International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:6, No:5, 2012

An LMI Approach of Robust H_∞ Fuzzy State-Feedback Controller Design for HIV/AIDS Infection System with Dual Drug Dosages

Wudhichai Assawinchaichote

***Abstract*— This paper examines the problem of designing robust H_∞ controllers for for HIV/AIDS infection system with dual drug dosages described by a Takagi-Sugeno (TS) fuzzy model. Based on a linear matrix inequality (LMI) approach, we develop an H_∞ controller which guarantees the $\mathcal{L}_2$-gain of the mapping from the exogenous input noise to the regulated output to be less than some prescribed value for the system. A sufficient condition of the controller for this system is given in term of Linear Matrix Inequalities (LMIs). The effectiveness of the proposed controller design methodology is finally demonstrated through simulation results. It has been shown that the anti-HIV vaccines are critically important in reducing the infected cells.**

***Keywords*— H_∞ Fuzzy control; Takagi-Sugeno (TS) fuzzy model; Linear Matrix Inequalities (LMIs); HIV/AIDS infection system**

I. Introduction

Over the past two decades, there has been rapidly growing interest in application of fuzzy logic to control problem. Researches have been focused on its application to industrial processes and a number of successful results have been reported in the literature. In spite of these successes, there are many basic issues remain to be addressed. One of them is how to achieve a systematic design that guarantees closed-loop stability and performance. Recently, a great amount of effort has been devoted to describing a nonlinear system using a Takagi-Sugeno fuzzy model; see [1]–[18]. The Takagi-sugeno fuzzy model represents a nonlinear system by a family of local linear models which smoothly blended together through fuzzy membership functions. Unlike conventional modelling techniques which use a single model to describe the global behavior of a nonlinear system, fuzzy modelling is essentially a multi-model approach in which simple sub-models (typically linear models) are fuzzily combined to described the global behavior of a nonlinear system. Based on this fuzzy model, a number of systematic model-based fuzzy control design methodologies have been developed.

The problems of HIV/AIDS are very important in present world. Basically, AIDS is a kind of a disease that can be treated by using expedient drugs. From the present research, the complete cure mechanism has not yet been found. Presently, some antiretroviral therapies use reverse transcriptase inhibitors for fight against an enzyme from infected cells that called viral protease. All of anti-HIV drugs aim at preventing the virus, but they cannot kill virus particles or infected cells [19]. The dynamic HIV/AIDS studies have been shown by many researchers such as J. Guedj et al. [20], R.A. Filter et al. proposed [21], and R. Motta J. et al. [22]. HIV is a retrovirus that primarily infects vital organs of the human immune system such as CD4+T cells (a subset of T cells), macrophages and dendritic cells. It directly and indirectly destroys CD4+T cells. Once HIV has killed so many CD4+T cells such that there are fewer than 200 of these cells per micro liter (μL) of blood then cellular immunity is lost. In the absence of antiretroviral therapy, the average time of progression from HIV infection to AIDS is about nine to ten years, and the average survival time after developing AIDS is only 9.2 months [19]. However, the rate of treated disease progression is varied between individuals, from two weeks up to 20 years. Figure 1 shows the natural history of HIV infections dynamics as currently accepted [19], [20], [21], [22]. When a body has been received HIV virus in primary infection, a number of HIV virus will dramatically increase in first 30 days (resulting CD4+T cells reduction). After the primary infection period, a body builds HIV antibodies for agent virus so that, the infection still stabilizes an approximate steady state. In the last period, the antibody of healthy CD4+T cells will be drastically reduced. Finally, the patient develops to be an AIDS person.

Over the past few decades, the nonlinear H_∞-control theory has been extensively studied by many researchers; see [27], [28], [29], [30]. The nonlinear H_∞-control problem can be stated as follows: given a dynamic system with the exogenous input noise and the measured output, find a controller such that the $\mathcal{L}_2$-gain of the mapping from the exogenous input noise to the regulated output is less than or equal to a prescribed value. Presently, there are two commonly used approaches for providing solutions to the nonlinear H_∞-control problems. The first approach is based on the dissipativity theory and theory of differential games; see [27], [31], [33]. The second approach is based on the nonlinear version of classical Bounded Real Lemma; see [29], [30], [32]. Both approaches show that the solution of the nonlinear H_∞-control problem is in fact related to the solvability of Hamilton-Jacobi inequalities (HJIs).

What we intend to do in this paper is to design a fuzzy H_∞ controller for HIV/AIDS infection system with dual drug dosages which can be represented by a Takagi-Sugeno (TS) fuzzy model. Based on an LMI approach, we develop a state-

W. Assawinchaichote is with the Department of Electronic and Telecommunication Engineering, King Mongkut's University of Technology Thonburi, 126 Pracha Uthit Rd.,Bangkok 10140, Thailand, email: wudhichai.asa@kmutt.ac.th

Manuscript received December 2, 2011; revised January 23, 2012. This work was supported by the Higher Education Research Promotion and National Research University Project of Thailand, Office of the Higher Education Commission.

