DERIVATION OF FUZZY CONTROL RULES FROM HUMAN OPERATOR'S CONTROL ACTIONS

T. Takagi and M. Sugeno

Department of Systems Science, Tokyo Institute of Technology 4259 Nagatsuta, Midori-ku, Yokohama 227, Japan

Abstract.

So called fuzzy control has been developed for the purpose of realization of a man-like controller with the aid of computer. However, most of fuzzy controllers have two very important problems. First is a defect of the reasoning algorithm. Second is a way to acquire control rules, particulaly the precise parameters in the rules. In this paper considering the above problems, we propose a realistic fuzzy reasoning algorithm and a method to identify control rules from human operator's actual control actions. Further we examine the performance of the proposed algorithm by applying it to water cleaning process control.

Keywords. Identification; Industrial control; Fuzzy Reasoning; Fuzzy Control; Modelling

1. INTRODUCTION

Among many fields related to fuzzy theory, fuzzy control is one of the most interesting fields since we have many real situations where fuzzy control is effectively applicable. As far as fuzzy control is concerned, we have had many theoretical and experimental studies so far. We can say that we are now prepared to deal with practical control problems. For instance a fuzzy controller for cement kiln control has been developed by F. L. Smidth Co.[2].

However there still remain some important problems, practical rather than theoretical.

1) fuzzy reasoning as a tool to describe processes
2) derivation of fuzzy control rules
3) design of conversational fuzzy controller
4) experience of real apllications

This paper discusses the first two problems from a practical point of view. It presents a very simple method of fuzzy reasoning for both fuzzy control and fuzzy modelling, and shows how to derive fuzzy control rules from human operator's control actions by using real data.

2. A SIMPLIFIED METHOD OF FUZZY REASONING

2-1 Some Problems of Past Reasoning Methods

Ordinary fuzzy reasoning is characterized by two parts: choice of unimodal fuzzy variables as are shown in Fig. 1 and fuzzy relational composition. There is a composition-like method used in practice but it is not so different from an ordinary one anyway. This reasoning method has some difficulties when we apply it especially to control problems.

In fuzzy control we use fuzzy implications called control rules such as

$$x \text{ is } A_1 \text{ and } y \text{ is } B_1 \rightarrow z \text{ is } C_1 \qquad (1)$$

$$x \text{ is } A_2 \text{ and } y \text{ is } B_2 \rightarrow z \text{ is } C_2, \text{ etc.}, \qquad (2)$$

where the problem is to infer "z is z_0" from a given premise "x is x_0" and "y is y_0".

We shall denote the membership function of a fuzzy variable A by A(x) in the sequel. The difficulties arise in the following parts.

First, if we choose fuzzy variables shown in Fig. 1, it is very difficult to distinguish two points x_0 and x_1 where $A_1(x_0) = A_1(x_1)$. To overcome this difficulty, we have to choose many variables such as "very small", "small", "medium" and so on.

Secondly, perhaps due to the above reason, if we use fuzzy relational composition, in general many control rules are necessary with respect to each dimension of the premise as has been seen in the past studies of fuzzy control. Suppose five fuzzy variables at one dimension, then the number of control rules in case of n-dimensions becomes 5^n. It causes a big problem in practical application, of course.

Finally, if we look at ordinary fuzzy reasoning as a mathematical tool to describe processes, it is not so powerful partly because of its nonlinearity. Suppose that we are given an underlying relation among three variables such as

$$z = ax + by. \tag{3}$$

Choose fuzzy variables A_1 and A_2 for x, B_1 and B_2 for y, then we can obtain by simple calculation of fuzzy numbers

$$C_{ij} = aA_i + bB_j, \tag{4}$$

$$i = 1,\ 2 \text{ and } j = 1,\ 2.$$

Then we have four implications

$$x \text{ is } A_i \text{ and } y \text{ is } B_j \rightarrow z \text{ is } C_{ij} \tag{5}$$

and from these follow fuzzy relations R_{ij}. The whole relation is given by

$$R = \bigcup_{i,j} R_{ij}. \tag{6}$$

Now given a premise "x is x_0 and y is y_0" where x_0 is located between A_1 and A_2, y_0 between B_1 and B_2, the value of z is inferred as a fuzzy number with the membership function $R(x_0, y_0, z)$ which is not equal to the expected value, i.e., $z_0 = ax_0 + by_0$ even if we take the value of z maximizing $R(x_0, y_0, z)$.

