Huang, Yongli, Yasunobu, Seiji, Cascade Fuzzy Controller Using to Large Scale System, The Transactions of The Institute of Electorical Engineers of Japan, Vol.119-C, No.12, pp.1548-1553, 1999

Paper

Cascade Fuzzy Controller Using to Large Scale System

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Fuzzy control behaves more robustness than conventional control that has been proved by many researches. A problem associated with the design of fuzzy control has been the size of the rule-base. As the number of system variable increases, the number of rules in a conventional complete rule set increases exponentially which will require the computer to process a huge data base, leading to memory overload and longer computational time. To make the problem manageable, cascade structure, in which the number of rules will increase linearly instead of exponentially with the number of system variables is proposed. This makes it possible to apply fuzzy rule based controllers to large scale system. On the other hand, cascade fuzzy controller is also an effective method to achieve a good performance such as robutness for a fuzzy control system. In this paper, the principle of cascade fuzzy controller is analyzed and its possibility and feasibility applying to large scale system have been discussed. Simulation results show the advantages of using the cascade structure fuzzy control to these models.

Keywords: Cascade Fuzzy Controller, Fuzzy Controller, Large Scale System

1. Introduction

One of the main objectives in design of a controller is a concord of the required high performance under species operating conditions, such as stability and robustness. Fuzzy control is proved to be rather robust to any changes in the environment, both for the plant and the controller itself. This feature was considered as one of the main advantages of the fuzzy control on its development. It has been known that robustness is the ability to preserve or to avoid significant decay in the performance after some operating conditions has changed. To achieve this goal two basic ways are widely exploited:

• An adjustment of the fuzzy control parameters after their initial choice that is the adaptive and learning fuzzy controllers.

• An application of special fuzzy control system structures, for example hierarchical or cascade control structures.

Although nearly all control researches treat many of the above-mentioned control structures, the design process is that a given controller corresponds to a given system. Few or nothing is said about the question of which method should be preferred under certain circumstances⁽¹⁾⁽²⁾. Cascade fuzzy control being as one of the important method remains lack a system analysis.

Another motivation to do this research is that in design fuzzy control a problem has been the size of the rule-base. As the number of system variables increases, the number of rules in a conventional complete rule set increase exponentially. That will require the computer to process a huge data base, leading to memory overload and longer computational time. To make the problem manageable, cascade structure, in which the number of rules will increase linearly instead of exponentially with the number of system variables is proposed ^{(3) (4)}. Owning to the cascade fuzzy controller, the number of rules is greatly reduced and makes it possible to apply fuzzy rule based controllers to large scale system.

Raju et al⁽³⁾proposed a multi-level, hierarchically structured controller. This approach ranks the inputs according to an order of influence on the process, which is determined by the system designer. The two most influential state inputs are evaluated in the first level; then, in subsequent levels, the output of the preceding level is evaluated with the next most influential state input. This method was applied to control the feedwater to a steam generator of a power plant. The simulation results show that the hierarchical fuzzy controller yields superior performance over the conventional PID controller. To improve the robust performance Raju et al⁽⁴⁾ also propose an adaptive hierarchical fuzzy control algorithm whose advantages is also proved by M.W.Tsang ⁽¹¹⁾ applying to a laboratory-scale process. A hierarchical multivariable fuzzy controller for learning with genetic algorithms was proposed by D.A.Linkens⁽¹²⁾ on how to design the fuzzy rules. Although they all show the advantage of cascade fuzzy control, the research is specific, no one do the work under what circumstance shows the cascade fuzzy controller should be preferred, that is a cascade fuzzy controller should be applied to what process and how to design it. In the paper the cascade fuzzy control is firstly applied to SISO (simpleinput simple-output) system, then it is extended to large-scale system such as SIMO (simple-input multipleoutput) and MIMO (multiple-input multiple-output) system. The goal of this work is to supply the method on how to design a cascade fuzzy controller on different process and evaluate their advantages. The principle of cascade fuzzy controller is analyzed. For a SISO process the type of processes suitable for a the cascade fuzzy control structure and its construct way is discussed. As one special application of cascade fuzzy control, it is applied to a ball-beam model that is a typical the SIMO system in section 3. For MIMO system, cascade fuzzy control is also an effective decomposition method.