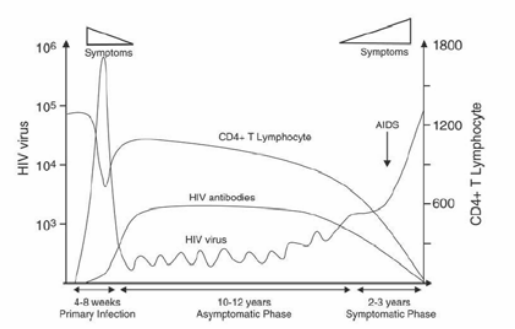

Fig. 1. The natural history of HIV infections dynamics as currently accepted [19], [20], [21], [22].

feedback controller for HIV/AIDS infection system with dual drug dosages such that the $\mathcal{L}_2$-gain of the mapping from the exogenous input noise to the regulated output is less than a prescribed value. This paper is organized as follows. In Section II, system descriptions and definition are presented. In Section III, based on an LMI approach we develop a technique for designing a fuzzy H_∞ controller for HIV/AIDS infection system with dual drug dosages that guarantees the $\mathcal{L}_2$-gain of the mapping from the exogenous input noise to the regulated output is less than a prescribed value. The validity of this approach is finally demonstrated through simulation results in Section IV. Finally in Section V, the conclusion is given.

II. System Descriptions and Definition

A. HIV dynamic model

Figure 2 shows HIV model which describes the interaction of three variables; the healthy cells, the free virus, and the infected cells. In most cases, HIV virus affects the level of CD4+T cells which these cells are important in helping a body fighting to infection. Free virus means the HIV virus found in blood plasma. The healthy CD4+T cells are produced from a source, such as the thymus represented by constant rate s and died at rate d. The coefficient β is the infection rate. The infected cells result from the infection of healthy CD4+T cells and die at a rate μ. A free-virus particle is known as virions, so called viral load, and cleared at a rate c (death rate of virus). The variable k is a rate of virions product per infection CD4+T cell.

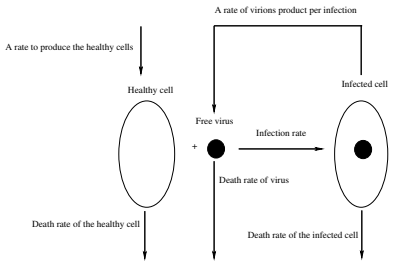

Fig. 2. Schematic illustration of the basic HIV model [19], [20], [21], [22].

The infection described previously can be summarized by differential equations [19].

$$\begin{aligned} \dot{x}_1(t) &= s - dx_1(t) + \beta x_1(t)x_3(t) \\ \dot{x}_2(t) &= \beta x_1(t)x_3(t) - \mu x_2(t) \\ \dot{x}_3(t) &= kx_2(t) - cx_3(t) \end{aligned} \quad (1)$$

where $x_1(t)$ is concentration of healthy cells or T cells, $x_2(t)$ is concentration of infected cells, $x_3(t)$ is concentration of virions (free virus particles), s is the constant rate to produced the healthy CD4+T cells, d is the death rate of the healthy CD4+T cells, β is the coefficient of the infection rate, μ is death rate of the infected cells, k is a rate of virions product per infection CD4+T cell, and c is death rate of virus.

Current treatment for HIV infection consists of highly active antiretroviral therapy, or HAART. The HAART treatment used drug in the group of protease inhibitor. The doctors will assess the viral load, CD4+T counts, rapidity of CD4+T decline, and patient readiness. While deciding, the doctors recommend initiating treatment to the patient [24]. The parameters and typical values are listed in Table 1 [23]. The information of HIV model parameters obtain from [23] which the initial conditions correspond to a healthy person infected with a virus given by Table I. In 2007, M. Barao and J.M. Lemos proposed the nonlinear dynamic model to describe HIV with treatment as follows [23]:

$$\begin{aligned} \dot{x}_1(t) &= s - dx_1(t) + (1-u_1(t))\beta x_1(t)x_3(t) \\ \dot{x}_2(t) &= (1-u_1(t))\beta x_1(t)x_3(t) - \mu x_2(t) \\ \dot{x}_3(t) &= (1-u_2(t))kx_2(t) - cx_3(t) \end{aligned} \quad (2)$$

where the controller input $u_1(t)$ and $u_2(t)$ are a number of expedient drugs in the treatment of HAART represented by Reverse Transcriptase Inhibitors-RTI (to reduce the virus performance) and Protease Inhibitors-PI (to reduce the productivity of free virions), respectively [23].The healthy CD4+T cells are produced from a source, such as the thymus represented by constant rate s and died at rate d. The coefficient β is the infection rate. The death rate of virus is described by c.