2-2 Format of Implications

The implication R we suggest in this paper is of the format

$$R : \text{If } f(\ x_1 = A_1,\ \cdots\cdots,\ x_k = A_k\ )$$
$$\text{then } y = g(\ x_1,\ \cdots\cdots,\ x_k\ ) \tag{7}$$

where each variable have following meaning.

- y : variable of the consequence whose value is inferred.
- $x_1 - x_k$: variables of the premise that appear also in the part of the consequence
- $A_1 - A_k$: fuzzy sets representing the area in which the rule R should be applied for a reasoning corresponding to $x_1 - x_k$, respectively.
- f : logical function defining the proposition of the premise.
- g : function which implies the value of y when $x_1 - x_k$ satisfy the premise condition.

Example

$$R : \text{If } x1 = \text{small and } x2 = \text{big}$$
$$\text{then } y = x1 + x2 \tag{8}$$

This implication states that if x1 is small and x2 is big, then the value of y would be equal to the sum of x1 and x2.

2-3 Algorithm of Presented Fuzzy Reasoning

The authors have suggested a method of multi-dimensional fuzzy reasoning[4] based on Lukasiewicz logic where fuzzy variables are assumed to have monotone membership functions which do not cause the case as $A_1(x_0) = A_1(x_1)$ for $x_0 \neq x_1$. The method enables one to represent any linear relation by using, for example, four implications in two dimensional case.

Now we suggest a simplified method of reasoning by developing the above idea. For the sake of simplicity, especially from a practical point of view, all the fuzzy variables are assumed to have linear membership functions.

Suppose that we have implications R^i ($i = 1, \cdots, n$) of the above format. When we are given

$$(\ x_1 = x_1^{\,o},\ \cdots\cdots,\ x_1 = x_k^{\,o}\ )$$

where $x_1^{\,o} - x_k^{\,o}$ are singletons, the predicted value of y is inferred in the following steps.

1) For each implication R^i, the value of y^i is calculated by the function g^i concerned with the consequence

$$y^o = g^i(\ x_1,\ \cdots\cdots,\ x_k\ ) \tag{9}$$

2) The truth value of the proposition

" $y = y^i$ " is calculated by the equation

$$/\ y = y^i\ / = /\ f^i(\ x_1^{\,o} = A^i_{\ 1},\ \cdots\cdots,\ x_k^{\,o} = A^i_{\ k}\ )\ /\ \wedge\ /\ R^i\ / \tag{10}$$

where /*/ means the truth value of proposition *. The truth value

$$/\ f^i(\ x_1^{\,o} = A^i_{\ 1},\ \cdots\cdots,\ x_k^{\,o} = A^i_{\ k}\ )\ /$$

is found according to the logical function f^i as a function of $/\ x_1^{\,o} = A^i_{\ k}\ /$, $\cdots\cdots$, $/\ x_k^{\,o} = A^i_{\ k}\ /$, where

$/\ x^o = A\ / = A(x^o)$,

i.e., the grade of the meambership of x^o.

It has been reported by Tsukamoto [5] that the value suggested in equation (10) is the least estimation of the truth value of the consequence in Goguen's multivalued logic.

