Predictive Fuzzy Control —Where is Fuzzy

Yongli Huang and Seiji Yasunobu

Institute of Engineering Mechanics and Systems
University of Tsukuba
{huang,yasunobu}@esys.tsukuba.ac.jp

Abstract

There are some kinds of predictive fuzzy control system in different fuzzy method. To design a control system, the most important is to find the suitable control method for a given plant. In this paper, the principle of some kinds of predictive fuzzy control systems are analyzed and its application examples have been given.

1 Introduction

Model based predictive controllers have a number of appealing features such as[1]:

- The ability to take into account the impact of the current control action on the future process state. This is a useful when dealing non- minimum phase behaviors, unknown or partially unknown dynamics.
- The ability to accommodate knowledge about future requirements on the plant state represented in terms of a pre-defined tracking reference signal
- Effectiveness of control even when the predictor is a coarse approximator of the plant dynamics.
- The ability to deal with multiple objectives and constraints.

On the other hand, human operators or process engineers have a remarkable adaptability to interpret linguistic statements about a process to a qualitative fashion. Fuzzy logic is one of the natural way to integrate linguistic statements into a robust and intelligent control to resolve nonlinear problems. Based on the property of controlled process, the experience knowledge to the system is different, and there are several forms of fuzzy control system applied to industry. Conventional fuzzy control is based on expert knowledge in the form of fuzzy if-then rules in which a process model is unnecessary. A general fuzzy inference rule can be described as *"if $x(k)$ is A_i and $y(k)$ is B_i then u is C_i"* which only use the former information of system. Because it is difficult to collect sufficient information to design a well-performing fuzzy controller, the desired controller behavior is achieved by tuning the membership functions, scaling factors, and other parameters by a trial-and-error method, using simulations or experiments on the process or its scale model. For complex system, this tuning may become a tedious and time-consuming trial-and-error procedure. In an industrial environment, on-line trial-and-error controller tuning is often not acceptable for safety, economical and environmental reasons. Hence, methods are needed to alleviate the ad hoc tuning procedures, while preserving the advantages of fuzzy control, such as the capability to control nonlinear systems in a transparent way, and the possibility to include heuristic knowledge.

Fuzzy Predictive Control techniques provide the methodology using both the human control skills and model based predictive strategies. It is based on the simultaneous use of various control principles, combining predictive strategies in a complex time varying fashion. There are some kinds of Predictive Fuzzy Control which the difference lies where the fuzzy inference is used. In these paper, we firstly analyze the principle of several kinds of Fuzzy Predictive Control, and give their application examples. Then we put the emphasis on analyzing the principle of Sendai Subway Fuzzy Predictive Control. Last we do some discussion on these methods.

2 Fuzzy Predictive Control

2.1 Model-based Predictive Control and Fuzzy

Generally, model-based predictive control (MBPC) scheme consists of three blocks as figure 1 which is a general methodology for solving control problems in the time domain[2, 3]. It is based on three main concepts :1.) Explicit use of a model to predict the process output at future discrete time instant, over a prediction horizon. 2.) Computation of a sequence of future control actions over a control horizon by minimizing a given objective function. 3.) Receding horizon strategy, so that only the first control action in the sequence is applied, the horizons are moved towards the future and optimization is repeated. Because of the optimization approach and the explicit use of the process model, model-based predictive control can realize multivariable optimal control, deal with nonlinear processes, and can efficiently handle constraints.

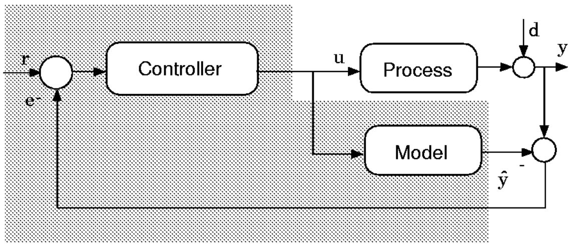

Figure 1: Predictive control scheme

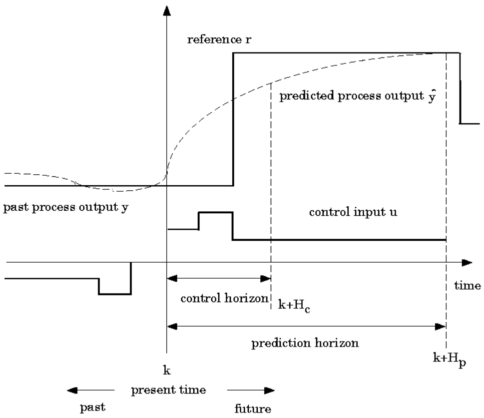

Figure 2: The basic principle of MBPC.

