行政院國家科學委員會專題研究計畫　期中進度報告

最佳線上即時智慧型控制系統的設計與作(2/3)

計畫類別：個別型計畫
計畫編號：NSC93-2213-E-009-045-
執行期間：93年08月01日至94年07月31日
執行單位：國立交通大學電機與控制工程學系(所)

計畫主持人：王啟旭
共同主持人：李祖添

報告類型：精簡報告
報告附件：出席國際會議研究心得報告及發表論文
處理方式：本計畫可公開查詢

中　華　民　國 94年5月23日

ABSTRACT

This report is for the second year of a three year project. This report mainly deals with a very practical issue which considers the maximum control input delay, i.e., the maximum allowable computational time to find controller, so that the closed-loop system is stable. The report for the first year (i.e., last year) assumes no control input delay to obtain the on-line intelligent adaptive controller. This second year report proposes another new closed-loop configuration to account for the inevitable control input delay of all computer-controlled systems. Critical Stability Constraints (CSC) criteria are applied to find the maximum computational time (i.e., maximum control input delay) for generating on-line controller, so that the closed-loop system can still meet the design specifications. Based on this information, a set of feasible computer hardware can be chosen to minimize the implementation cost. The inverted pendulum system, which is fully illustrated in the previous year report, will be illustrated again in this report to show the effectiveness of this new approach. Simulation results of the inverted pendulum system show excellent results of this new intelligent adaptive controller with maximum computational time for complicated controller, such as the FNN controller.

1. INTRODUCTION

Most existing design techniques to control unknown nonlinear dynamical systems are based on a good understanding of the plant under consideration and its environment. However, in a number of instances, the plant to be controlled is too complex and the basic physical processes in it are not fully understood. Hence, design methods need to be augmented with an identification technique [1]-[4] aimed at obtaining a progressively better understanding of the plant to be controlled. For a well-specified nonlinear system, such as the inverted pendulum system, the mass damper system and the Chua's chaotic circuit, the linearized Takagi-Sugeno fuzzy model [4] can be obtained by using the Jacobian matrix to locally linearize the nonlinear systems. Thus the well-specified nonlinear system can be well-controlled by all means, such as the local and global optimal controllers [5]-[7]. For unknown nonlinear dynamical systems, the linearized TS-type fuzzy model can not be obtained. Therefore a special type (i.e., the Ishidori-Byrnes canonical form [8]) of unknown nonlinear dynamical system was thus brought into discussion and both direct and indirect adaptive FNN (IAC FNN and DAC FNN) controllers are obtained [9]-[11] for the tracking of a sinusoidal signal. If the unknown nonlinear dynamical system is not in the Ishidori-Byrnes canonical form, then FNN (or Recurrent FNN) is applied as the on-line identifier and using the command error to fine tune the classical PID controller with sliding mode learning convergence [12]. However the sliding mode training will cause chattering effects in order to have faster convergence [12] and the determination of sliding surface is very complicated and may not be feasible for on-line purpose. Further we must know that **a**ll the FNN-based adaptive controllers or FNN-based closed-loop control system will require significant computational time. They are actually the sample-data control systems. However, all the existing research literature [1] - [12] neglected the computational time and sampling process to present their simulation results. In actual hardware implementation, if the computational time does not include as the time delay, all the design algorithms are doom to fail in real implementation.

The main theme of this report is to follow the results from the first year of this project, which assumed no computational delay for the FNN controller, to develop an off-line algorithm for the finding the maximum computational time, so that the overall closed-loop will be stable. First an equivalent mathematical sampled-data system, which can describe the effect of computational time delay on the closed-loop control system, will be proposed. The sampling time of the converted closed-loop sampled data system is actually the computational time delay of the FNN controller. We adopt

Jury stability test [13, 14] on the closed-loop system with linearized TS-type fuzzy model. Then the maximum computational time delay can be determined easily from four graphical plots of critical constraint functions. This implies that control signal must be generated within the maximum allowable time so that the plant can be well controlled to maintain the overall stability. The inverted pendulum is applied as the illustrating example to show the effectiveness of this approach. Excellent results are obtained which shows the agreement of theoretical and simulating results.

2. Equivalent Model for the Computation of Controller

For a computer controlled system, it is obvious that the computer has to wait for its input and needs time to compute next controller signal for the plant to be controlled. In other words, the current FNN-based adaptive controllers or FNN-based closed-loop control system requires significant computational time which can not be neglected. Otherwise, it is will be failed in hardware implementation. Figure 1 shows the timing sequences with fixed T_d to account for the required computational time of the controller..

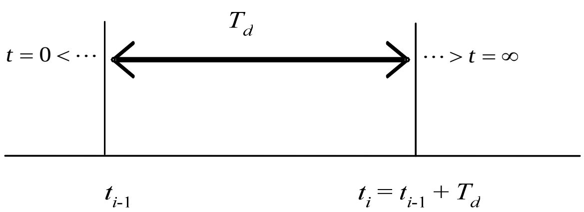

Fig. 1. Time interval [$t_{i\text{-}1}$ t_i] with fixed T_d for computing controller

Furthermore, Fig. 2 shows the inclusion of a pure time delay $e^{-T_d s}$ in front of the controller. This is to account for the fact that the controller can only have the error signal $\boldsymbol{e}(t)$ delayed by time T_d and the controller will then take time less than T_d to compute $U(s)$. Therefore T_d is a vital factor for selecting the computer and other relevant components in actual hardware implementation.