For simplicity in this paper we assume

$$/\ R^i\ / = 1, \tag{11}$$

so the truth value of consequence is obtained as

$$/\ y = y^i\ / = /\ f^i(\ x_1 = A^i_{\ 1},\ \cdots\cdots,\ x_k = A^i_{\ k}\ )\ / \tag{12}$$

3) The final output y infered from n implications is calculated as the weighted average of all y^i's with the weights $/ y = y^i /$:

$$y = \frac{\sum / y = y^i / \times y^i}{\sum / y = y^i /}$$

$$= \frac{\sum /f^i(x_1 = A^i{}_1, \cdots\cdots, x_k = A^i{}_k)/ \times g^i(x_1, \cdots\cdots, x_k)}{\sum /f^i(x^i = A^i 1, \cdots\cdots, x_k = A^i{}_k)/} \tag{13}$$

Example

Suppose that we have the following three implications,

R^1 : IF x_1 = $small_1$ and x_2 = $small_2$

then $y^1 = x_1$ (14)

R^2 : If $x_1 = big_1$

then $y^2 = 2 \times x_1$ (15)

R^3 : If $x_2 = big_2$

then $y^3 = 3 \times x_2$ (16)

Table 1 shows that reasoing process by each implication when we are given $x_1 = 12$, $x_2 = 5$.

The column "Premise" in Table 1 shows the membership functions of the fuzzy sets small and big in the premises. The column "Consequence" shows the value of y^i calculated by the function g^i of each implication and "Tv" shows the truth value of $/y = y_i/$ which is calculated, according to the logical connective in the premise. For example,

$$/ y = y^i / = / x_1{}^o = small_1 / \wedge / x_2{}^o = small_2 /$$

$$= small_1(x_1{}^o) \wedge small_2(x_2{}^o)$$

$$= 0.25 \tag{17}$$

The value inferred by the implications is obtained

$$y = \frac{0.25 \times 17 + 0.2 \times 24 + 0.375 \times 15}{0.25 + 0.2 + 0.375}$$

$$\approx 17.8 \tag{18}$$

3. DERIVATION OF FUZZY CONTROL RULES

3-1 Three Types of Derivation

There are, in general, four methods to derive fuzzy control rules. We shall briefly discuss them. In this paper we deal with the third one.

1) based on operator's experiance and/or control engineer's knowledge

Most of the reported fuzzy controllers have been designed by this method[3]. One of those aspects are hueristics, trial and error, or something like that. So the method is not always generalized nor formalized up to so called a design procedure of a fuzzy controller.

Here we just mention the following. Sometimes we face the fact that an operator cannot tell linguistically in details why he takes such and such a control action in some particular situation.

2) based on the fuzzy model of a process

Some studies[1, 4] have been reported on this basis. The idea itself is nothing but what is adopted in classic or modern control theory. So it seems to be very desirable and could be said logical in a sense. It also provides a way to theoretically analyse fuzzy control systems. A problem here is concerned with a method of fuzzy identification of a process by which we mean parameter identification in a fuzzy model. We need to this purpose a general mathemataical tool to describe a process just like a linear equation. The method of fuzzy reasoning discussed in this paper has been developed also under this respect.

3) based on operator's control actions

First let us notice that deriving fuzzy control rules is the same as making a fuzzy model of operator's control.

If we have a way to express a human operator's control actions by a set of fuzzy control rules, this method becomes very useful when operation data are available. Fortunately in cases where computer control is planned in place of human control it is easy to obtained a lot of data concerned with operator's control actions. To the aim of identification we have to make a format of a control rule, and reduce the problem to parameter identification.

4) based on leraning

Theoretically the self-organizing design of a fuzzy controller[6] is vary interesting. There are, however, is many difficulties in applying this method to industrial process except the case where experiments using real plants are possible.

3-2 Algorithm to Derive Control Rules

Now let us consider an algorithm of the identification. The format of a control rule is the same to that previously discussed.

When a set of data $(x1j, x2j, \cdots\cdots, x_kj) \rightarrow yj$ ($j = 1, \cdots, n$) is given, the outline of the algorithm is the following.