TABLE I
HIV MODEL PARAMETERS [23]

Parameter	Typical Value	Unit
t	-	Days
d	0.02	Per Day
k	100	Count Cell^{-1}
s	100 mm^3	Per Day
β	2.4 x 10^{-5} mm^3	Per Day
c	2.4	Per Day
μ	0.24	Per Day

The model includes antiretroviral treatment and factors such as adhesion and medication potency. The concepts of our proposes are joined with fuzzy set theory and exogenous input noise with biological variable values such as person factor, mental state etc.

Mostly, HIV virus dynamics are modeled using a nonlinear represented by cell. Each cell represents an uninfected cell, an infected cell of the type T lymphocyte of CD4+, a free virus particle, or specific antibodies such as CTL (Cytotoxic T Lymphocyte). Due to the inherent uncertainties of HIV,

the antiretroviral treatment is modeled using a fuzzy rule-based system whose output depends on the medication potency and the rate of adhesion to the treatment. The fuzzy rule-based system consists of input processor, fuzzy rule-based (a collection of fuzzy rules), fuzzy inference machine, and output processor. Inputs processors are encoded into fuzzy sets on the respective universes of the input variables. While the rule-based is a component of fuzzy rule-based systems, which is a collection of fuzzy conditional propositions in the form of if-then rules. Fuzzy rules are an effective mean to encode expert knowledge expressed through linguistic statements. In general, if-then rules describe relationships between linguistic variables. Fuzzy machine performs an approximate reasoning use the compositional rule of inference. Finally, in fuzzy rule-based systems, the inferred output is a fuzzy set. Often, especially in biological systems model, we require a real-valued output.

B. Nonlinear fuzzy model

In this subsection, we generalize the TS fuzzy system to represent a TS fuzzy system with parametric uncertainties. In this paper, we examine a TS fuzzy system with parametric uncertainties as follows:

$$\begin{aligned}
\dot{x}(t) &= \sum_{i=1}^{r}\mu_i(\nu(t))\Big[[A_i+\Delta A_i]x(t) \\
&\quad +[B_{1_i}+\Delta B_{1_i}]w(t) \\
&\quad +[B_{2_i}+\Delta B_{2_i}]u(t)\Big], \qquad x(0)=0 \\
z(t) &= \sum_{i=1}^{r}\mu_i(\nu(t))\Big[[C_{1_i}+\Delta C_{1_i}]x(t) \\
&\quad +[D_{12_i}+\Delta D_{12_i}]u(t)\Big] \\
y(t) &= \sum_{i=1}^{r}\mu_i(\nu(t))\Big[[C_{2_i}+\Delta C_{2_i}]x(t) \\
&\quad +[D_{21_i}+\Delta D_{21_i}]w(t)\Big]
\end{aligned} \tag{3}$$

where $\nu(t)=[\nu_1(t)\ \cdots\ \nu_\vartheta(t)]$ is the premise variable vector that may depend on states in many cases, $\mu_i(\nu(t))$ denotes the normalized time-varying fuzzy weighting functions for each rule (i.e., $\mu_i(\nu(t))\geq 0$ and $\sum_{i=1}^{r}\mu_i(\nu(t))=1$), ϑ is the number of fuzzy sets, $x(t)\in\Re^n$ is the state vector, $u(t)\in\Re^m$ is the input, $w(t)\in\Re^p$ is the disturbance which belongs to $\mathcal{L}_2[0,\infty)$, $y(t)\in\Re^\ell$ is the measurement, $z(t)\in\Re^s$ is the controlled output, the matrices $A_i, B_{1_i}, B_{2_i}, C_{1_i}, C_{2_i}, D_{12_i}$ and D_{21_i} are of appropriate dimensions, and r is the number of IF-THEN rules. The matrices $\Delta A_i, \Delta B_{1_i}, \Delta B_{2_i}, \Delta C_{1_i}, \Delta C_{2_i}, \Delta D_{12_i}$ and ΔD_{21_i} represent the uncertainties in the system and satisfy the following assumption.

Assumption 1:

$$\Delta A_i = F(x(t),t)H_{1_i},$$

$$\Delta B_{1_i} = F(x(t),t)H_{2_i},\ \ \Delta B_{2_i} = F(x(t),t)H_{3_i},$$

$$\Delta C_{1_i} = F(x(t),t)H_{4_i},\ \ \Delta C_{2_i} = F(x(t),t)H_{5_i},$$

$$\Delta D_{12_i} = F(x(t),t)H_{6_i}\ \ \textit{and}\ \ \Delta D_{21_i} = F(x(t),t)H_{7_i}$$

where H_{j_i}, $j=1,2,\cdots,7$ are known matrix functions which characterize the structure of the uncertainties. Furthermore, the following inequality holds:

$$\|F(x(t),t)\|\leq\rho \tag{4}$$

for any known positive constant ρ.