The structure and principle of MBPC depicted in figure 1 and figure 2. The future process outputs are predictived over the prediction horizon H_p using a model of the process: $\hat{y}(k+i)$ for $i = 1, \ldots, H_p$. These values depend on the current process state, and on the future control signals $u(k+i)$ for $i = 0, \ldots, H_c - 1$, where $H_c \leq H_p$ is the control horizon. The control variable is manipulated only with the control horizon and remains constant afterwards, i.e.,$u(k+i) = u(k + H_c - 1)$ for $i = H_c, \ldots, H_p - 1$.

A typical objective function of MBPC can be described as:

$$J = \sum_{i=1}^{H_p} \alpha_i (r(k+i) - \hat{y}(k+i))^2 + \sum_{i=1}^{H_c} \beta_i \triangle u(k+i-1)^2 \tag{1}$$

The first term accounts for minimizing the variance of the process output from the reference, while the second term represents a penalty on the control efforts. The latter term can also be expressed by using u itself, or other filtered forms of u, depending on the problem. The coefficients α_i and β_i define the weighting of the output error and the control effort with respect to each other. Level and rate constraints of the control input, or other process variables can be specified as a part of the optimization problem.

When one or more part of MBPC are substituted by

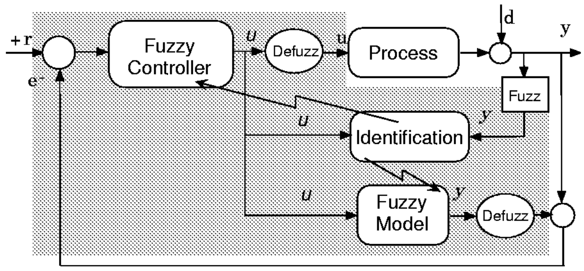

Figure 3: Fuzzy relational-based predictive control scheme

fuzzy inference, the control system is called predictive fuzzy control. There are some kinds of predictive fuzzy control. For example, If the model is constituted by fuzzy model, and the controller is implemented as an inverse of the process' dynamics, it is one kind of predictive fuzzy called Fuzzy Relational-Based Predictive Controller [4, 6]. If the model is constituted by fuzzy model, but a general objective function is used to do optimal calculation like conventional predictive control[1], It is called fuzzy-model based predictive control. Another kind of predictive fuzzy control is based on a receding control horizon, a fuzzy description of system consequences via model predictions is employed[9]. This controller considers the gains and losses associated with each control action, is compatible with robust design objectives, and permits flexible defuzzifier design. In the following, each type of predictive fuzzy control will be analysized and its application example will be given.

2.2 Fuzzy Relational-Based Predictive Controller

The artificial application of fuzzy logic leads to some confusion and questions about the need for fuzzy technology. However, there are several application areas where the process dynamics are in fuzzy sense that the process input, output or the model are inherently uncertain. Considered these facts, a Fuzzy Relational-Based Predictive Controller was proposed by Mary M. Bourke [4] which has a structure similar to conventional model-based predictive controllers as figure 3. Its structure can be depicted as fuzzy model is as predictive and the inverse of this fuzzy model is used as fuzzy controller.

The process model is assumed to be the first order fuzzy state model with time delay,τ.

$$\tilde{y}(k+1) = \tilde{R}^o \tilde{y}(k)^o \tilde{u}(k-\tau) \tag{2}$$

The prediction model is also a first order plus delay fuzzy state model.

The approach adopted for the proposed predictive fuzzy controller is as follows:

1. Calculate the mean-level or steady control action, $u_{gain}(k)$.

2. Calculate the one-step-ahead or deadbeat control action, $u_{dync}(k)$.

3. Define the actual controller output at time k as a linear combination of $u_{gain}(k)$ and $u_{dync}(k)$.

$$u(k) = \alpha \cdot u_{gain}(k) + (1 - \alpha) \cdot u_{dync}(k) \tag{3}$$

This method is applied to a non-linear, simulated process defined such that the large process gain variations made feedback control very difficult with the objective of good overall control, minimum overshoot and non-oscillatory control action. Simulation results show that clearly good overall control is obtained over the entire process range and the manipulated variable, u, is relatively smooth and does not show any sudden jumps with setpoint changes. This method gave better servo performance when applied to a very non-linear process.

