac{\bar{v}_i^2}{2\lambda} + \frac{(k_i \bar{\theta}_i + v_i^m \bar{\theta}_i)^2}{2k_i} \right]. \end{aligned} \quad (13)$$

令 $M_i = \frac{\eta \bar{\varphi}_i}{4} + \frac{\bar{v}_i^2}{2\lambda} + \frac{(k_i \bar{\theta}_i + v_i^m \bar{\theta}_i)^2}{2k_i}$, 则当 $|\tilde{x}_i| > \sqrt{\frac{2M_i}{\lambda}}$ 或 $\|\tilde{\theta}_i\| > \sqrt{\frac{2M_i}{k_i}}$ 时, 有 $V_i < 0$.

可见, 状态和参数估计误差都一致有界. 因此, 在自适应学习算法(11)作用下, 系统仍然稳定.

2 仿真实验

2.1 仿真对象

仿真对象是三容水箱 DTS200, 其系统可描述为:

$$\begin{aligned} A \frac{dh_1}{dt} &= -Q_{13} + Q_1, \\ A \frac{dh_3}{dt} &= Q_{13} - Q_{32}, \\ A \frac{dh_2}{dt} &= Q_{32} - Q_{20} + Q_2. \end{aligned} \quad (14)$$

其中:

$$\begin{cases} Q_{13} = a_{z_1} S_n \text{sign}(h_1 - h_3) \sqrt{2g|h_1 - h_3|}, \\ Q_{32} = a_{z_3} S_n \text{sign}(h_3 - h_2) \sqrt{2g|h_3 - h_2|}, \\ Q_{20} = a_{z_2} S_n \sqrt{2gh_2}. \end{cases} \quad (15)$$

则状态变量为 $\mathbf{x} = [h_1, h_2, h_3]^T$, 控制量为 $\mathbf{u} = [Q_1, Q_2]^T$; 系统的真实参数为: $A = 0.0154 \text{ m}^2$, $S_n = 5 \times 10^{-5} \text{ m}^2$, $Q_{1\max} = Q_{2\max} = 100 \text{ mL/s}$, $h_{\max} = (62 \pm 1) \text{ cm}$, $g = 9.81 \text{ m/s}^2$, $a_{z_1}^0 = 0.490471$, $a_{z_2}^0 = 0.611429$, $a_{z_3}^0 = 0.450223$.

设建模时流出系数 a_{z_1} , a_{z_2} , a_{z_3} 具有一定的误差, 即:

$$a_{z_i} = a_{z_i}^0 + \Delta a_{z_i} \quad (i = 1, 2, 3).$$

则按式 (1) 的形式, 建模不确定项为:

$$\begin{aligned} \Phi(\mathbf{x}, \mathbf{u}) = & \frac{1}{A} \begin{bmatrix} \Delta a_{z_1} S_n \text{sign}(h_1 - h_3) \sqrt{2g|h_1 - h_3|} \\ - \Delta a_{z_1} S_n \text{sign}(h_1 - h_3) \sqrt{2g|h_1 - h_3|} + \\ \Delta a_{z_3} S_n \text{sign}(h_1 - h_3) \sqrt{2g|h_3 - h_2|} \\ - \Delta a_{z_3} S_n \text{sign}(h_3 - h_2) \sqrt{2g|h_3 - h_2|} + \\ \Delta a_{z_2} S_n \sqrt{2gh_2} \end{bmatrix}. \end{aligned} \quad (16)$$

建模误差上界分别取为: $\bar{\varphi}_1 = 2 \times 10^{-4} \text{ m/s}$, $\bar{\varphi}_3 = 4 \times 10^{-4} \text{ m/s}$, $\bar{\varphi}_2 = 4 \times 10^{-4} \text{ m/s}$ (对应于 a_{z_1} , a_{z_2} , a_{z_3} 分别有约 4% 的误差). 对 1 号和 2 号水箱采用输出反馈的 PI 控制, 其设定值分别为 $h_1^0 = 0.5 \text{ m}$, $h_2^0 = 0.3 \text{ m}$; 对 PI 控制器, $P = 1$, $I = 1$.