Next, let us recall the following definition.

Definition 2.1: Suppose γ is a given positive number. A system (3) is said to have an $\mathcal{L}_2$-gain less than or equal to γ if

$$\int_0^{T_f} z^T(t)z(t)dt \leq \gamma^2\left[\int_0^{T_f} w^T(t)w(t)dt\right],\ x(0)=0 \tag{5}$$

for all $T_f\geq 0$ and $w(t)\in\mathcal{L}_2[0,T_f]$.

Note that for the symmetric block matrices, we use $(*)$ as an ellipsis for terms that are induced by symmetry.

III. Robust H_∞ fuzzy state-feedback controller for HIV/AIDS infection system

The aim of this section is to design a robust $\mathcal{H}_\infty$ fuzzy state-feedback controller of the form

$$u(t)=\sum_{j=1}^{r}\mu_j K_j x(t) \tag{6}$$

where K_j is the controller gain, such that the inequality (5) holds. The state space form of the fuzzy system model (3) with the controller (6) is given by

$$\begin{aligned}
\dot{x}(t) &= \sum_{i=1}^{r}\sum_{j=1}^{r}\mu_i\mu_j\Big[[(A_i+B_{2_i}K_j) \\
&\quad +(\Delta A_i+\Delta B_{2_i}K_j)]x(t)+[B_{1_i}+\Delta B_{1_i}]w(t)\Big]
\end{aligned} \tag{7}$$

where $x(0)=0$. The following theorem provides sufficient conditions for the existence of a robust $\mathcal{H}_\infty$ fuzzy state-feedback controller. These sufficient conditions can be derived by the Lyapunov approach.

Theorem 1: Consider the system (3). Given a prescribed $\mathcal{H}_\infty$ performance $\gamma>0$ and a positive constant δ, if there exist a matrix $P=P^T$ and matrices Y_j, $j=1,2,\cdots,r$, satisfying the following linear matrix inequalities:

$$P > 0 \tag{8}$$

$$\Omega_{ii} < 0,\quad i=1,2,\cdots,r \tag{9}$$

$$\Omega_{ij}+\Omega_{ji} < 0,\quad i<j\leq r \tag{10}$$

where

$$\Omega_{ij}=\begin{pmatrix} \begin{pmatrix} A_iP+PA_i^T \\ +B_{2_i}Y_j+Y_j^TB_{2_i}^T \end{pmatrix} & (*)^T & (*)^T \\ \tilde{B}_{1_i}^T & -\gamma I & (*)^T \\ \tilde{C}_{1_i}P+\tilde{D}_{12_i}Y_j & 0 & -\gamma I \end{pmatrix} \tag{11}$$

with

$$\tilde{B}_{1_i}=\begin{bmatrix} \delta I & I & \delta I & B_{1_i} \end{bmatrix},$$

$$\tilde{C}_{1_i} = \left[\begin{array}{cccc} \frac{\gamma\rho}{\delta} H_{1_i}^T & 0 & \sqrt{2}\lambda\rho H_{4_i}^T & \sqrt{2}\lambda C_{1_i}^T \end{array} \right]^T,$$
$$\tilde{D}_{12_i} = \left[\begin{array}{cccc} 0 & \frac{\gamma\rho}{\delta} H_{3_i}^T & \sqrt{2}\lambda\rho H_{6_i}^T & \sqrt{2}\lambda D_{12_i}^T \end{array} \right]^T,$$
$$\lambda = \left(1 + \rho^2 \sum_{i=1}^{r} \sum_{j=1}^{r} \left[\| H_{2_i}^T H_{2_j} \| \right] \right)^{\frac{1}{2}},$$

then the inequality (5) holds. Furthermore, a suitable choice of the fuzzy controller is

$$u(t) = \sum_{j=1}^{r} \mu_j K_j x(t) \tag{12}$$

where

$$K_j = Y_j P^{-1}. \tag{13}$$

Proof: The detail of the proof is omitted for brevity. ■

IV. Simulation results

A simulation result is given in this section to illustrate the procedure of designing a fuzzy controller. Let us recall (2) included with noise term. The parameters and typical values are listed in Table 1.

$$\begin{array}{rcl} \dot{x}_1(t) & = & s - dx_1(t) - (1 - u_1(t))\beta x_1(t)x_3(t) + w_1(t) \\ \dot{x}_2(t) & = & (1 - u_1(t))\beta x_1(t)x_3(t) - \mu x_2(t) + w_2(t) \\ \dot{x}_3(t) & = & (1 - u_2(t))kx_2(t) - cx_3(t) + w_3(t) \end{array} \tag{14}$$

where $w_1(t)$, $w_2(t)$ and $w_3(t)$are the disturbance factor from the patients and the controlled output is

$$z(t) = [x_1(t) \;\; u_1(t) \;\; u_2(t)]^T. \tag{15}$$

The nonlinear system plant can be approximated by TS fuzzy rules. Let us choose the membership functions of the fuzzy sets as follows.