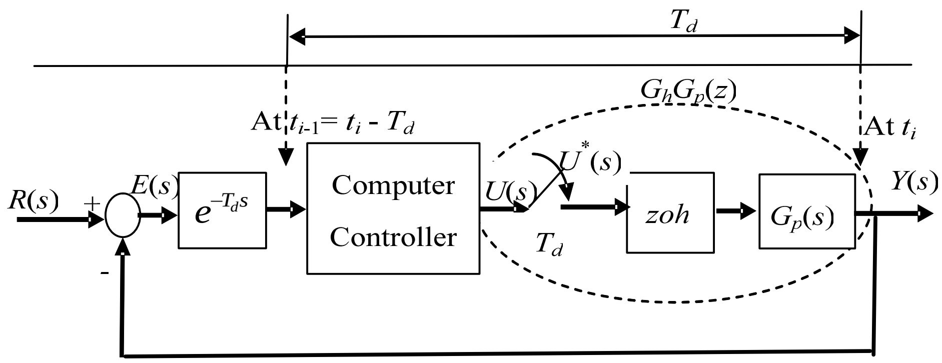

Fig. 2. Closed-loop system with time delay

We assume that the time of the signal propagation can be neglected. From Figs. 1 and 2, we know that at time instant t_{i-1} the computer obtains input data (error between the actual system output and the reference) and finishes computing controller signal before t_i. Once time t reaches t_i, the plant receives the controller signal as input to control its operation. Thus the difference between t_i and t_{i-1} (i.e., T_d) can be treated as the time required for the computation of the controller. Therefore the determination of maximum allowable T_d to guarantee the stability of the closed-loop system is a critical issue which will be discussed in the next section.

3. Critical Stability Constraints for Finding the Maximum T_d

Let $G_p(s)$ in Eq.(1) be a continuous-time transfer function of a strictly proper and rational system and be sampled by a zero-order hold device shown in Fig. 2.

$$G_p(s) = \frac{e_1 + e_2 s + \cdots + e_{n-1}s^{n-2} + e_n s^{n-1}}{g_1 + g_2 s + \cdots + g_n s^{n-1} + s^n} \tag{1}$$

The transformed form of the sampled system can be found as

$$G_hG_p(z) = \frac{p_1 + p_2 z + \cdots + p_{n-1}z^{n-2} + p_n z^{n-1}}{q_1 + q_2 z + \cdots + q_n z^{n-1} + q_{n+1}z^n} \tag{2}$$

Suppose a discrete-time polynomial function $C(z)\in\Re[z]_n$ of the form

$$C(z) = \sum_{i=0}^{n} c_i z^i = c_0 + c_1 z + c_2 z^2 + \cdots + c_{n-1}z^{n-1} + c_n z^n \tag{3}$$

$$c_n > 0$$

and let $C(z) = 0$ be the characteristic equation of the closed-loop system in Fig. 2. For simplicity, the above equation is normalized and rewritten as

$$D(z) = c_0/c_n + c_1/c_n\, z + c_2/c_n\, z^2 + \cdots + c_{n-1}/c_n\, z^{n-1} + c_n/c_n\, z^n$$

$$= d_0 + d_1 z + d_2 z^2 + \cdots + d_{n-1} z^{n-1} + z^n \qquad (4)$$

To ensure all roots of (4) are inside the unit circle, the following four Critical Stability Constraints of Jury's Test [13, 14] should be satisfied:

$$T_0 = d_n = 1 > 0,$$

$$T_1 = D(1) > 0, \qquad (5)$$

$$T_2 = (-1)^n D(-1) > 0, \qquad (6)$$

$$T_3 = \left|\Phi_{n-1} - \Psi_{n-1}\right| > 0 \qquad (7)$$

Where

$$\Phi_{n-1} = \begin{bmatrix} d_n & d_{n-1} & d_{n-2} & \cdots & d_2 \\ 0 & d_n & d_{n-1} & \cdots & d_3 \\ 0 & 0 & d_n & \cdots & d_4 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & d_n \end{bmatrix} \in \Re^{(n-1)\times(n-1)},$$

$$\Psi_{n-1} = \begin{bmatrix} 0 & 0 & 0 & \cdots & d_0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & d_0 & \cdots & d_{n-4} \\ 0 & d_0 & d_1 & \ddots & d_{n-3} \\ d_0 & d_1 & d_2 & \cdots & d_{n-2} \end{bmatrix} \in \Re^{(n-1)\times(n-1)}.$$

Equations (5), (6) and (7) are actually functions of sampling-time T_d. By taking advantage of the embedded power of a symbolic manipulation package such as Maple or Matlab, we can easily resolve issue of finding the sampling-time range which can satisfy all the constraints of $T_0 > 0$, $T_1(T) > 0$, $T_2(T) > 0$, and $T_3(T) > 0$.

4. The Inverted Pendulum System with Maximum T_d

In this section, we will apply our optimal on-line training to design a tracking controller to control the inverted pendulum to track a sinusoidal signal. For robustness test, the inverted pendulum system will be added with extra 50% of mass to simulate the case of sudden model change or noise at any time instant. Theoretically, the whole procedure is divided into off-line and on-line stages. In the off-line stage, the main goal is to find the sampling time range and then specify a sampling time for the following on-line stage.

Example 1: Consider the inverted pendulum system [14] as shown in Fig.3. Let $x_1 = \theta$ be the angle of the pendulum with respect to the vertical line.

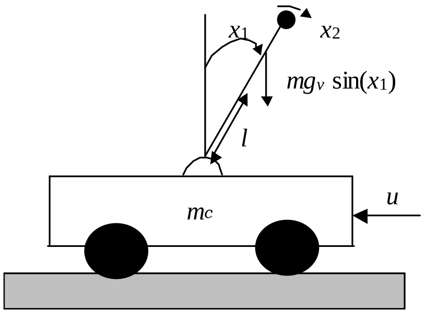

Fig. 3 The inverted pendulum system

The dynamic equations of the inverted pendulum system [15] are

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} (f + gu), \tag{8}$$

where

$$f = \frac{g_v \sin x_1 - \dfrac{mlx_2^2 \cos x_1 \sin x_1}{m_c + m}}{l(\dfrac{4}{3} - \dfrac{m\cos^2 x_1}{m_c + m})} ; g = \frac{\dfrac{\cos x_1}{m_c + m}}{l(\dfrac{4}{3} - \dfrac{m\cos^2 x_1}{m_c + m})}$$

and $g_v = 9.8 meter/sec^2$ is the acceleration due to gravity, m_c is the mass of the cart, l is the half-length of the pole, m is the mass of the pole and u is the control input. In this example, we assume that $m_c = 2kg$, $m = 0.21kg$ and $l = 0.75$ *meter*.