仿真故障设置为: 10 s 时 1 号水箱底部漏水. 设漏水孔的半径为 r , 则漏水量为: $Q_{\text{leak}} = a_{z_1} \pi r^2 \sqrt{2gh_1}$, 1 号水箱的动态方程变为:

$$A \frac{dh_1}{dt} = -Q_{13} + Q_1 - Q_{\text{leak}}. \quad (17)$$

则按式 (1) 的形式, 故障项为: $f_1(\mathbf{x}, \mathbf{u}, t) = -Q_{\text{leak}}/A$, 在下面的仿真中取 $r = 0.0025 \text{ m}$, 其余仿真参数分别为: $\Lambda = I_3$; $\eta_i = 1 \times 10^{-6} \text{ m/s}$ (由定理 1 可推出 $\xi_i = \eta_i = 1 \times 10^{-6}$, $i = 1, 2, 3$); 流出系数的标称值分别为: $a_{z_1} = 0.5$, $a_{z_2} = 0.6$, $a_{z_3} = 0.45$ (可验证该组参数满足上面所给建模误差上界). 为了简单, 仿真中对 f_1 只取 h_1 作为输入量, RBF 神经网络 9 个基函数的中心均匀分布在 $[-2, 2]$, 且方差都为 1, 并取 $\Gamma_1 = 5I_9$, $k_1 = 0.05$. 仿真软件为 matlab6.1 的 simulink, 最大步长为 0.001 s.

观测器状态估计误差如图 1 所示. 可见: 故障发生前, 3 个状态估计的误差都在设定的阈值内; 而在第 10 s 发生故障后, 状态 1 的估计误差很快越过了

阈值 1×10^{-6} , 从而检测出 1 号水箱发生故障. 而状态 2 和 3 的估计误差仍保持在阈值内, 即 2 号水箱和 3 号水箱无故障, 这与实际情况相符. 图 2 反映了在线估计器对故障的估计情况, 可见, 经过很短的时间, 在线估计器就能跟踪故障, 实现对故障比较准确的估计.

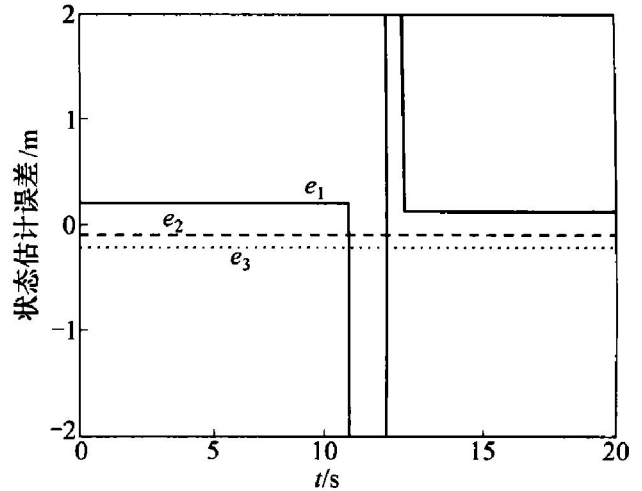


图 1 观测器状态估计的误差

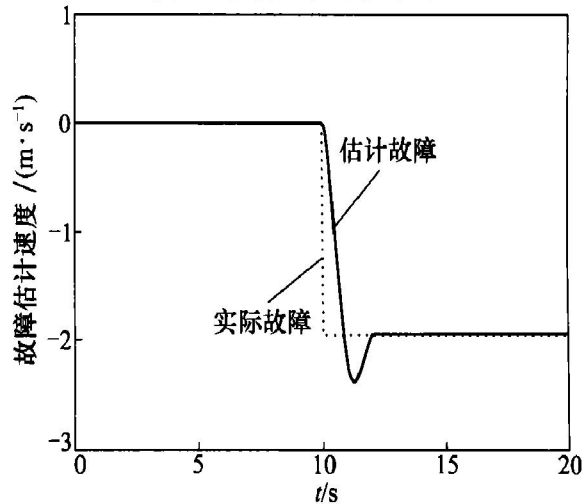


图 2 在线估计器对故障的估计

2.2 故障检测时间

将图 2 所示故障估计值在 10 s 附近放大, 可以看到在线估计器开始学习的时间约为 10.0007 s, 即故障检测时间比实际故障发生时间延后约 0.0007 s (也可由图 1 所示状态估计误差超过阈值来判断故障检测时间). 因此, 采用该方法可以很快检测出故障. 而采用 M. A. Demetriou 等提出的方法^[2], 在相同仿真参数下, 可看出其故障检测时间延后约 0.14 s (见图 3).