$$M_1(x_1(t)) = \begin{cases} 1 & ; x_1(t) \le 200 \\ 3 - 0.01x_1(t) & ; 200 < x_1(t) \le 300 \\ 0 & ; x_1(t) > 300 \end{cases}$$

$$M_2(x_1(t)) = \begin{cases} 0.01x_1(t) - 2 & ; 200 < x_1(t) \le 300 \\ 1 & ; 300 < x_1(t) \le 500 \\ 6 - 0.01x_1(t) & ; 500 < x_1(t) \le 600 \end{cases}$$

$$M_3(x_1(t)) = \begin{cases} 0 & ; x_1(t) \le 500 \\ 0.01x_1(t) - 5 & ; 500 < x_1(t) \le 600 \\ 1 & ; x_1(t) > 600 \end{cases}$$

$$N_1(x_2(t)) = \begin{cases} 1 & ; x_2(t) \le 10 \\ 2 - 0.1x_2(t) & ; 10 < x_2(t) \le 20 \\ 0 & ; x_2(t) > 20 \end{cases}$$

$$N_2(x_2(t)) = \begin{cases} 0.1x_2(t) - 1 & ; 10 < x_2(t) \le 20 \\ 1 & ; 20 < x_2(t) \le 90 \\ 10 - 0.1x_2(t) & ; 90 < x_2(t) \le 100 \end{cases}$$

$$N_3(x_2(t)) = \begin{cases} 0 & ; x_2(t) \le 90 \\ 0.1x_2(t) - 9 & ; 90 < x_2(t) \le 100 \\ 1 & ; x_2(t) > 100 \end{cases}$$

$$q_1(x_3(t)) = \begin{cases} 1 & ; x_3(t) \le 1 \\ 2 - x_3(t) & ; 1 < x_3(t) \le 2 \\ 0 & ; x_3(t) > 2 \end{cases}$$

$$q_2(x_3(t)) = \begin{cases} x_3(t) - 2 & ; 1 < x_3(t) \le 2 \\ 1 & ; 2 < x_3(t) \le 3 \\ 4 - x_3(t) & ; 3 < x_3(t) \le 4 \end{cases}$$

$$q_3(x_3(t)) = \begin{cases} 0 & ; x_3(t) \le 3 \\ x_3(t) - 3 & ; 3 < x_3(t) \le 4 \\ 1 & ; x_3(t) > 4 \end{cases}$$

The membership functions of three variables which are the healthy cell of CD4+T, the infected cells and the free cells are shown in Figure 3. The TS fuzzy plant model can be obtained as:

Plant Rule i:

IF $x_1(t)$ is M_i and $x_2(t)$ is N_j and $x_3(t)$ is q_k THEN

$$\begin{array}{rcl} \dot{x}(t) & = & [A_i + \Delta A_i]x(t) + B_i u(t) + B_w w(t), \\ z(t) & = & Cx(t) + Du(t) \end{array}$$

where $i, j, k = 1, \cdots, 3$

$$A_i = \left[\begin{array}{ccc} -d & 0 & -\beta x_1(t) \\ 0 & -\mu & \beta x_1(t) \\ 0 & k & -c \end{array} \right], \quad B_w = \left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right],$$

$$B_i = \left[\begin{array}{cc} \beta x_1(t)x_3(t) & 0 \\ -\beta x_1(t)x_3(t) & 0 \\ 0 & kx_2(t) \end{array} \right], C = \left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array} \right],$$

$$D = \left[\begin{array}{cc} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{array} \right], \quad \Delta A_i = F(x(t), t)H_{1_i},$$

$$x(t) = [x_1^T(t) \;\; x_2^T(t) \;\; x_3^T(t)]^T$$

and $w(t) = [w_1^T(t) \;\; w_2^T(t) \;\; w_3^T(t)]^T$.

Now by assuming that in (2), $\|F(x(t), t)\| \le \rho = 1$ and since the value of μ, d, and c are uncertain but bounded within 10% of their nominal value in (14), we have

$$H_{1_i} = \left[\begin{array}{ccc} -0.1d & 0 & 0 \\ 0 & -0.1\mu & 0 \\ 0 & 0 & -0.1c \end{array} \right].$$

Using the LMI optimization algorithm and following Theorem 1 with set as $\gamma = 0.1$, we obtain the results given in Figure 4 - 6.