We define three membership functions for each state variable as shown in Fig. 4. The Median membership function is defined as:

$$M_m(x_i) = e^{-(\frac{x_i - center_j}{width_j})^2} \tag{9}$$

The positive and negative membership functions (M_p and M_n) are defined as:

$$M_p(x_i)=\begin{cases} e^{-(\frac{x_i-center_i(3)}{width_i(3)})^2} & for \quad x_i < center_i(3) \\ 1 & else \end{cases}$$
$$M_n(x_i)=\begin{cases} e^{-(\frac{x_i-center_i(1)}{width_i(1)})^2} & for \quad x_i > center_i(1) \\ 1 & else \end{cases} \qquad (10)$$

For state x_1, $center_1 = [-0.4 \quad 0 \quad 0.4]$ and $width_1 = [0.2 \quad 0.2 \quad 0.2]$. For state x_2, $center_2 = [-1 \quad 0 \quad 1]$ and $width_2 = [0.5 \quad 0.5 \quad 0.5]$.

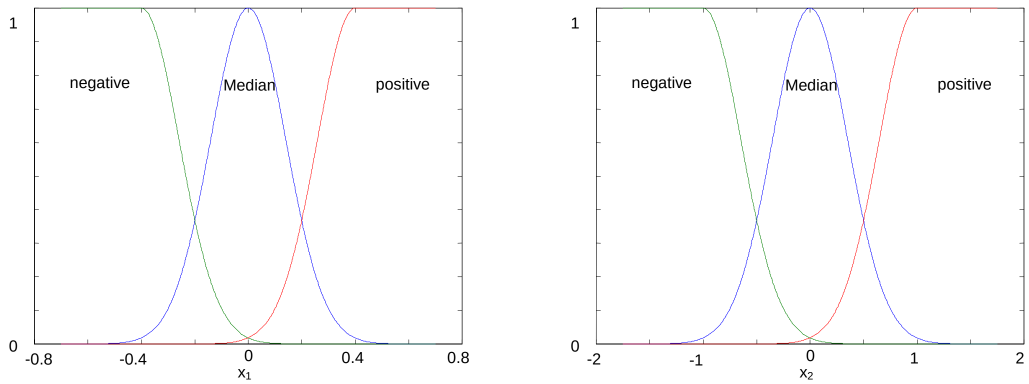

Fig. 4. The membership functions for inverted pendulum system

Following the design procedure as discussed in the report of the previous year, the intelligent closed-loop indirect adaptive controller design for inverted pendulum can be shown in the following steps:

[Step 1]: Apply a light input u = 0.1$sin(t)$ to excite the nonlinear uncertain system, then measure sufficient data information of $x(t)$, $\dot{x}(t)$ and $u(t)$.

[Step 2]: Apply ***Algorithm I*** of the report of the previous year to perform the dynamical optimal training of TS-type fuzzy model with least-squared initialization. The initial parameters for the nine linear subsystems are:

$$A_1=\begin{bmatrix}0 & 1\\ 20.6251 & -0.6866\end{bmatrix}, A_2=\begin{bmatrix}0 & 1\\ 18.9598 & 0.2051\end{bmatrix}, A_3=\begin{bmatrix}0 & 1\\ 22.6312 & 1.5709\end{bmatrix},$$

$$A_4=\begin{bmatrix}0 & 1\\ 20.9676 & -0.0116\end{bmatrix}, A_5=\begin{bmatrix}0 & 1\\ 19.9498 & -0\end{bmatrix}, A_6=\begin{bmatrix}0 & 1\\ 21.1859 & -0.0139\end{bmatrix},$$

$$A_7=\begin{bmatrix}0 & 1\\ 20.6313 & 0.7084\end{bmatrix}, A_8=\begin{bmatrix}0 & 1\\ 19.0468 & -0.2568\end{bmatrix},, A_9=\begin{bmatrix}0 & 1\\ 23.1741 & -1.6748\end{bmatrix}$$

$$B_1=\begin{bmatrix}0\\ 0.8174\end{bmatrix}, B_2=\begin{bmatrix}0\\ 0.8478\end{bmatrix}, B_3=\begin{bmatrix}0\\ 0.8992\end{bmatrix}, B_4=\begin{bmatrix}0\\ 0.9327\end{bmatrix}, B_5=\begin{bmatrix}0\\ 0.9211\end{bmatrix},$$

$$B_6 = \begin{bmatrix} 0 \\ 0.9072 \end{bmatrix}, B_7 = \begin{bmatrix} 0 \\ 0.8236 \end{bmatrix}, B_8 = \begin{bmatrix} 0 \\ 0.8473 \end{bmatrix} B_9 = \begin{bmatrix} 0 \\ 0.8743 \end{bmatrix}$$

By applying fuzzy defuzzification, the initial state space equation of the linear system can be obtained as:

$$A_f = \begin{bmatrix} 0 & 1 \\ 20.6317 & 0.7069 \end{bmatrix}, \ B_f = \begin{bmatrix} 0 \\ 0.8238 \end{bmatrix}, \ C = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, D = 0$$

Compute the range of the sampling-time, and then select a sampling-time T_d.

[Step 3]: Specify closed-loop poles as -10 and –15 and apply ***Algorithm II*** of the report of the previous year to design an on-line stable tracking controller for the closed-loop system.