1) Divide fuzzily k-dimentional space concerned with the variables $x_1 \sim x_k$ into some number of areas. It is performd by human operator's or engineer's knowledge, e.g., what type of propositions to be set for instance, $A_1(x_1)$ incresing, $A_2(x_2)$ decreasing so and so. These areas mean the premises of rules. In each area the following three steps are performed.

2) Form the logical function f and calculate the truth value

$$/ f(x_1 = A_1, \cdots\cdots, x_k = A_k)/$$

corresponding to each data $x_{1j} - x_{kj}$ ($j = 1, \cdots, m$) available in this area, which is called a weighting factor w_j to j-th datum.

3) Calculate the parameters $p_0, \cdots\cdots, p_k$ in equation (19) by the weighted linear regression analysis using the data with weighting factor w_j.

$$y = p_0 + p_1 \times x_1 + \cdots\cdots + p_1 \times x_k \quad (19)$$

4) Rule R in this area is finally expressed as

$$R : \text{If } f(x_1 = A_1, \cdots\cdots, x_k = A_k)$$

$$\text{then } y = p_0 + p_1 \times x_1 + \cdots\cdots + p_k \times x_k \quad (20)$$

The weighted regression is derived from natural extension dividing the input space into fuzzy subspaces instead of crisp ones.

Other methods deriving control rules roughly discussed above are desirable to be combined with each other since for instance the obtained data may not always cover the whole control area: in some area there may be no data or few for identifidation.

4. FUZZY MODELLING OF HUMAN OPERATOR'S CONTROL ACTIONS

4-1 Water Cleaning Process

We shall now show a real example where operator's control actions are fuzzily modelled.

The control process is a water cleaning process for civil water supply as is illustrated in Fig. 2. In the process, turbed river water first comes into a mixing tank where chemical products called PAC and also chlorine are put and mixed in the water. Then the mixed water flows into a sedimentation tank where the turbed part of water is cohered with the aid of PAC and settled to the bottom. After sedimentation which takes about 3 - 5 hours depending on the capacity of the tank, the treated water finally flows into a filtration tank producing clean water. Chlorine is put only for sterilization of water.

The main control problem of a human operator in this process is to decide the amount of PAC to be put so that the turbidity of the treated water is kept below a certain level. There is the optimal amount not too little nor much depending on the properties of the turbed water. The amount of PAC must be controlled also from an economical point of view.

The process is characterized by a lack of physical model, thus the great importance of operator's experience, big change of the turbidity of river water and the fact that turbidity itself is not clearly defined nor accurately measured.

However, a number of variables influencing sedimentaion process have been found so far which can be measured. Let us first list up all the variables concerned.

TB1 : turbidity of the original water(ppm)
TB2 : turbidity of the treated water(ppm)
PAC : amount of PAC(ppm)
TE : temparture of water(°C)
PH : pH
AL : alkalinity
CL : amount of chlorine(ppm)

For example if TE is lower, then PAC is more necesarry. Both PH and AL affect nonlinearly the necessary amount of PAC. The optimal PAC depends on these variables: the relation among them is not clear. There are some other variables influencing the process, e.g., plankton in the river water which increases in Spring time but cannot be measured at present.

In most of water cleaning plants a statistical model has been built. However the models are are not accurate. These cover only steady state, i.e., a small range of TB1. TB1 increases for example 100 times more when it rains. So an operator controls PAC taking into account of TB1, TE, PH, AL, TB2. Now our process can be illustrated as in Fig. 3.

4-2 Decision of Conrol Rules

The authors have got a lot of operation data where all the variables are measured every hour for four months. That is, the number of data is 24 hours x 30 days x 4 months = 2880. Table 2 shows a part of them.

Among the data we have used about 600 for the identification which are taken in June and July. June in Japan is a rainy season and July is summer.

According to the identification algorithm discussed previously, 64 control rules are derived which can be called a fuzzy model of operator's control as is stated, where a control rule is of the form

(TB1, TB2, PH, TE) → PAC (21)

where AL is omitted for simplicity. Some of them are shown in Fig. 4.