2.3 Model-Based Predictive Control in Fuzzy Cost Function

This kind of MBPC behave the same structure as conventional, the only difference is the objective function as equation is valued by fuzzy goals and fuzzy constraints1[7, 8]. Generally, any other suitable cost function can be used in a objective function of MBFC, but for a quadratic cost function, a linear, time-variant model, and, in the absence of constraints, an explicit analytic solution of the above optimization problem can be obtained. Otherwise, in the presence of nonlinearilities and constraints, a nonconvex optimization problem must be solved iteratively at each sampling period. This hampers the application of nonlinear MBPC to fast systems where iterative optimization techniques cannot be properly used, due to short sampling times and extensive computation times. Iterative optimization usually converge to local minimal, which results in poor solutions of the optimization problem. Fuzzy multi-criteria decision making is an approach that translates objectives and constraints to predictive control in a transparent way. In this kind of MBPC, the decision goals and constraints are defined on the relevant system variables. Both the goals and the constraints are represented by membership functions and the decision making algorithm does not distinguish between them.

In the time domain, specified control objectives of designed controller are usually specified in terms of desired rise time, the overshoot, settling time, steady-state error. Since the model-based predictive control are determined by optimizing an objective function, these control goals must be translated and represented in the function. Two main methods can be distinguish to achieve this goal. In the first method, one expresses explicitly the control goal in the objective function as equation (1). This usually leads to long term predictions of the behavior of the system from which one must determine quantities such as the rise time and the overshoot. If accurate predictions of the system behavior

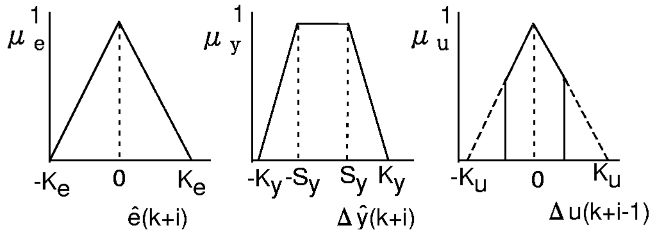

Figure 4: Member ship functions that represent the fuzzy goals

are sought, this method requires highly accurate process models which may not always be available. In the second method, the short-term predictions are used in the objective function. In that case, the overall control objectives must be translated into the short-term objectives. Since this translation is not unique and because it is application dependent, tuning of some parameters in the objective function is usually required.

Kaymak give a example of fuzzy goals which are represented by terms corresponding to the minimization of the output error, the output change, and the change of the control action as figure 4[8]. The minimization of the output error and the control effect are represented by the triangular membership functions $\mu_e(\hat{e}(k+i))$ and $\mu_u(\Delta u(k+i-1))$ around zero as figure 4, which are defined on the respective universes of discourse. When there is a crisp rate constraints on the control actions, this can be represented by suitably modifying the membership function $\mu_e(\hat{e}(k+i))$. The satisfaction of the change in the output is indicated by the trapezoidal membership function $\mu_y(\Delta\hat{y}(k+i))$. Then the fuzzy cost function can be defined as,

$$\begin{aligned} \mu_{\pi'} &= \sum_{i=m_1}^{n_1} (\bar{\mu_e}(\hat{e}(k+i)))^p + \sum_{i=m_2}^{n_2} (\bar{\mu_y}(\Delta\hat{y}(k+i)))^p \\ &+ \sum_{i=m_3}^{n_3} (\bar{\mu_u}(\Delta\hat{u}(k+i-1)))^p \quad p > 0 \qquad (4) \\ \mu_\pi &= \max(0, 1 - \mu_{\pi'}^{1/p}) \quad p > 0, \end{aligned}$$

Compared to conventional MBPC, there are more parameters can be tuned in the fuzzy cost function. Especially for the situation when the additional parameters of the decision function influences the optimization results in a way that cannot be expressed by the weight factors. This proposed method has been applied to a nonminimum phase, open loop linear system and an air conditioning system with nonlinear dynamics. Simulation results show that the predictive control scheme with fuzzy criteria reveals better performance due to the additional flexibility that one obtains for expressing the control goals. Despite the additional number of parameters, tuning the fuzzy criteria is not more tedious than tuning the conventional objective function because of a better understanding of the influence of various parameters.