2. The Principle of Cascade Fuzzy Controller

2.1 **Fuzzy Controller** Conceptually, fuzzy controller is a rule-based expert system. Considering a MISO system fuzzy set R, the if-then rule j is of the form:

$$R^{(j)}: IF x_1 is A_{I1}, x_2 is A_{I2}, \cdots x_L is A_{I_L}$$

THEN y is B_j (1)

Where $j = 1, 2, \dots, N$, and N is the number of fuzzy rules, $x_i (i = 1, 2, \dots, L) \in \mathbb{R}^L$ are the input variables of the fuzzy system, $y \in \mathbb{R}$ is the output variable, A_I and B are linguistic terms characterized by the fuzzy membership functions $\mu_{A_I}(x_i)$ and $\mu_B(y)$, respectively. Each fuzzy rule R_j can be viewed a fuzzy implication $A_{I_1} \times \cdots \times A_{I_L}$. Practice has shown that human knowledge in a variety of applications can be formulated in the form(1).

On the other hand, fuzzy control is also a nonlinear map which from the fuzzy sets of the input universe of discourse U_x to the fuzzy sets of the output universe of discourse U_y . In order to use these rules the first question is interpret them to a nonlinear map ⁽⁹⁾. For the fuzzy rule (1), a fuzzy implication can be interpreted as $A_{I_1} \times \cdots \times A_{I_L} \to B_j$ in $U_x \times U_y$ with the membership function determined as

or

where

$$\mu_{A_{I_1} \times \cdots \times A_{I_L}}(x) = \prod_{i=1}^L \mu_{A_{I_i}}(x_i) \quad \dots \quad \dots \quad (4)$$

or

$$\mu_{A_{I_1} \times \cdots \times A_{I_L}}(x) = \min_{1 \ll i \ll L} \mu_{A_{I_i}}(x_i) \quad \dots \dots \quad (5)$$

Let fuzzy set A'_{I_i} in U_x be the input to the fuzzy inference engine and $x = (x_1, \dots, x_L)^T$, then each rule of R_j determine a fuzzy set B_j based on the following sup-min or sup-product compositional rule:

$$\mu_{B_j}(y) = \sup_{x \in U_x} \min[\mu'_{A_I}(x), \mu_{A_{I_1} \times \dots \times A_{I_L} \to B_j}(x, y)]$$
(6)

or

$$\mu_{B_j}(y) = \sup_{x \in U_x} [\mu'_{A_I}(x) \mu_{A_{I_1} \times \dots \times A_{I_L} \to B_j}(x, y)] (7)$$

Now the N fuzzy rules in the form of (1) determine a

mapping from a fuzzy set A'_I in R^L to a collection of N fuzzy sets U_y in R. The defuzzier performs a mapping from fuzzy set to a crisp point y. This mapping is generally chosen as the center average defuzzier:

$$y_{i} = \frac{\sum_{l=1}^{n} y_{l}^{l}(\mu_{B_{l}}(y_{l}^{l}))}{\sum_{l=1}^{n}(\mu_{B_{l}}(y_{l}^{l}))} \quad \dots \dots \dots \dots \dots \dots \dots \dots (8)$$

where y_i^l is the center point in R at which $\mu_{B_i}(y_i)$ achieves its maximum value in the *i*th fuzzy controller.