[Step 4]: Apply ***Algorithm III***, the Adaptive Rules of the report of the previous year, to update the TS-type fuzzy model and tracking controller to stabilize the closed-loop system in Fig. 3.

We assume the initial states of x_1 is $[-0.5\ 1.2]^T$. The reference trajectory for state x_1 is $y_r = 0.2sin(2\pi t)$ and the reference trajectory for state x_2 is $\dot{y}_r = 0.4\pi cos(2\pi t)$.

Putting the state space in [Step 2] into Matlab control command ***ss2tf*** to compute the transfer function of the system, we have

$$\frac{0.8238}{s^2 - 0.7069s - 20.6317}$$

Using the theorem of CSC, Matlab commands and Maple related commands, we can obtain $T_0(T)$ and the equations (36)-(38) of $T_1(T)$, and $T_2(T)$, and $T_3(T)$.

$$T_0(T) = 1$$

$$\begin{aligned} T_1(T) = & -7.3188 + 7.3188 e^{4.9094T} + 7.3188 e^{-2.3247\times10^{12} T} + 7.3188 e^{-4.2025T} \\ & -7.3188 e^{-4.2025T} \ e^{-2.3247\times10^{12} T} - 7.3188 e^{4.9094T} \ e^{-2.3247\times10^{12} T} - 7.3188 e^{0.7069T} \\ & +7.3188 e^{0.7069T} \ e^{-2.3247\times10^{12} T} \end{aligned} \quad (11)$$

$$\begin{aligned} T_2(T) = & - 7.3188 + 6.0191 e^{4.9094T} - 9.3188 e^{-2.3247\times10^{12} T} - 4.0191 e^{-4.2025T} \\ & -4.0191 e^{-4.2025T} \ e^{-2.3247\times10^{12} T} + 6.0191 e^{4.9094T} \ e^{-2.3247\times10^{12} T} + 9.3188 e^{0.7069T} \\ & +9.3188 e^{0.7069T} \ e^{-2.3247\times10^{12} T} \end{aligned} \quad (12)$$

As the equation of $T_3(T)$ is very complicated and long, it is omitted here.

Figures 5, 6 and 7 are trajectories of $T_1(t)$, $T_2(T)$ and $T_3(T)$, respectively.

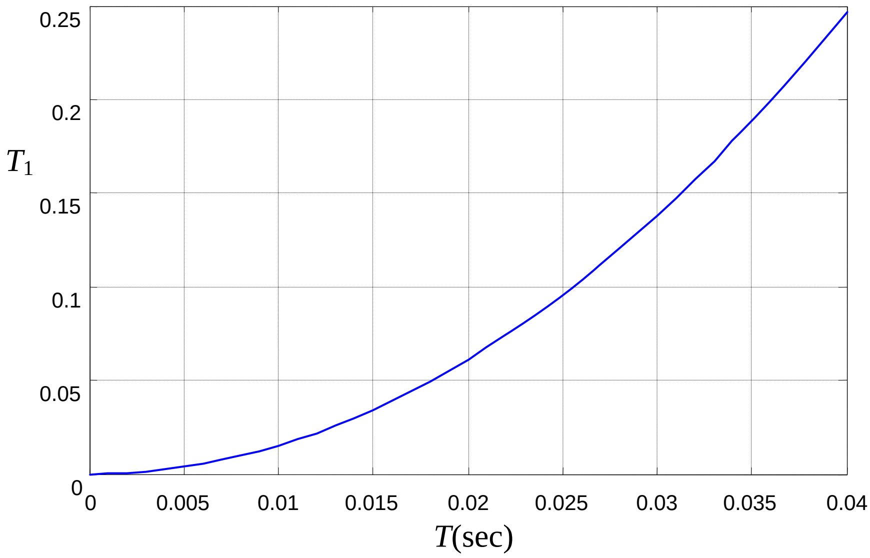

Fig. 5. Trajectory of T_1.

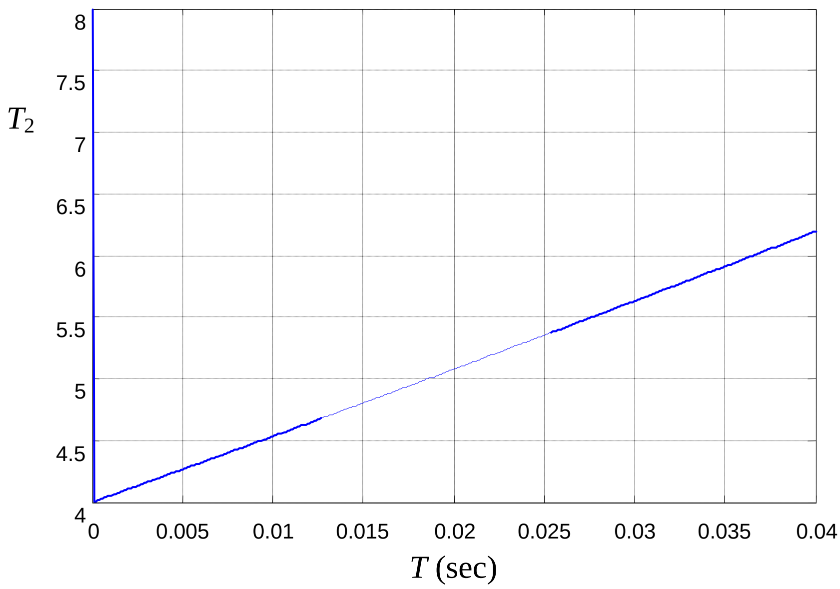

Fig. 6. Trajectory of T_2.