4-3 Results of Fuzzy Control

The results obtained from a fuzzy model are shown in Table 3 as well as operator's control and the results of a statistical model. Table 2 shows that an operator's control actions are well modelled in the form of fuzzy control rules.

We have divided the original data set into two sets; identifying data and testing one. The testing data is used as we can test the performance of the identified rules in various cases.

The statistical model is represented in equation (22) that is often used in water cleaning process.

$$D = 9.11\sqrt{TB1} - 79.8pH + 12.7Cl + 1255.6 \quad (22)$$

The average of absolute differences between operator's action and the results of fuzzy model, and statistical model for 38 testing data are

fuzzy model	:	72.6
satatistical model	:	128.0

These results show the excellence of the fuzzy model.

5. CONCLUSIONS

The authors started this work to implement a fuzzy controller in a water cleaning plant. To this aim it is necessary to derive control rules from operator's control actions since we faced the fact that operators could not tell well what they ware doing when they ware interviewed.

In this paper we have presented a fuzzy reasoning algorithm and a rule identification algorithm based on the operator's control action's. Further applying these algorithms to the control of water cleaning process we have observed the efficiency of the proposed methods.

The algorithm for deriving control rules still depends partly on try and error. Both theoretical study and experience are necessary to systemize it.

The suggested method concerned with reasoning has been developed as a general tool for fuzzy modelling of a sytem. To this respect fuzzy modelling of a dynamical system is now also under consideration.

REFERENCES

[1] Braae, M., and D. A. Rutherford (1979). Theoretical and Linguistic Aspects of the Fuzzy Logic Controller, Automatica, 15, 553-557

[2] Holmblad, L. P., and J. J. Ostergaard (1982). Control of a Cement Kiln by Fuzzy Logic, in Fuzzy Information and Decision Process (M. M. Gupta and E. Sanchez eds.) North-Holland

[3] Mamdani, E. H., and S. Assilian (1975). An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller, Int. J. Man-Mach. Stud., 7, 1-13

[4] Sugeno, M. and T. Takagi (1982). A New Approach to Designe of Fuzzy Controller, in Advances in Fuzzy Set Theory and Applications, (P.P Wang ed.) Plenum

[5] Tsukamoto, Y., (1975). An approach to fuzzy reasoning method, in Advances in Fuzzy Set Theory and Applications (M.M. Gupta ed.), pp 407-428

[6] Yamazaki, T., and E. H. Mandani (1982). On the Performance of a Rule-based Self-organising Controller, Proc. of IEEE Conf. of Applications of Adaptive and Mutivariable Control, Hull