2.2 The Structure of Cascade Fuzzy Controller From the above analysis, a MISO control system is actually a nonlinear map which connects the input and output. In many studies on fuzzy logic control, only single variable (SISO) control has been considered. In most of these cases the control algorithms involve only two rule antecedents, a state and a change of state, and one consequent a control variable. As a result, the most common approach to multi-variable fuzzy control is to extent the single-variable case by combining more state-variable pairs. This referred to as multiple inference fuzzy control. This approach result in high-dimensional rule-bases that may not be implementable in practical systems. A fuzzy controller, which has L input state variable, each of which can take $R^{j}(j=1,2,\cdots,N)$ fuzzy rules, will comprise a total of $R^1 \times R^2 \times \cdots \times R^N$ rules. On the other hand, if the state variables are fuzzy sets drawn from the same universe of discourse then the total number of rules is R^N . It can be seen from the above that for each additional state variable the number of rules increases exponentially. Cascade fuzzy control is one of the effectiveness method to handle this problem. By this cascade structure, the number of rules will increase linearly. A typical cascade fuzzy controller with m stages is shown as figure 1, where x_0, x_1, \dots, x_m are the inputs of cascade fuzzy controller, y_1, y_2, \cdots, y_m are the outputs for each stage. Fuzzy controller in each stage is in two-input oneoutput. The fuzzy rule in each stage can be expressed as:

Stage 1:

$$IF x_0 is A_{I_0}^1 and x_1 is A_{I_1}^1 THEN y_1 is B_1$$

 $IF x_0 is A_{I_0}^n and x_1 is A_{I_1}^n THEN y_1 is B_n \quad \cdot \quad (9)$

Stage
$$i (i = 2, 3, \dots, m)$$
:

IF
$$y_{i-1}$$
 is $A_{I_0}^1$ and x_i is $A_{I_1}^1$ THEN y_i is B_1

$$IF y_{i-1} is A_{I_0}^n and x_i is A_{I_1}^n THEN y_i is B_n$$
(10)

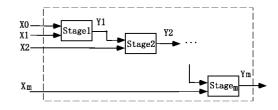


Fig. 1. The cascade fuzzy controller

Because there is no a general method to adjust the parameters of a fuzzy controller, turning the cascade fuzzy controller is more difficult lies in there are more parameters should be turned. The design examples are turned as follows ⁽¹³⁾:

• The rule is initialized using knowledge on the system;

• Input scaling factors are equivalent to normalization gains. It is easy to know the maximal values of the input variables by means of the reference model.

• Output scalings are initialized by the characteristics of the process and the physical limitations.

• The membership functions are triangular and regularly spaced onto a normalized universe of discourse. Then the membership function was turned by SQP(Sequential Quadratic Programming)⁽¹³⁾.

3. Plants Suitable for Cascade Fuzzy Control

3.1 SISO System For a SISO system if the intermediate signal is available, a cascade control system can be constructed as figure 2. Cascade Fuzzy controller is composed two fuzzy controller control1 and control2. The feedback of controlled goal is on the outside loop and the feedback of the other intermediate state of the model is used as the inside loop. The plant is divided into two parts P_1 and P_2 . The property of this cascade fuzzy controller is the influence of disturbance d and the dynamic of plant P_1 can be restrained by the inside feedback before it affect on the outside feedback. So it can achieve more precisely control goals with a reference model expressing the desired dynamical performance. For a SISO plant, two conditions are necessary to design a cascade fuzzy controller. One is the plant can be divided P_1 and P_2 suitably and its intermediate signal is available. The other is the inside feedback behave a rapid response than the outside feedback.