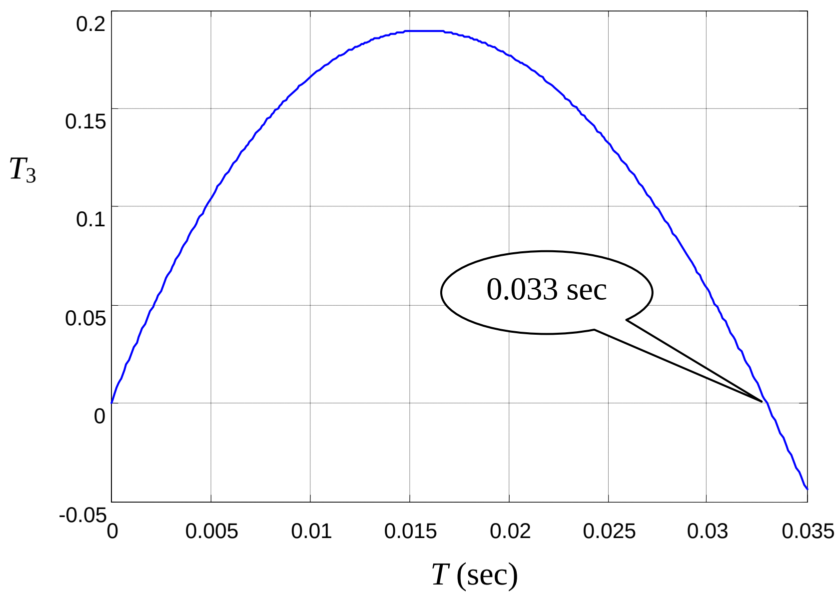

Fig. 7. Trajectory of T_3.and the upper bound of T_d = 0.033 seconds.

From the above three figures, we can conclude that the upper bound of the range of the sampling-time is close to 0.033 seconds. Assume that re-training of the TS-type model is occurred, and the new transfer function is obtained as $\frac{0.9204}{s^2 - 0.3376s - 19.9208}$. The trajectories of new $T_1(t)$, $T_2(t)$ are similar to those in Figs. 5 and 6. However the new $T_3(t)$ is plotted in Fig. 8, which shows that the upper bound of the range of sampling-time of this new transfer function is shifted from to 0.0336 seconds.

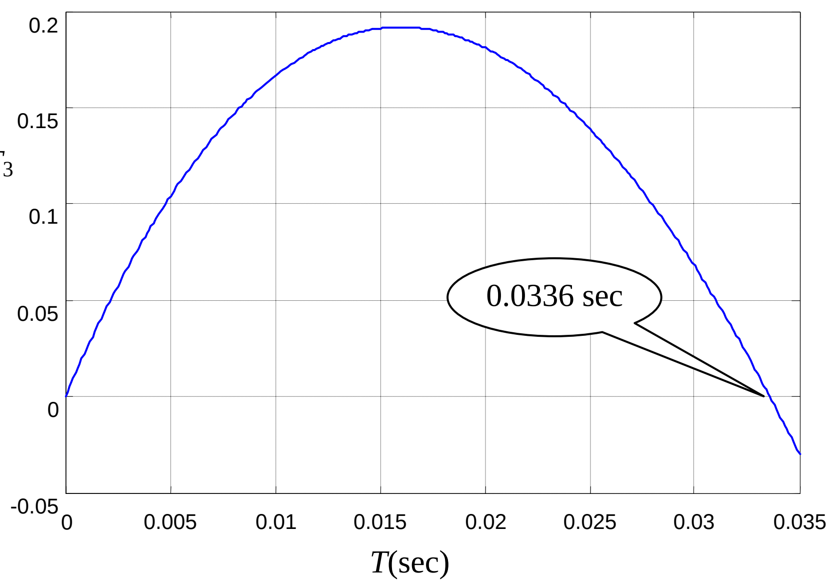

Fig. 8. Trajectory of T_3.and the upper bound of T_d= 0.0336 seconds.

Assume that re-training of the TS-type model is occurred again, and the new transfer function is obtained as $\frac{0.9166}{s^2 + 0.1118s - 21.1264}$. Another upper bound of the range of the sampling-time can be decided by the trajectory in Fig. 9, which is shifted to 0.0341 seconds.

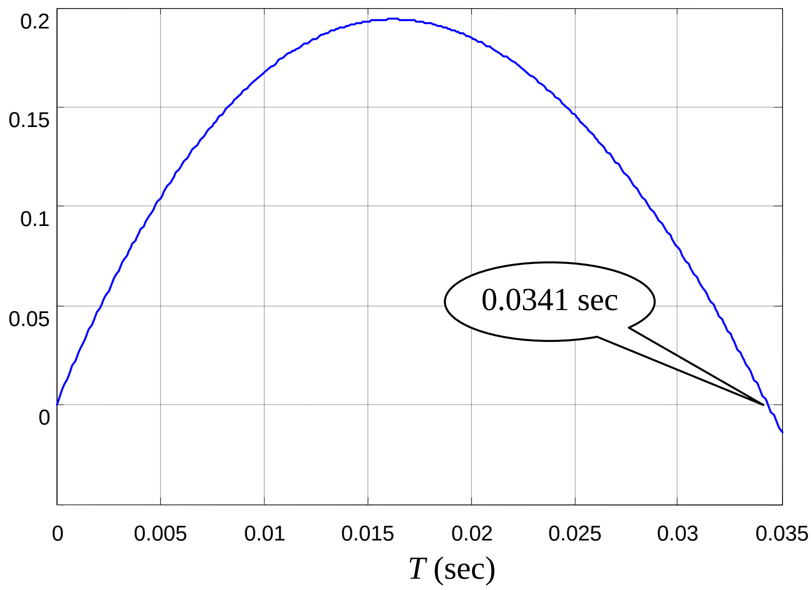

Fig. 9. Trajectory of T_3.and the limit of T_d = 0.0341 second.

Hence, we see that the chosen sampling-time T_d should not be beyond 0.033 second which is a minimum value of the three figures. The above process is actually the observations of simulation by following the design procedure in above design steps.