Remark 1: When a body has been received HIV virus in primary infection (about 4-8 weeks), the doctors will assess the viral load, CD4+T counts, rapidity of CD4+T decline, and patient readiness before beginning treatment. The simulation results given in Figure 4 show the level of CD4+T counts, reverse transcriptase inhibitors-RTI to reduce the virus performance, and protease inhibitors-PI to reduce the productivity of free virions. Figure 4 shows the plot of healthy calls, i.e.,

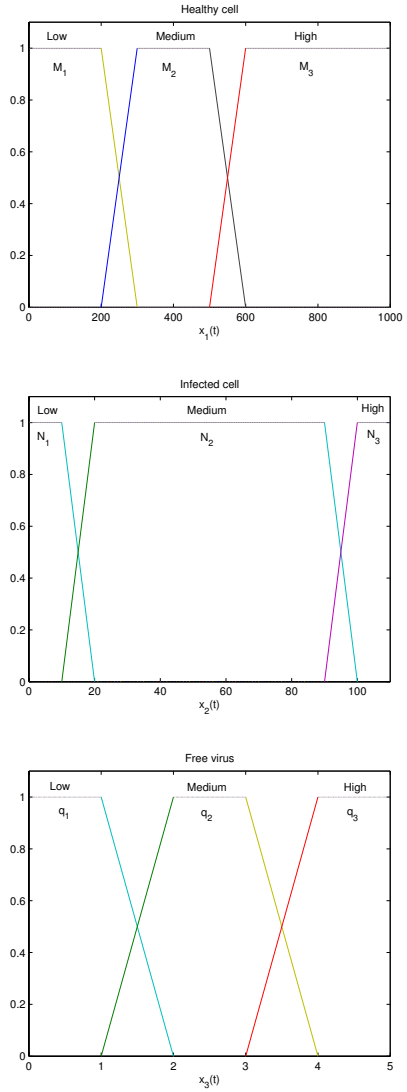

Fig. 3. Membership function of three variables.

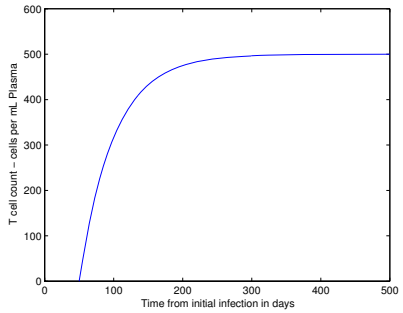

Fig. 4. The simulation result of dual drug dosages for healthy cell, $x_1(t)$.

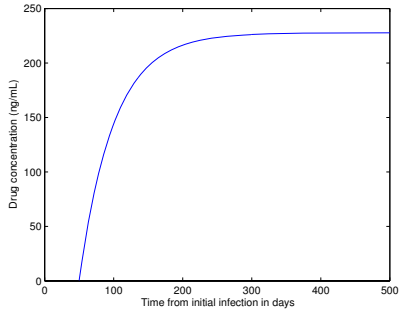

Fig. 5. The simulation result of dual drug dosages for RTI, $u_1(t)$.

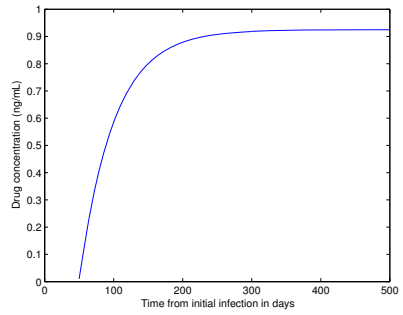

Fig. 6. The simulation result of dual drug dosages for PI, $u_2(t)$.

if CD4+T are more than 500 cells/μL the patient will develop the disease of HIV at low risk. Figure 5 shows the plot of Reverse Transcriptase Inhibitors-RTI, which are a class of antiretroviral drug used to treat HIV infection, tumors, and cancer. RTIs inhibit activity of reverse transcriptase, a viral DNA polymerase enzyme that retroviruses need to reduce the virus performance, and Figure 6 shows the plot of Protease Inhibitors-PI, which are molecules that inhibit the function of proteases.

V. Conclusion

This paper has presented a robust H_∞ fuzzy state-feedback control design for nonlinear positive HIV infection dynamic model. This paper has developed a fuzzy controller for applying in HIV nonlinear dynamic model to solve with antiretroviral therapy by using a fuzzy rule-based system with two inputs, the medication potency and the treatment adhesion rate. The effective of controller can prevent infection. The progression is the key to success of fighting against AIDS.

Acknowledgment

This work was supported by the Higher Education Research Promotion and National Research University Project of Thailand, Office of the Higher Education Commission. The author also would like to acknowledge to the Department of Electronic and Telecommnunication Engineering, King Mongkut's University of Technology Thonburi for their supports in this research work.