A laboratory liquid level regulation system that simulates plant widely involved with dairy chemical or heat-

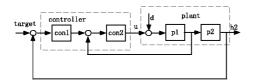


Fig. 2. The structure of cascade fuzzy controller for SISO System

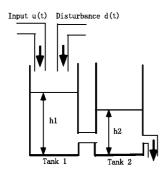


Fig. 3. The structure of tank model

Table 1. rule base of fuzzy controller1

е	Ν	Ζ	Р	
u	Ν	Ζ	Р	

Table 2. rule base of fuzzy controller2

ė∖e	Ν	Z	Р
N	NB	NS	ZO
Z	NS	ZO	PS
Р	ZO	\mathbf{PS}	PB

balancing process is used as the design example $^{(5)}$. It is a coupled nonlinear system as figure 3 and described by the state-space differential equation set:

$$\begin{bmatrix} \dot{h}_1 \\ \dot{h}_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{A} & \frac{1}{A} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ d \end{bmatrix} + \begin{bmatrix} \frac{-\frac{C_1 a_1}{A}}{\sqrt{2g(h_1 - h_2)}} \\ \frac{C_1 a_1}{A} \sqrt{2g(h_1 - h_2)} - \frac{C_2 a_2}{A} \sqrt{2g(h_2 - h_0)} \end{bmatrix}$$
(11)

Here, $h_1(t)$ and $h_2(t)$ are the liquid levels of tank1 and tank2, respectively; u(t) is an input flow rate mapped from a pump voltage; d(t) is also a pumped input but is used to test the rejection of disturbance when need; C_1 and C_2 are discharge constants; a_1 and a_2 are orifice areas; A is the cross-sectional area of both tanks; and g is the gravitational constant. There are two practical constants imposed on this system. One is by its physical structure, the minimum liquid level bounded by the

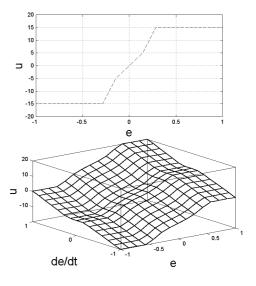


Fig. 4. The control surface of two fuzzy controllers

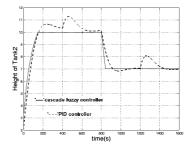


Fig. 5. The response result of cascade fuzzy controller $% \left[{{{\rm{cont}}} \right]_{\rm{cont}}} \right]$

height of the orifices. The other is by the upper limit of the pump capacity.

The parameters of tank system are following: $C_1=C_2=0.58; a_1=0.976 \text{ cm}^2; a_2=0.386 \text{ cm}^2; A=100 \text{ cm}^2;$ $g=981 \text{ cm}^{-2}; h_0=3 \text{ cm}; max(u)=33.3 \text{ cm}^3 \text{ s}^{-1}.$

The objective of this control system is to drive, through the input to tank1, the liquid level at tank2 towards the desired level of 10 cm as fast as possible with minimal overshoot and steady-state error. Subsequently a step- down command of 5cm is given at 800s. A disturbance inflow of $8 \text{ cm}^3 \text{s}^{-1}$ is added at 400s and 800s respectively.

Based on its the property, this model can be divided two parts tank1 and tank2 and the liquid level of tank1 is being as the intermediate feedback. Fuzzy controller1 is a one-input one-output controller composed by 3 rules. Fuzzy controller2 is two-input one-output with 9 rules. The rule base is in table 1 and table 2 respectively. This cascade controller only uses 12 rules. After turning, the control surfaces of the two controllers are as figure 4. The simulation result is as figure 5. Compared PID controller, the cascade fuzzy control behaves high performance, especially robustness.

3.2 **SIMO system** The SIMO system is thought as one type of special plant lies in that these plants are an uncontrollable problem in control theory which the controllability matrix does not exist due to the number of variables to control is greater than the number of the controlling input. There is this kind of models such as a nonlinear cart-ball balancing (CBB) system ⁽⁵⁾, the translational oscillations with a rotational actuator (TORA) system⁽⁶⁾ and the ball-and-beam (BB) dynamical model system⁽⁷⁾. A fuzzy control system can successfully control this classically uncontrollable system has been reported^{(8) (13)}.

It has been proven⁽¹⁴⁾⁽¹⁵⁾conventional fuzzy controllers is one type of PID controller. The vast majority of fuzzy controllers are limited to systems with predominantly second-order dynamics. For higher order system, the system may not be stabilized by a conventional fuzzy controller.