2.4 Model Predictive Satisfying Fuzzy Logic Control

Conventional optimal control assumes not only that an explicit model of the plant exists, but also that an implicit expert is available to prescribe a cost function that can be solved using optimization methods. Though frequently effective for control design, some problems are not appropriately addressed by optimally-based methods.

There exist problems that can benefit from the best of both optimal and fuzzy approaches to controller design. Considered a subset of such problems where an explicit model of the system exists and an explicit expert is used to transform local model predictions into global evaluations of gains and losses, Goodrich [9, 10]proposed a method called Model Predictive Satisficing Fuzzy Logic Control. This kind of predictive fuzzy is based on an explicit model of the system exists and an explicit expert is used to transform local model predictions into globe evaluations of gains and loss. Such an approach is necessary when complexity and uncertainty prevent precise predictions about global plant behavior, but when useful information is available from local plant predictions.

For the nonlinear system design, satisfying decisions is partitioned into a generalized type of benefit called accuracy and a generalized type of cost called liability. Evaluating the gains and losses of a control action using model predictions is based on the comparative "cost/benefit" structure of A Strongly Satisfying Decision Theory (SSDT). SSDT provides a method by which the accuracy and liability set membership functions can be merged: to avoid error, a decision maker accepts those decisions which are ACCURATE $\mu_A$and NOT LIABLE μ_B. In SSDT, the set of all decisions which cannot be justifiably eliminated is called the satisfying set and is linguistically defined as

SATISFICING=ACCURATE and not(LIABLE)

Consider a discrete time, time-varying single input nonlinear plant of the form

$$x(t+1) = f_1[x(t),t]+f_2[x(t),t]u(t)+g[x(t),t]v(t) \quad (5)$$

where $x(t)$ represents the system state, $u(t)$is the system input, and $v(t)$ is a disturbance. Since modeling is subject to uncertain, it is desirable to develop controllers that work for multiple system models. It is also desirable to develop controllers that operate effectively in the presence of external disturbances v. This research restrict attention to problems for which precise measurements of x are available, thereby focusing emphasis on robustness with respect to nonwhite disturbances as well as with respect to model uncertainty.

A notion of an influence vector $\chi(u)$ is also developed. Then the accuracy cost functional for a single step control horizon as the terminal cost portion of the receding horizon cost is defined as

$$\Phi(u;\theta) = \chi^T(t)P\chi(T) \quad (6)$$

and a liability cost functional for a single step control horizon as the "cost-to-go" portion of the receding horizon cost function is

$$\Lambda(u;\theta) = \chi^T(t)Q\chi(T) + u^T(t)Ru(t) \quad (7)$$

By normaling (6),(7), μ_A and μ_L can be dertamined as

$$\mu_A(u;\theta) = \kappa\Big[\max_{z\in U}\Phi(z;\theta) - \Phi(u;\theta)\Big] \quad (8)$$

$$\mu_A(u;\theta) = \kappa\Big[\Lambda(u;\theta) - \min_{z\in U}\Lambda(z;\theta)\Big] \quad (9)$$

The proposed method is applied to the rotational translation actuator and the inverted pendulum and demostrated robustness properties with respect to model uncertain.

3 Sendai Subway Fuzzy Predictive Control

3.1 Principle of Sendai Subway Fuzzy Predictive Control

Fuzzy logic can also be used to express an agent's goals that can be partially satisfied. In fact, long before the agent paradigm became popular, fuzzy logic had already been successfully used in representing "fuzzy goals". One of the most well known examples of such is Hitachi's Sendai Subway control system uses fuzzy goals to evaluate alternative control decisions. The use of fuzzy goal enables an agent to maximize its overall satisfaction degree by considering options that partially satisfies each individual goal. For example, this is especially useful when an agent needs to deal with multiple goals that are potentially conflicting in nature[5].