REFERENCES

[1] Z.X. Han, and G. Feng, 'State-feedback H^∞ Controller Design of Fuzzy Dynamic System Using LMI Techniques,' *Fuzzy-IEEE'98*, pp. 538–544, 1998.

[2] B.S. Chen, C.S. Tseng, and Y.Y. He, 'Mixed H_2/H_∞ Fuzzy Output Feedback Control Design for Nonlinear Dynamic Systems: An LMI Approach,' *IEEE Trans. Fuzzy Syst.*, vol. 8, pp. 249–265, 2000.

[3] K. Tanaka, T. Ikeda, and H.O. Wang, 'Robust Stabilization of a Class of Uncertain Nonlinear Systems via Fuzzy Control: Quadratic Stability, H_∞ Control Theory, and Linear Martix Inequality,' *IEEE Trans. Fuzzy. Syst.*, vol. 4, pp. 1–13, 1996.

[4] Z.X. Han, G. Feng, B.L. Walcott, and Y.M. Zhang, 'H^∞ Controller Design of Fuzzy Dynamic Systems with Pole Placement Constraints,' *Proc. American Control Conf.*, pp. 1939–1943, 2000.

[5] T. Takagi, and M. Sugeno, 'Fuzzy Identification of Systems and Its Applications to Model and Control,' *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, no. 1, pp. 116–132, 1985.

[6] L.X. Wang, 'Design and Analysis of Fuzzy Identifiers of Nonlinear Dynamic Systems,' *IEEE Trans. Automat. Control*, vol. 40, pp. 11–23, 1995.

[7] M. Sugeno, and G.T. Kang, 'Structure Identification of Fuzzy Model,' *Fuzzy Sets Syst.*, vol. 28, pp. 15–33, 1988.

[8] H.O. Wang, K. Tanaka, and M.F. Griffin, 'An Approach to Fuzzy Control of Nonlinear Systems: Stability and Design Issues,' *IEEE Trans. Fuzzy Syst.*, vol. 4, no. 1, pp. 14–23, 1996.

[9] J. Joh, Y.H. Chen, and R. Langari, 'On the Stability Issues of Linear Takagi-Sugeno Fuzzy Models,' *IEEE Trans. Fuzzy Syst.*, vol. 6, pp. 402–410, 1998.

[10] S.G. Cao, N.W. Ree, and G. Feng, 'Quadratic Stabilities Analysis and Design of Continuous-Time Fuzzy Control Systems,' *Int. J. Syst. Sci.*, vol. 27, pp. 193–203, 1996.

[11] K. Tanaka, T. Ikeda, and H.O. Wang, 'Robust Stabilization of A Class of Uncertain Nonlinear Systems Via Fuzzy Control: Quadratic Stabilizability, H_∞ Control Theory, and Linear Matrix Inequalities,' *IEEE Trans. Fuzzy Syst.*, vol. 4, 1996.

[12] K. Tanaka, T. Taniguchi, and H.O. Wang, 'Fuzzy Control based on Quadratic Performance Function - A Linear Matrix Inequality Approach,' *Proc. IEEE Conf. Decision and Control*, pp. 2914–2919, 1998.

[13] K. Tanaka, and H.O. Wang, 'Fuzzy Regulators and Fuzzy Observers: A Linear Matrix Inequality Approach,' *Proc. IEEE Conf. Decision and Control*, pp. 1315–1320, 1997.

[14] S.K. Nguang, and P. Shi, 'H_∞ Fuzzy Output Feedback Control Design for Nonlinear Systems: An LMI Approach,' *Proc. IEEE Conf. Decision and Control*, pp. 4352–4357, 2001.

[15] W. Assawinchaichote, and S.K. Nguang, 'Fuzzy Control Design for Singularly Perturbed Nonlinear Systems: An LMI Approach,' *ICAIET*, Malaysia, 2002.

[16] W. Assawinchaichote, S.K. Nguang, P. Shi and E.K. Boukas, 'H_∞ Fuzzy State-Feedback Control Design for Nonlinear Systems with Stability Constraints: An LMI Approach,' *Int. J. Mathematics and Computers in Simulation*, vol. 78, pp. 514-531, 2008.

[17] W. Assawinchaichote, 'A New Approach to Non-Fragile H_∞ Fuzzy Filter of Uncertain Markovian Jump Nonlinear Systems,' *Int. J. Mathematics and Computers in Simulation*, vol. 2, pp. 21–33, 2010.

[18] W. Assawinchaichote, 'A New Approach to Non-Fragile H_∞ Fuzzy Controller for Uncertain Fuzzy Dynamical Systems with Multiple Time-Scales,' *Int. J. of Signal System Control and Engineering Application*, vol. 3, pp. 49–64, 2010.

[19] Sebastian. B., John M. Coffin, and Martin A. Nowak, 'Human Immunodeficiency Virus Drug Therapy and Virus Load,' *American Society for Microbiology*, pp. 3275–3278, 1997.