In the design of a fuzzy logic controller for this kind

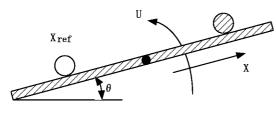


Fig. 6. Ball and beam system.

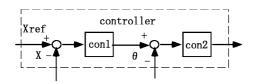


Fig. 7. The cascade fuzzy controller for ball-beam system

system, it is important to identify appropriate decision variables that constitute to an effective control action. This kind of systems also has the same property that they two or more controlled objects, but there is only one nonzero object. The multi-output whose object values are zeros can also be regarded as the intermediate state of plants. That is why the cascade fuzzy control is an effective method to handle this problem.

In our primitive work $^{(13)}$, this cascade fuzzy controller has been applied to a ROTA system and it had been proven that it has better performance than a conventional cascade controller. A systematic design method for the cascade fuzzy control design is also given in that paper. In this paper, as an example of control design, the cascade fuzzy control is applied to the ball-andbeam. Its schematic is as figure 6 ⁽⁸⁾.

The dynamics of this system are:

$$1.4\ddot{x} = x\dot{\theta}^2 - g\sin\theta$$

$$(\psi + m^2)\ddot{\theta} = -2mx\dot{x}\dot{\theta} - mgx\cos\theta + U \quad \cdots (12)$$

Where the parameters of the beam being: the rotational inertia of the beam $\psi=0.0079 \text{ kg m}^2$, the acceleration due to gravity is $g=9.8 \text{ m/s}^2$, the mass of the ball assumed to be a solid sphere m=0.01679 kg. Further, due to physical constraints the states are limited as fol-

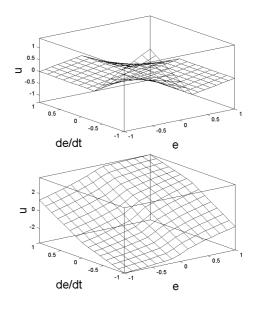


Fig. 8. The control surface of two fuzzy controllers

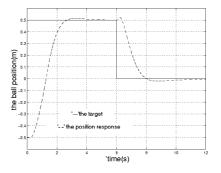


Fig. 9. The ball-beam control response.

lows: due to the beam being 1 m, |x| < 0.5 m, and due to the mounting of the beam, $|\theta| < 0.5 \text{ rads}$.

The cascade fuzzy controller is composed two fuzzy controllers as figure 7. Each of the fuzzy controllers is composed of two-input two-output which has the same rule base as table2. The cascade fuzzy controller only uses 18 rules. After turning, the fuzzy control surface as figure 8. The objective is to force the ball's actual position to correspond to the desired position. When the target position is given as -0.5 m to 0.5 m at 0 s and 0.5 m to 0 m at 6 s, the control result is as figure 9.

3.3 **MIMO system** In a large scale system, there is such a high interaction between the controlled variables that a multi-input multi-output control structure is needed. A typical multivariable fuzzy control system with L inputs and M outputs can be described as:

$$R^{(j)} : IF x_1^{(j)} is A_{I1}, x_2^{(j)} is A_{I2}, \cdots x_L^{(j)} is A_{I_L}$$

THEN $y_1^{(j)} is B_{I1}, y_2^{(j)} is B_{I2}, \cdots y_L^{(j)} is B_{I_M}$ (13)

Where $j = 1, 2, \dots, N$ is the number of fuzzy rules. If the outputs $y_1^{(j)}, y_2^{(j)}, \dots, y_m^{(j)}$ are independent variables, the MIMO controller can be separated in a set of MISO system as (1) which could lead to the implementation of a controller. Unfortunately, in most real case the assumption of independent output variable is not impossible.