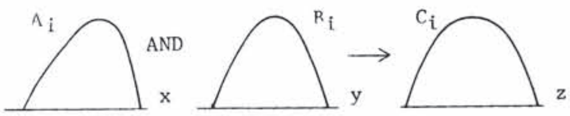


Fig. 1. Ordinary Fuzzy Implication

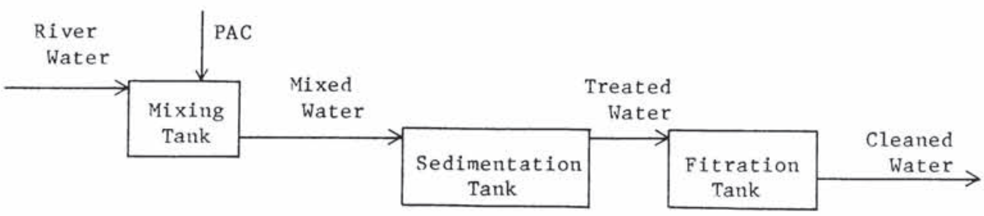


Fig. 2. Water Cleaning Process

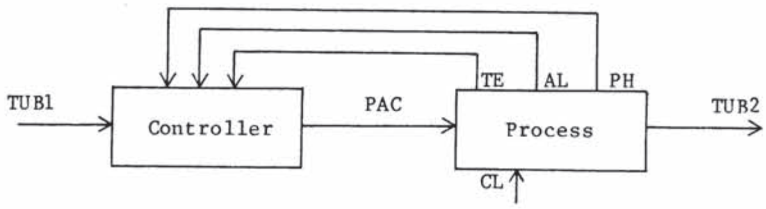
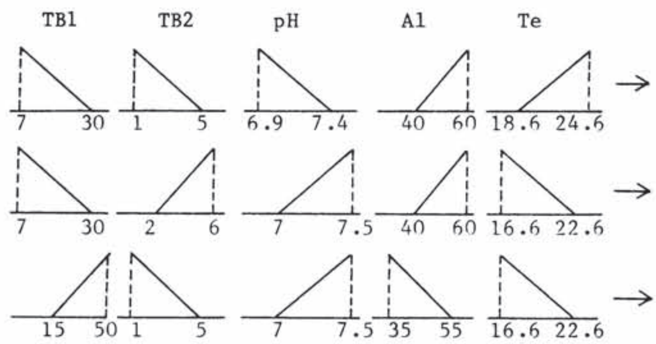


Fig. 3. Diagram of Control Process



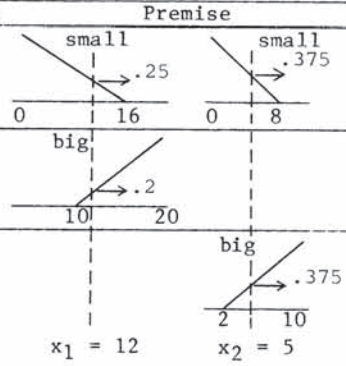
$D = 21.5TB1 - 0.7TB2 + 242.6\,pH - 1.7Al - 28Te - 370.4$

$D = 9.7TB1 - 40.1TB2 + 934.5pH - 11.8Al + 7.8Te - 5369.4$

$D = 13.8TB1 - 49.8TB2 + 650.2pH - 8.2Al + 23.7Te - 3806.1$

Fig. 4. Example of Control Rules

TABLE 1 Reasoning Algorithm



Rule	Premise	Consequence	Tv
R1		$y = 12 + 5 = 17$	$.25 \wedge .375 = .25$
R2		$y = 2 \times 12 = 24$	.2
R3		$y = 3 \times 5 = 15$	.375

TABLE 2 Operation Data

TUB1	PH	TE	PAC	TUB2
10.0	7.1	18.8	1300	1.0
17.0	7.0	18.6	1300	1.0
22.0	7.3	19.4	1400	2.0
50.0	7.1	19.5	1400	1.0
9.0	7.3	23.3	900	4.0
11.0	7.1	20.7	900	1.0
12.0	7.2	21.3	900	3.0
14.0	7.2	23.6	900	4.0
35.0	7.0	17.8	1200	1.0
20.0	7.0	16.6	1100	1.0
20.0	6.9	17.8	1100	1.0
18.0	7.1	17.3	1100	1.0
12.0	7.2	18.8	900	3.0
8.0	7.2	18.0	1000	1.5
11.0	7.1	19.2	1000	2.0
50.0	7.0	18.0	1200	1.5
35.0	7.0	17.7	1200	1.5
30.0	7.0	17.3	1100	1.5
16.0	7.1	19.3	1100	3.0

TABLE 3 Result of Fuzzy Control

Operator	Statistical Model	Fuzzy Model
1300	994.7	1105.7
1300	995.9	973.5
1300	1119.6	1102.0
1400	1151.1	1242.0
1400	1409.4	1472.4
900	1066.4	920.1
900	1068.9	952.5
900	1012.3	865.9
1200	1286.8	1171.7
1200	1246.8	1154.3
1100	1151.4	1131.4
1100	1199.5	1145.6
1100	1159.4	1114.2
1000	985.7	930.2
1000	1009.3	941.6
1000	1038.2	940.7
1200	1398.3	1219.6
1200	1290.6	1164.3