再考虑时变的故障, 即上述漏水孔大小为时变的情形. 假设漏水孔的大小先缓慢变大, 然后又突变. 其半径变化规律如下:

$$r = \begin{cases} 0, & t < 10; \\ 0.0005(t-10), & 10 \leq t < 20; \\ 0.007, & t \geq 20. \end{cases} \quad (19)$$

3 结 论

由图 4 所示的仿真结果可以看到, 作者所提出的方法对系统的缓变故障和突变故障都能较好地检测和估计.

a. 改进了 M. A. Demetriou 等提出的方法, 在自适应观测器中引入了滑模项, 并且提出了一种新的自适应学习算法.

b. 通过 Lyapunov 函数从理论上导出了鲁棒故障检测的充分条件, 并证明了在故障发生后, 系统状态和参数估计误差都一致有界.

c. 对三容水箱 DTS200 进行数值仿真, 结果表明该方法与理论推导结果相符, 可以对非线性不确定系统进行故障检测和估计, 而且适用于闭环控制的故障检测和估计.

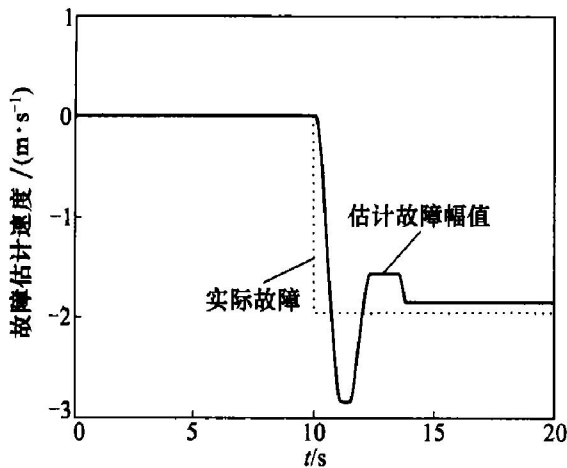


图 3 采用文献[2]方法所得的时变故障估计

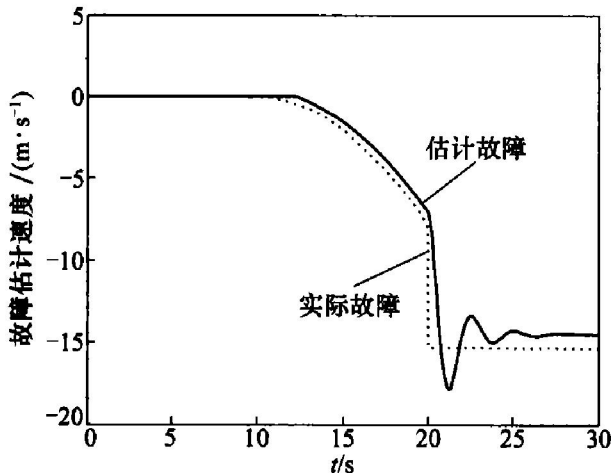


图 4 在线估计器对时变故障的估计

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Fast and robust fault diagnosis of a class of nonlinear systems

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Abstract: In recent years, robust fault diagnosis of nonlinear systems has become one of the most difficult problems in the fault diagnosis community. By combining the Polycarpou's approximator with sliding mode observers, a novel approach to robust fault diagnosis of a class of nonlinear uncertain systems is proposed in this article, in which a new adaptive learning algorithm we proposed is applied. Exact state estimates are obtained by the sliding mode observers, which can eliminate the impact of modelling uncertainties, and meanwhile, the online approximator is used to estimate the fault amplitude in real time. By use of Lyapunov function, it is proved that the errors of state and parameter estimates are consistently bounded. Simulation results on a three tank system DTS200 demonstrate the effectiveness of the proposed approach. In addition, the fault detection time of the proposed approach is greatly shortened due to the introduction of the sliding mode, which is superior to the well known online approximator method proposed by Polycarpou.

Key words: nonlinear systems; fault diagnosis; self-adaptive; sliding mode observer