Much fuzzy decomposition methods have been proposed which is divided to passive decomposition, active decomposition and direct decomposition ⁽¹⁸⁾. The passive decomposition method is composed of cascade fuzzy controllers. When the system has a two-input two-output structure, the controller can be constructed by two sets of cascade fuzzy controller as figure 10. It has being proved that this controller is functionally equivalent to a multiple input fuzzy controller⁽¹⁰⁾ (⁽¹⁷⁾).

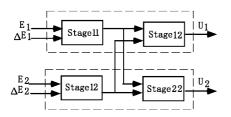


Fig. 10. An example of MIMO cascade fuzzy controller.

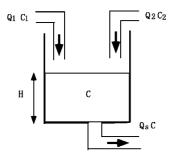


Fig. 11. Scheme of the mixing tank.

Validation of the MIMO cascade fuzzy controller method has been done on an academic example: a twoinput two-output mixing tank ⁽¹⁶⁾. The process consists of mixing streams of two flow liquids in a continuously stirred tank. A schematic of the system is given in figure 11.

The control inputs are the two flow rates Q_1 and Q_2 . C_1 and C_2 are respectively the concentrations of two inputs. The output liquid has a flow rate Q_s and a concentrations C. The regulated outputs are the tank level H, and the tank concentration C. The non-linear model of the process is:

$$\frac{dH}{dt} = \frac{Q_1}{S} + \frac{Q_2}{S} - \frac{1}{S}\sqrt{H}$$
$$\frac{dC}{dt} = \frac{1}{H} \left(\frac{Q_1}{S} \left(C_1 - C\right) + \frac{Q_2}{S} \left(C_2 - C\right)\right) \quad (14)$$

Where $C_1=1$ mole/l and $C_2=2$ mole/l, S=1 m² is the section of the tank. Based on figure 10, two control input are $E_1=H$ and $E_2=Q$. $U_1=Q_1$ and $U_2=Q_2$ are two control outputs, each of four fuzzy controllers use the same fuzzy rule base as table2. The fuzzy control surface of stage11 and stage12 are in figure 12.

When the first operating point is in $H_0=1$ m, $C_0=1.25$ mole/l, $Q_10=15$ l/s and $Q_20=5$ l/s, two process are carried to evaluate the control performance. First, regulate the tank level point. Keep the tank concentraction in $C_0=1.25$ mole/l, change the tank level from $H_0=1$ m to H=1.1 m, the control result is in figure 13. Then regulate the tank concentration level point. Keep the tank height, the constrastion is from $C_0=1.25$ mole/l to C=1.26 mole/l, the control result is in figure 14. The fuzzy control results in same situation are also shown in the same figure.

4. Conclusion

In the paper, the principal of cascade fuzzy control is analyzed and its possibility and feasibility to SISO,

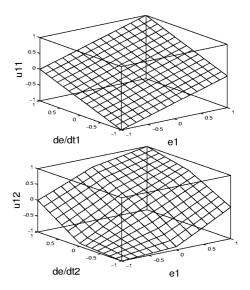


Fig. 12. The control surface of stage11 and stage12.

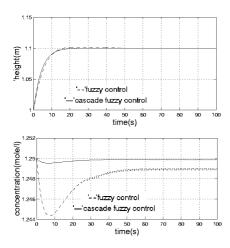


Fig. 13. The tank concentration change when the tank height have a change 0.1 m.

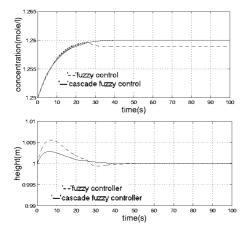


Fig. 14. The tank level change when the tank concentration have a change 0.01 mole/l.

SIMO and MIMO system are discussed. Simulatiom exhibit when a cascade fuzzy control is applied to a SISO process, it can improve the control performance especially the robustness. It also has been proven that it is the most suitable method for a SIMO system. The composition of cascade fuzzy control is also a useful method to handle the MIMO system. These results show the cascade fuzzy control is a good method to get a robutness for a large scale system.

(Manuscript received February 4, 1999)

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