To test the robustness of the proposed controller, we increase the weight of the car from 2*kg*s to 3*kg*s at t = 8 seconds. The results are shown in the Fig. 10 and 11. The states of the nonlinear system with two different chosen sampling-times 0.029 seconds, 0.0327 seconds can finally converge to the reference state. We can see that the tracking performance of the case with T_d = 0.029 seconds is better than that of the case with T_d = 0.0327 seconds. The tracking can be well maintained even when there is a 50% increase of m_c, no matter T_d is 0.029 seconds or 0.0327 seconds.

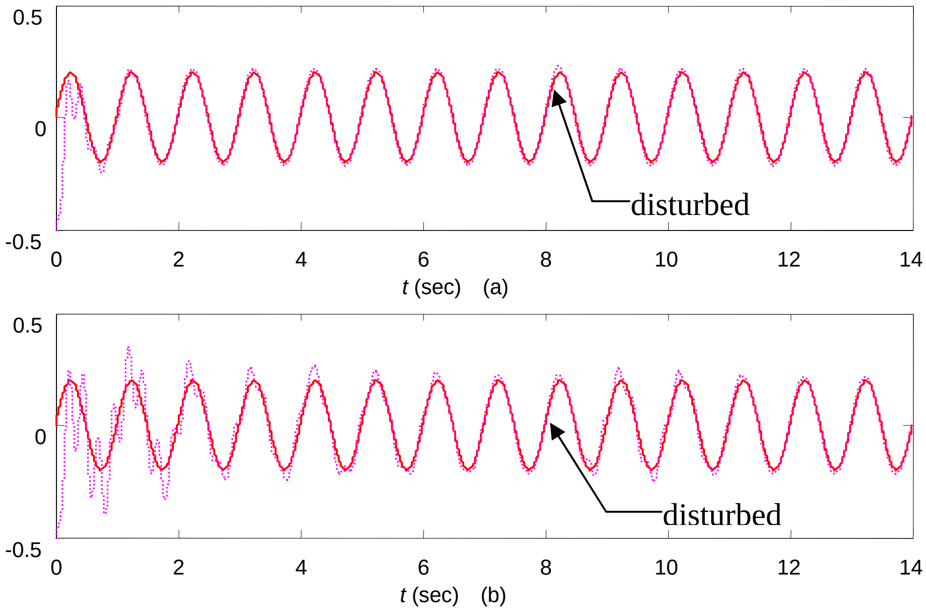

Fig. 10. Trajectories of reference y_r (solid line), (a) state $\boldsymbol{x}_1$ (dotted line) with T_d = 0.029 seconds, (b) state $\boldsymbol{x}_1$ (dotted line) with T_d = 0.0327seconds.

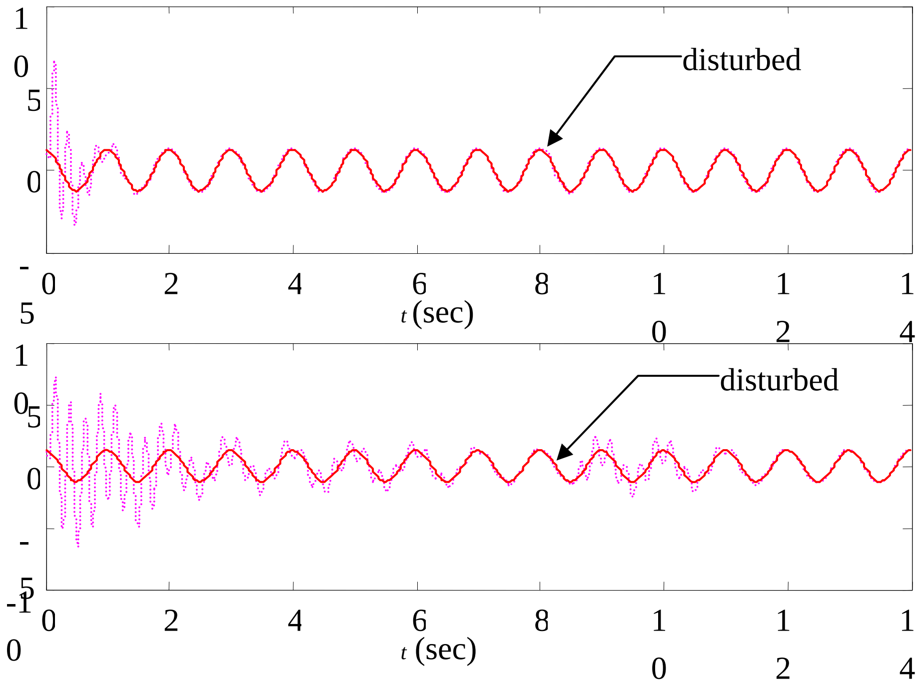

Fig. 11. Trajectories of reference $\dot{y}_r$ (solid line), (a) state $\boldsymbol{x}_2$ (dotted line) with T_d = 0.029 seconds, (b) state $\boldsymbol{x}_2$ (dotted line) with T_d = 0.0327 seconds.

Fig. 12 (a) shows that the input $u(t)$ with T_d = 0.029 seconds. We observe the fact that input $u(t)$ can be restored quickly after 2 seconds although the system is disturbed at t = 8 seconds. This was implied by the fact that the overall tracking controller can let the output track the reference successfully. Fig. 11 (b) shows the enlarged u for $7.65 < t < 9.4$ sec.