Before the Sendai Subway Fuzzy Predictive Control (SSFPC) was proposed[12], almost all of the train operation systems are based on PID control which use an objective pattern of train speed as target shown as figure 5. Cross

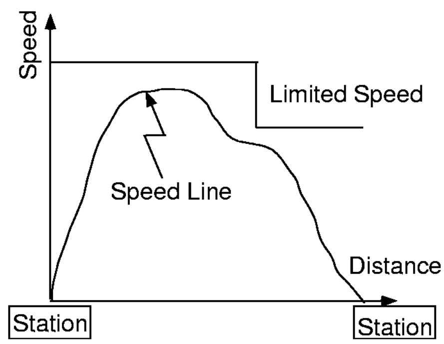

Figure 5: A pattern of the speed of train

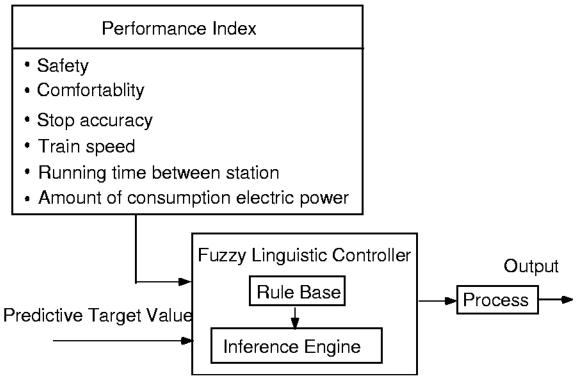

Figure 6: Fuzzy linguistic system derived from multiple performance indices

axis represents the distance between two stations, and spindle represents the train speed. Speed line represents the desirable speed of train between two stations. For the train system, control objective can be described as striving to keep the train speed as the speed line shown as figure 5. The problem of this kind of control system is that in order to keep the train speed as the desirable speed line, speeding up and speeding down occurred frequently, which lead to the uncomfortable for passengers. Besides, many important factors such as safety, stop accuracy and amount of consumption electric power are also not considered.

It was well known for experienced train operators, predictive rules are used when they operate the trains. For example, when the train will stop in the station, they use the experience rule as *If brake now and stop accuracy is good then let us brake*. Based on that, a general fuzzy inference rule of PFC at the interval k can be described as *"if $u(k) \in C_i \longrightarrow y_1(k+i)$ is A_i and $y_2(k+i)$ is B_i then $u(k)$"* $u(k)$ lying to the left of "$\longrightarrow$" is not a fuzzy number, which is a actual manipulate value based on the constraints of control system and the control moment. C_i is a possible manipulated variable set based on the constraints of controlled system and dynamic property of controlled process. The $y_1(k+i)$ and $y_2(k+i)$ lying to the right of "$\longrightarrow$ " are the predictive fuzzy objective functions which can be composed two or more based on the property of process. The meaning of the control rules can be described as *"at the time interval k the manipulate value $u \in C_i$ is applied to the model, if at the predictive interval $k+i$ the control objective A_i is good and B_i is good then at the time interval k the control output is u."*

The architecture of SSFPC is shown as figure 6. SSFPC can reflect most directly the many performance criteria of relevance to the process industries and is capable of utilizing any available process model. The inference process of SSFPC is composed three main concepts: 1.)Explicit use of a model to predict the process output at future discrete time interval. 2.)The control objective is represented by membership function. 3.)At each sampling calculate the future optimal control output period according to predictive fuzzy rules instead of an objective optimal function.

Classical and modern control theory has successfully synthesized optimal control functions based upon one or more cost function [11]. SSFPC behaves strongly robust in two respects: it provides a local mathematical model otherwise not available or difficult to obtain analytically. It can also handle the many performance indices in an adaptive manner.

3.2 Succeeding Work

After SSFPC was successfully used in Sendai subway, SSFPC has been applied to some other nonlinear plant which is difficult for conventional control. The following are some control systems based on SSFPC.

- *Predictive control of a container crane* The container crane control problem is also a multi-objective control problem such as small error in the horizontal position and for a small swing. Control system using SSFPC is used to a actual crane system. Good results are got as expected[13].

- *Swing up Fuzzy Controller for Inverted Pendulum* The inverted pendulum is known as a typical control problems. Because the swing control has strong nonlinearity with the angle of the pendulum, it is difficult to handle the swing up control by the linear control theory. SSFPC is applied to the inverted pendulum that have unknown characteristics such as the length and the mass [14].

- *Predictive Fuzzy Control for Time-delay Nonlinear System* For time-delay nonlinear system, it is difficult to get a good control result by conventional PID controller. Simulation results show SSFPC is also suitable for this kind of controlled plant[15].