[20] J. Guedj, R. Thiebaut, and D. Commenges, 'Practical identifiability of HIV dynamics models,' *Bulletin of Mathematical Biology*, vol. 69, pp. 2493–2513, 2007.

[21] R.A. Filter, X. Xia, and C.M. Gray, 'Dynamic HIV/AIDS parameter estimation with application to a vaccine readiness study in southern Africa,' *IEEE Transactions on Biomedical Engineering*, vol. 52, pp. 784–791, 2005.

[22] R.M. Jafelice, B.F.Z. Bechara, L.C. Barros R.C. Bassanezi, and F. Gomide. 'Cellular automata with fuzzy parameters in microscopic study of positive HIV individuals,' *Mathematical and Computer Modeling*, vol. 50, pp. 32–44, 2009.

[23] M. Barao a, and J.M. Lemos, 'Nonlinear control of HIV-1 infection with a singular perturbation model,' *Biomedical Signal Processing and Control*, vol. 2, pp. 248–257, 2007.

[24] Christine Brennan, and Demetrius J. Porche., 'HIV immunopathogenesis,' *Journal of the Association of Nurses in AIDS care*, vol. 8,pp. 7–22, 1997.

[25] S. Junhom, and W. Assawinchaichote, 'A design of H_∞ fuzzy controller for HIV/AIDS infection system with dual drug dosages,' *5th International Symposium on Medical Information and Communication Technology*, pp. 152–155, 2011.

[26] S. Junhom, and W. Assawinchaichote, 'A new approach of H_∞ fuzzy controller design for nonlinear positive HIV/AIDS infection dynamic model,' *3rd International Conference on Machine Learning and Computing*, pp. 420–424, 2011.

[27] J.A. Ball, and J.W. Helton, 'H_∞ Control for Nonlinear Plants: Connection with Differential Games,' *IEEE Conf. Decision and Control*, pp. 956–962, 1989.

[28] A.J. van der Schaft, '$\mathcal{L}_2$-Gain Analysis of Nonlinear Systems and Nonlinear State Feedback H_∞ Control,' *IEEE Trans. Automat. Control*, vol. 37, pp. 770–784, 1992.

[29] A. Isidori, and A. Astofi, 'Disturbance Attenuation and H_∞-Control via Measurement Feedback in Nonlinear Systems,' *IEEE Trans. Automat. Control*, vol. 37, pp. 1283–1293, 1992.

[30] A. Isidori, 'Feedback Control of Nonlinear Systems,' *Proc. First European Contr. Conf.*, pp. 1001–1012, 1991.

[31] D.J. Hill, and P.J. Moylan, 'Dissipative Dynamical Systems: Basic Input-Output and State Properties,' *J. Franklin Inst.*, vol. 309, pp. 327–357, 1980.

[32] A.J. van der Schaft, 'A State-Space Approach to Nonlinear H_∞ Control,' *Syst. Contr. Letters.*, vol. 16, pp. 1-8, 1991.

[33] J.C. Willems, 'Dissipative Dynamic Systems Part I: General Theory,' *Arch. Raitonal Mech. Anal.*, vol. 45, pp. 321–351, 1972.

[34] B.D.O. Anderson, and J.B. Moore, *Optimal Control: Linear Quadratic Methods*, Prentice-Hall, New Jersey, 1990.

[35] P. Gahinet, A. Nemirovski, A.J. Laub, and M. Chilali, *LMI Control Toolbox – For Use with MATLAB*, The MathWorks,Inc., MA, 1995.

[36] M. Chilali, and P. Gahinet, 'H_∞ Design with Pole Placement Contraints: An LMI Approach,' *IEEE Trans. Automat. Control*, vol. 41, pp. 358–367, 1996.

[37] S. Boyd, L. El Ghaoui, E. Feron, and V. Balakrishnan, *Linear Matrix Inequalities in Systems and Control Theory*, vol. 15, Philadelphia: SIAM, 1994.

[38] B. Anderson, and S. Vongpantlerd, *Network Analysis and Synthesis: A Modern System Theory Approach*, Prentice-Hall, Englewood Cliffs, NJ, 1973.

Wudhichai Assawinchaichote received the B.Eng. (Hons) degree in Electronic Engineering from Assumption University, Bangkok, Thailand, in 1994; the M.S. degree in Electrical Engineering from the Pennsylvania State University (Main Campus), PA, USA, in 1997 and the Ph.D. degree with the Department of Electrical and Computer Engineering from the University of Auckland, New Zealand (2001-2004). He is currently working as a lecturer in the Department of Electronic and Telecommunication Engineering at King Mongkut's University of Technology Thonburi, Bangkok, Thailand. His research interests include fuzzy control, robust control and filtering, Markovian jump systems and singularly perturbed systems.