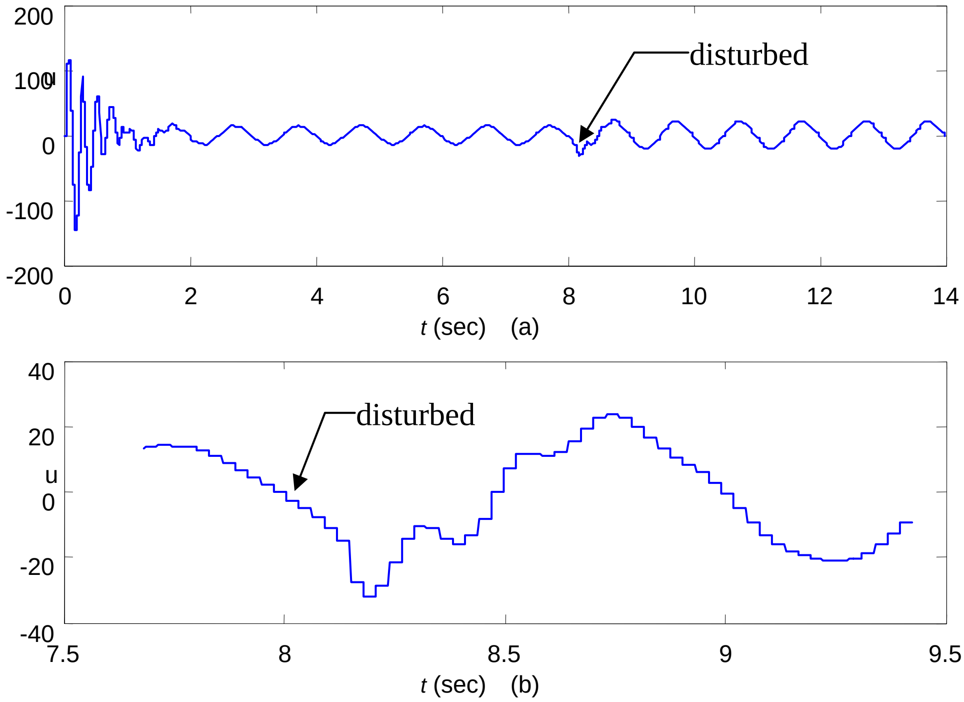

Fig. 12. (a) Input u for case with T_d =0.029 sec. (b) u is zoomed for $7.65 < t < 9.4$ sec.

Similarly, input $u(t)$ with T_d = 0.0327 seconds is shown in Fig. 13 (a). The input $u(t)$ can return to be normal after 12 seconds although the system is disturbed when t is at 8 seconds too. Fig. 13(b) shows the enlarged u for $t < 1.6$ sec.

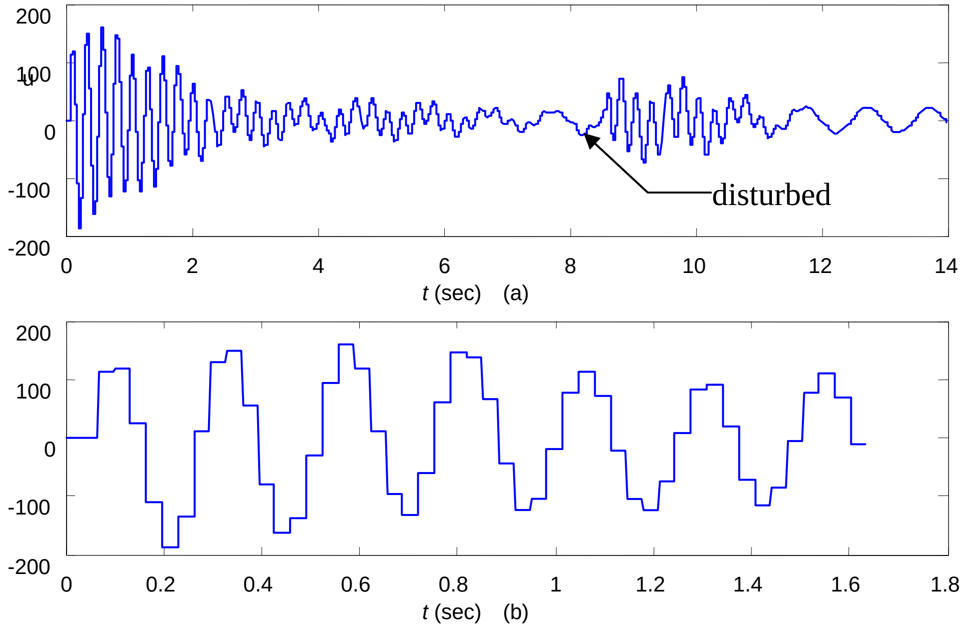

Fig. 13. (a) Input u for case with T_d =0.0327 sec., (b) its enlarged u for 0 <

$t < 1.6$ sec.

The time instants when the update of the TS-type fuzzy model is necessary, i.e., when $\|\underline{\varepsilon}(t)\|$ >*Threshold*=0.05, are recorded as p^{th} time interval > 0.1. This phenomenon can be observed obviously from Figs. 10 and 11 since the initial conditions of x_1 and x_2 will generate large tracking error (for $0 \leq t < 3$) and thus the re-training needs to be performed frequently in the beginning. We use T_d = 0.0327 seconds to illustrate the training process. At t = 0.3041 seconds, $\|\underline{\varepsilon}(t)\|$ = 3.3258 > 0.05, so the optimal learning rate can be found as 5.8649×10^{-5} and the re-trained TS-type fuzzy model and K_p are:

$$A_f = \begin{bmatrix} 0 & 1 \\ 21.0861 & 0.0602 \end{bmatrix}, \quad B_f = \begin{bmatrix} 0 \\ 0.9230 \end{bmatrix}, \quad K_p = [186.4474 \quad 27.2599].$$

After t>12 seconds, the tracking performance reaches the stable steady state so that the update of the overall indirect adaptive controller is no longer necessary. The next figure shows the performance of extra case with T_d = 0.035 seconds selected. Apparently the trajectory of the state x_1 can not track the reference y_r and is completely divergent.