4 Concluding Remarks

This paper presents some kinds of Predictive Fuzzy Control Methods. The question which arises from this: which one is better and all these methods are mature enough to be applied to process control in terms of tuning and stability analysis?

In the course of analyzing before, we recognize the fact that there is no unique approach to accomplish our objective. Theoretically speaking, a FLC or fuzzy expert system can exist in any single loop of a multiple-loop control system[11].

On the other hand, fuzzy logic controllers should seek applications where conventional control technologies perform poorly but human operators can do excellent job. The concept of fuzzy control is intuitive and simple, but the tuning is much more complex. By classifying these new architectures, it will trigger new novel design of systems for solving new problems.

References

[1] J.Valente de Oliveira,J.M. Lemos, "Long-range Predictive Adaptive Fuzzy Relational Control," *Fuzzy Sets and Systems*, vol.70, pp.337-357, 1995

[2] D.Clarke, C. Mohtadi and P.Tuffs, "Generalized predictive control," *Automatica*, Vol.23, pp.137-160, 1987.

[3] Carlos E.Garcia, David M.Prett and Manfred Morari, "Model Predictive Control: Theory and Practice —a Survey," *Automatica*, Vol.25, pp.335-348, 1989.

[4] Mary M.Bouke and D.Grant Fisher, "Development of a Fuzzy Relational-Based Predictive Controller," *Advances in Fuzzy Control*, pp.283-315, Physica-Verlag Heidelberg 1998

[5] John Yen, Magy SeifEl-Nasr, Tomas R. Ioerger, "Fuzzy Logic and Intelligent Agents," *1999 IEEE International Fuzzy Systems Conference Proceedings*, vol.1, pp.342-343, Aug. 1999.

[6] D. Saez and A. Cipriano, "Design of Fuzzy Model based Predictive Controllers and its Application to a Inverted Pendulum," *In Proceedings of the sixth IEEE International Conference on Fuzzy Systems*, Vol.2, pp.915-919, 1997.

[7] J. M. Sousa and R. Basuska, "Comparison of Conventional and Fuzzy Predictive Control," *In Proceedings of the fifth IEEE International Conference on Fuzzy Systems*, Vol.3, pp.1782-1787, 1996.

[8] U. Kaymak, J. M. Sousa and H. B. Verbruggen, "A Comparative Study of Fuzzy and Conventional Criteria in Model-Based Predictive Control," *In Proceedings of the sixth IEEE International Conference on Fuzzy Systems*, Vol.2, pp.907-914, 1997.

[9] Michael A. Goodrich, Wynn C. Stirling, and Richard L. Frost, "Model Predictive Satisficing Fuzzy Logic Control," *IEEE Transactions on Fuzzy Systems*, vol.7, pp.319-332, 1999.

[10] Michael A. Goodrich, Wynn C. Stirling, and Richard L. Frost, "A theory of Satisficing Decisions and Control," *IEEE Transactions on Systems, Man, Cybernetics —Part A: Systems and Humans*, vol.28, pp.763-779, 1998.

[11] Paul.P.Wang and Ching-yu Tyan, "Fuzzy Dynamic System and Fuzzy Linguistic Controller Classification," *Automatica*, Vol.30, pp.1769-1774, 1994.

[12] S.Yasunobu, S.Miyamoto and H.Ihara, "Fuzzy Control For Automatic Train Operation System," *Proceeding of the 4th IFAC/IFIP/IFORS Conference*, pp33-39, 1983

[13] S.Yasunobu and T.Hasegawa, "Evaluation of Automatic Container Crane Operation System based on Predictive Fuzzy Control," *Control Theory and Advanced Technology*, Vol.2, pp419-432, 1986

[14] Seiji Yasunobu and Munehito Mori, "Swing up Fuzzy Controller for Invert for Inverted Pendulum Based on a Human Control Strategy, " *1999 IEEE International Fuzzy Systems Conference Proceedings*, Vol.3, pp1621-1625, 1997.

[15] Yongli Huang and Seiji Yasunobu, "A General Predictive Fuzzy Control with Disturbance Rejection Preperty and its Application to the Time-delay Nonlinear System," *Proceedings of the Eighth International Fuzzy Systems Association World Congress*, Vol.1, pp.524-527, 1999.