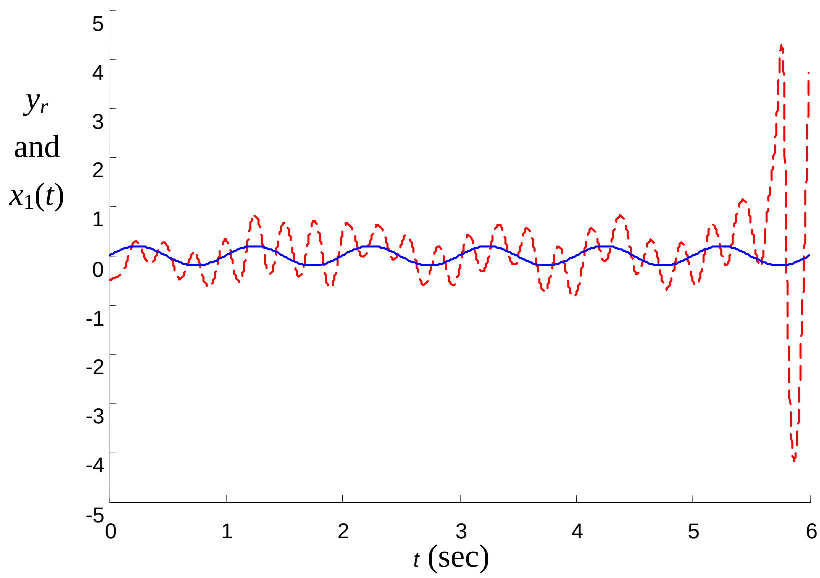

Fig. 14. Trajectories of reference y_r (solid line), state (dashed line) $\mathbf{x}_1$ with T_d =0.035s.

5. CONCLUSION

The Jury's stability test of critical stability constraint (CSC) are applied successfully for the determination of maximum computational time for complicated controllers, such as the on-line adaptive FNN controller. Based on this maximum sampling time, the suitable computing power with other relevant components can be selected with minimum cost in actual hardware implementation. One of popular nonlinear systems, i.e., inverted pendulum system, is assumed to be uncertain and the on-line indirect intelligent adaptive tracking controllers are designed to track sinusoidal signals with maximum computational time. Excellent agreement of the theoretical maximum computational with that obtained by simulation is achieved. The robustness of this new approach is also demonstrated via the inverted pendulum system by adding an extra 50% of mass at a certain time instant.

REFERENCES

[1] T. C. Hsia, "System Identification", Lexington Books, 1977.

[2] G. A. Rovithakis and M. A. Christodoulou, "Direct Adaptive Regulation of Unknown Nonlinear Dynamical Systems via Dynamic Neural Networks," *IEEE Trans. Syst., Man, Cybern*., vol. 25, pp. 1578-1594, Dec. 1995.

[3] H. O. Wang, K. Tanaka, M. F. Griffin, "An approach to fuzzy control of nonlinear systems: stability and design issues", *IEEE Transactions on Fuzzy Systems*, Vol. 4, p.p. 14-23, Feb. 1996.

[4] T. Takagi and M. Sugeno, "Fuzzy Identification of Systems and Its Applications to Modeling and control," *IEEE Trans. Syst., Man, Cybern*., Vol. 15, pp. 116-132, Jan./Feb., 1985.

[5] Shing-Jen Wu and Chih-Teng Lin, "Optimal Fuzzy Controller Design: Local Concept Approach," *IEEE Trans. On Fuzzy Systems*, Vol. 8, No. 2, pp. 171-183, April 2000.

[6] Shing-Jen Wu and Chih-Teng Lin, "Optimal Fuzzy Controller Design in Continuous Fuzzy System: Global Concept Approach," *IEEE Trans. On Fuzzy Systems*, Vol. 8, No. 6, pp. 713-729, Dec., 2000.

[7] Shing-Jen Wu and Chih-Teng Lin, "Discrete-Time Optimal Fuzzy Controller Design: Global Concept Approach," *IEEE Trans. On Fuzzy Systems*, Vol. 10, No. 1, pp. 21-38, Feb., 2002.

[8]. A. Isidori, Nonlinear Control Systems, 2^{nd} ed., Berlin, Germany: Springer-Verlag, 1989.

[9] Y. G. Leu, T. T. Lee and W. Y. Wang, “Observer-based adaptive fuzzy-neural control for unknown nonlinear dynamical systems,” *IEEE Trans. Syst., Man, Cybern. Part B: Cybernetics*, vol. 29, pp. 583-591, Oct., 1999.

[10] C. H. Wang, H. L. Liu and T. C. Lin, “Direct Adaptive Fuzzy-Neural Control With State Observer and Supervisory Controller for Unknown Nonlinear Dynamical Systems,” *IEEE Trans. On Fuzzy Systems*, Vol. 10, No. 1, Feb., 2002.

[11] B. S. Chen, C. H. Lee, and Y. C. Chang, “H^{∞} tracking design of uncertain nonlinear SISO systems: Adaptive fuzzy approach,” *IEEE Trans. Fuzzy Syst.* vol. 4, pp. 32-43, Feb. 1996.

[12]. A. V. Topalov and O. Kaynak, “Online Learning in Adaptive Neurocontrol Schemes with a Sliding Mode Algorithm,” *IEEE Trans. Syst., Man, Cybern. Part B: Cybernetics*, Vol. 31, No. 3, pp. 445-450, June 2001.

[13] Jury, E. I., “*Sampled-Data Control System*,” 1958, New York: Wiley; “*Theory and Application of Z-Transform*,” 1964, New York: Wiley.

[14]. Chi-Hsu Wang, Chen-Chien Hsu, "*Approximate z-transform using higher-order integrators and its applications in sampled-data control systems*,", *International Journal of Systems Science*, Vol. 29, No. 6, pp. 559-604, 1998.

[15] C.H. Wang, H.L. Liu, T.C. Lin, “Direct adaptive fuzzy-neural control with state observer and supervisory controller for unknown nonlinear dynamical systems”, *IEEE Transactions on Fuzzy Systems*, vol. 10, p.p. 39-49,Feb. 2002.